Supporting firefighter training through visualising indoor positioning, motion and time use data

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ABSTRACT

Providing feedback to smoke divers following their training exercises is constrained by limitations on the opportunities for observation by instructors, as the buildings are filled with smoke. Yet, sensors that can be used to track and provide data on various aspects of the smoke divers training are becoming available. This paper describes a study of how to support firefighters and their instructors with visualisations of their training performance. The study has involved the development of a training support tool, FireTracker, that visualises data from firefighters smoke diving activity, and an evaluation of FireTracker in use. FireTracker uses data from sensors such as Bluetooth Beacons and gyroscopes to detect and visualize the smoke diver's movement and work patterns during smoke diving exercises. We found that there is a training need for these visualisations, but clear limitations on the positioning data that currently can be provided.

Keywords

Smoke diver training, multimodal data, data visualisations

INTRODUCTION

Global satellite navigation systems (GNSS) have become widespread, providing positioning data from several, separate yet combinable (Zhang et al. 2013) systems for the general public, and there are a plethora of applications and systems that build on them. GNSS data are not suitable for indoor localisation, however, mainly because of the need for skywards line-of-sight to obtain data, and data disturbances caused by presence of buildings (Yassin et al. 2017). Indoor positioning technologies (IPS) are still developing. While GNSS systems work more or less the same way, IPS systems are technologically much more diverse and rapidly changing (Brena et al. 2017; Liu et al. 2007), and the ideal IPS technology depends on the purpose and use situation. This study represents an endeavor to utilise IPS enhanced by additional sensor data, to visualise indoor movement and work performed by smoke diver during training exercises, with the purpose enhancing the post-exercise evaluations.

This paper describes the development and evaluation of a tool, FireTracker, that provides data driven ICT-support for firefighter and smoke diver training. The overall goal for the study has been to develop ways of supporting training for smoke divers with data based visualisations of their smoke diving activity, with emphasis of movement, to improve training efficiency and enhance the post exercise evaluation sessions. The goal for the tool is to combine different sensor data to create visualisations of the indoor training activity of cold smoke diving. The visualisations are intended to be used by instructors and firefighters to retrospectively assess and evaluate training performances. At the current stage of the study we have developed a first working prototype of FireTracker that provides tracks of the smoke diver's movement, activeness, and time use on locations in a house during smoke diving training

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exercises. Firetracker has also been evaluated in use during a cold smoke diving exercise. The paper addresses the 2019 ISCRAM Advanced Technologies for First Responders workshop topics of (1) emerging mobile trends in first responder technology, and (2) multimodal data fusion, representation, and visualisation.

As a study about improving the conditions for self-reflection and learning, the underlying pedagogical rationale for development is inspired by Computer Supported Collaborative Learning (CSCL) (Koschmann 2012), a perspective on learning that emphasises the social, goal-driven and artefact-mediated nature of human activity. As an initiative to develop support for group-oriented learning and training in the workplace, our study also takes a data-driven and analytics approach to understanding learning, and is influenced by the field of Learning Analytics (LA) (Siemens 2013). In an overview of the field of LA (Misiejuk and Wasson 2017) find that there are a number of examples of using LA to understand small-group learning processes. For example, (Goggins et al. 2015) visualised activity analytics from student group work in order to give feedback to teachers, so they could provide support or make relevant interventions in their students work. Another example is (Martinez-Maldonado et al. 2017), who studied nurses mobility in healthcare simulations. (Worsley 2018) argues that using mobility data is an emerging trend within multi-modal learning analytics.

The approach of using sensor data visualisations to improve and enhance the training of first responders and firefighters is novel, although there are examples of using digital indoor navigation support for actual firefighting (Fischer and Gellersen 2010). Getting "lost inside" or, becoming disoriented inside a burning building is one of the most common sources of accidents and injury in firefighting (Fischer and Gellersen 2010). (Ojeda and Borenstein 2007) describe a non-GPS based navigation support system directed at walking persons, for example for first responders inside buildings. By inserting an Intertial Measurement Unit in the wearers' boots, the system uses gait to predict movement. The system feeds the data to a central control, that can build an overview, for example, of rooms that have been visited in a building. (Koch et al. 2007) have used RFID to build a system for locating humans and objects indoors, although not directly for firefighters. (Feese et al. 2013) developed a smartphone based sensing system for monitoring temporal and behavioral performance in firefighting missions. Their goal was to use the collected data to compare the performance metrics between firefighter teams participating in the same mission. They used sensors on smartphones to sample data which was stored on the smartphone and transmitted the data so it could be used for real-time monitoring.

(Fortenbacher et al. 2017) used physical and environmental sensor data to capture and understand the emotional states of firefighters in training, and how the data can be used to support self-regulatory learning. In other studies not explicitly focused on training, it has been studied how networked robots and sensors (Kumar et al. 2004) and communication networks (Wilson et al. 2007) could be utilized to expand firefigthers and other first responders situational awareness. (Wang et al. 2015) describe a firefighter training system utilizing sensors embedded in the firefighters training clothes, as a way of interacting with a VR game. When nearing a fire in VR, temperature sensors increases the temperature within the clothes. (Backlund et al. 2007) and (Lebram et al. 2009) have also taken a game-based approach involving sensors and haptic feedback to firefighter training. Through the cave-based game Sidh, firefighters can train smoke diving using their own bodily movements as input, and receive feedback on surrounding screens. Evaluation of the game with firefighters highlighted the highly motivational aspect of this mode of training.

iComPAss

The study has been carried out as part of the iComPAss (inquire Competence for better Practice and Assessment) project (Netteland et al. 2016). At many workplaces training and learning is a continuous process, that includes courses, training exercises, further education, certification, and re-certification, and is often integrated with work processes. The training and learning takes place to increase the employees and the organization's competences, and is particularly relevant for firefighters who dedicate much of their workday to training and honing skills. The iComPAss project studies data (i.e., evidence) based decision making by examining how digital tools that use competence modelling, learning analytics, and visualizations can support decision making within healthcare and firefighting.

The questions that have guided the research are:

- How does FireTracker affect and support firefighter training?
- How can data from FireTracker support and enhance the evaluation of smoke diving exercises?

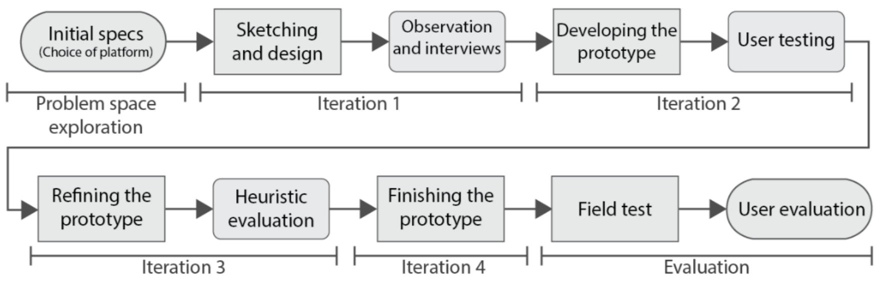


Figure 1. Overview of the development process

METHOD

The development process has been inspired by the perspectives of design science (Hevner et al. 2004), and Human Computer Interaction, and we have taken a data-driven and iterative approach to development. The approach to development is particularly inspired by the Interaction design life cycle, as described by (Preece et al. 2015), where design requirements are turned into design alternatives, which are developed into prototypes, which are then evaluated, forming the basis of new understanding of the requirements.

The research and development was carried out in collaboration with a firefighter department located in Western Norway. We interacted mainly with firefighters in three roles: smoke divers; smoke dive exercise leaders; and, departmental training officer. To understand the problem space, and the particular needs and contingencies of smoke dive training, we studied firefighter training manuals, observed and took part in smoke diving exercises and post-exercise evaluations, and interviewed exercise leaders and smoke divers about firefighter training needs in semi-structured interviews, throughout the development process. The smoke divers and exercise leaders have also given direct feedback on the different versions of the prototypes in interview sessions, following training exercises. All interviews were recorded and transcribed, and field notes were written following observations.

Early prototypes were evaluated using Nielsen's heuristics (Nielsen and Molich 1990), and we carried out our own testing of beacon precision and localisation algorithms. The development was carried out in four phases (see Figure 1), and included (1) problem domain understanding and requirements specification, (2 & 3) developing and refining the prototype, and (4) developing the currently final version.

The final version was evaluated as a field trial (Brown et al. 2011) in a dedicated smoke diving exercise, where we tested different configurations of BLE beacon placement, and assessed how these affected the localisation visualisations. Two instructors and two smoke divers took part, using their regular equipment. Following the exercise, they were interviewed on usability and usefulness issues, and they also evaluated FireTracker using the System Usability Scale (Brooke 2013). One of the exercise leaders had evaluated earlier versions, while one used FireTracker for the first time. The two smoke divers used it for the first time. The results from the field trial are presented in the section "Evaluating FireTracker".

FIRETRACKER

FireTracker is a smoke diver data capture and visualisation tool, used to create data-driven improvements in training smoke diving. FireTracker has two main components: 1) an app to capture data from different sensors (Figure 2), and 2) a learning authoring tool, to be used by instructors to set up training exercises, and present the resulting visualisations during post-exercise evaluation sessions (Figure 3). The app is installed on a mobile phone attached to the smoke diver, and the authoring tool is (usually) installed on an iPad carried by the training exercise leader.

Requirements

The rationale for FireTracker is that smoke diving takes place according to a set of standards and heuristics for communication, movement pattern, order of the work, etc. The standards exist to ensure firefighter safety and efficiency in an otherwise hazardous environment. By nature, these activities are carried out in partial or total blindness for both the instructor/exercise leader and the firefighters. By creating visualisations of how these activities are carried out in practice, and making them available for inspection and discussion immediately after the exercise, we can increase smoke divers ability to understand and discuss how a particular exercise went, and better support post-reflections on the training activity.

(a) Session list (b) Tracking activity (c) Active tracking (d) Session uploading

Figure 2. The FireTracker Mobile Interface

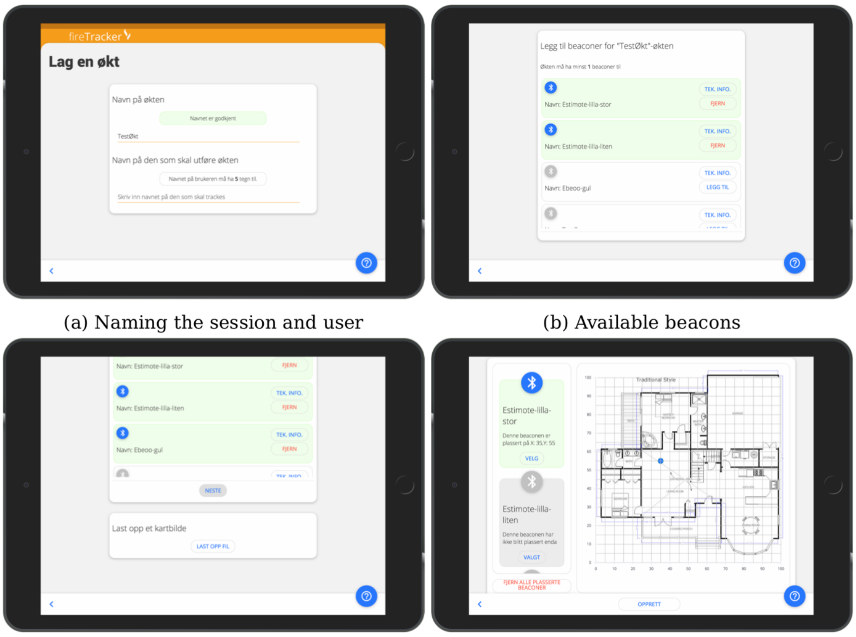
Requirements for FireTracker were developed and refined throughout the design and development iterations, in close conversation with exercise leaders, overall training leaders, and smoke divers. The most important requirements were:

- Portability: FireTracker should facilitate rapid deployment at any site, rather than be installed in a fixed location, as the firefighters avoid training cold smoke diving at any one location for too long. For the firefighters, it is an important aspect of the training to avoid becoming too familiar with the layout of a building, and that the deployment phase doesn't become routine. This requirement limited the choice of positioning technology; it is generally easier to integrate position technology in a fixed building or site (Li et al. 2014) than to rely on a portable system.
- Transportability: The physical equipment should be easy to bring along on an exercise, and not require a lot of time to set up by the exercise organisers. Any physical equipment should not restrict firefighter movement, or be in the way of the smoke divers in the building.
- Build on handheld devices: The firefighter department that took part in the study already uses handheld devices for various purposes during their exercises, and carry out their post smoke dive evaluations immediately after the exercise, at the location of the exercise. To support the feedback and evaluation session, visualisations should be available for display right away, and to be passed around in a circle, rather than require a desk- or laptop computer.
- Data presentation efficiency: The data visualisation tracks should be easy to read, and provide a clear and precise picture of the smoke diver movement inside a building filled with smoke.

Infrastructure and sensors

FireTracker consists of (1) an app for tracking a set of Bluetooth Low Energy (BLE) beacons on a mobile phone to gather positioning data, and (2) a web-based administration tool on a tablet, to enable the exercise leader to set up FireTracker for the exercise, and have a suitable screen for visualising the data. BLE beacons are placed around the building that is the site for the exercise, and the mobile phone is attached to the helmet of each smoke diver.

FireTracker builds datasets from the set of BLE sensors placed around a building and the gyroscope and accelerometer sensors on the mobile phone, and the mobile phone clock. When the firefighters search through the building, the mobile phone collects data from the beacons and combines it with data from the mobile phone sensors, which are used for determining if the firefighters are moving their head or walking. During development we discovered that sometimes during exercises the smoke divers would stand still/not walk. The reasons for not walking varied, for example for sorting out confusion, or for searching for casualties. Usually, the reason for not walking carried significance to their activity, and we found to interesting to attempt to capture more aspects of non-movement. Thus we needed additional sensor data. The mobile phone accelerometer was used to detect and estimate the number of steps taken by the smoke diver. By comparing the number of steps taken in a time interval, it was possible to determine whether the smoke diver was moving or standing still at a location. The gyroscope was used to determine



(a) Naming the session and user (b) Available beacons

(c) Uploading map (d) Placing the beacons

Figure 3. The FireTracker administration tool

relative orientation of the device. By using the same method as with the accelerometer to determine movement, it was possible to compare the time interval with the gyroscope orientation values to see whether the smoke diver was rotating the device at any time. The data are visualised as a track on a map of the building indicating the path of the smoke diver during the exercise. The track is enhanced with mobility data from the gyroscope, in addition to time use data.

The positioning algorithm can be described as proximity positioning, based on the received signal strength of the beacon. The mobile app constantly scans a list of available beacons. It connects to the beacon with the strongest signal, from the list of available beacons specified in the administration tool before the exercise starts, and creates a location for that beacon. The beacon has a known location on a map. It calculates the time it has been connected to the current beacon, in addition to the other sensor data, as long as that beacon emits the strongest signal. When a stronger signal is received from another beacon, it creates a new location, and adds the data from the previous location to a list of locations. Different approaches to data cleaning were experimented with during the development process, to create as clear and accurate tracks as possible.

Using FireTracker

Figure 3 illustrates FireTracker administration tool in use. To set up an exercise, the exercise leader uses the administration tool to create a session (session translates to exercise) and entering his or her name (Figure 3a). Then, he or she searches for available beacons, and include them in the session (Figure 3b). Next a map of the building is uploaded (Figure 3c). The map is easily created by either taking a picture of the floor plan of the building (usually available near the floor entrances in public buildings), or creating a map of the floor plan by hand beforehand. Finally, beacons are placed throughout the building (Figure 3d), and their position is recorded by tapping on a spot on the corresponding map. Each beacon is represented by a blue dot on the map.

The sessions are selected on mobile phones, which in turn are attached to the firefighters' helmets. Figure 2, a-d illustrates a use cycle of the tracking app. Before starting the smoke dive, the app is set to start recording data on the mobile phone. During the smoke dive, the app tracks data from BLE beacons, gyroscope, accelerometer and clock. After the exercise has been completed, the data are uploaded and rendered as a track on the map of the building, which also visualises use of time and activity level at each position. The administration tool is designed to work on an iPad, to better support the physical aspect of moving around and being on your feet, which is very much a part of the exercise both for the instructors and firefighters.

The administration tool then produces a map of the activity, as can be seen in Figure 4, one for each smoke diver. The visualisation shows how the firefighters have moved in the building, illustrated as a series of locations (the

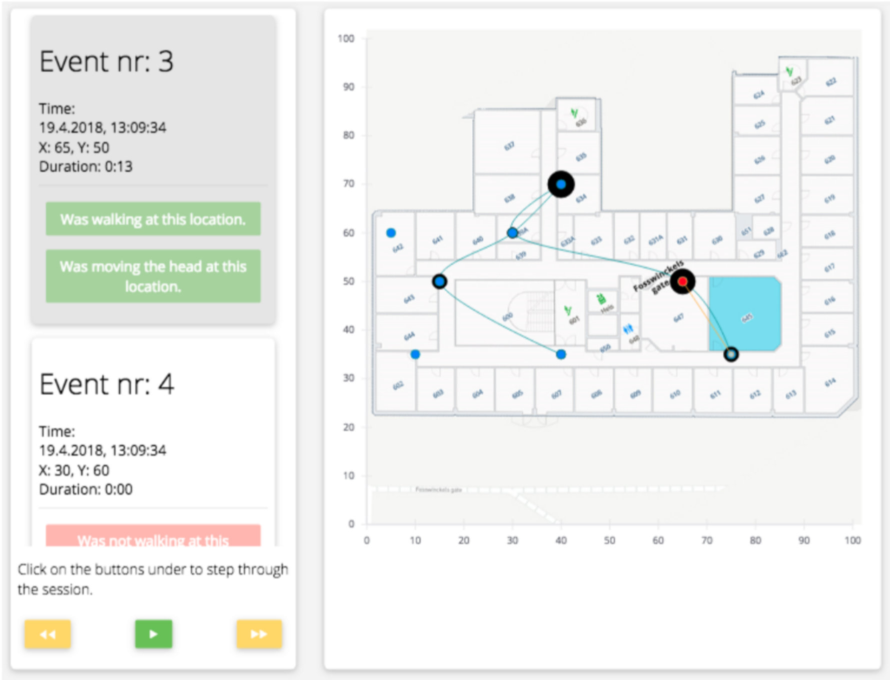


Figure 4. FireTracker Data Visualisation

circles). The blue dots represents the beacons, and if the circle is enhanced by a encompassing black circle, the location is deemed to have been visited. The movement can be replayed as a linear track, using the green "play" icon in the bottom left corner of the screen. The track can also be replayed by clicking on the list of events. Additional information is tied to each location. The size of the circle indicates for how long the location was visited – the larger the circle, the longer the stay. The red centre at one of the locations in Figure 4, represents that it is currently selected for viewing. "Playing" the track will have the red dot jump through all the locations in the order they were visited. The boxes on the left displays more information about each location, such as a time stamp, map coordinates, duration of stay, whether the firefighter was walking around or standing still at the location, and finally whether the firefighter was moving his or her head. The left boxes correspond to the red-dotted location on the map.

EVALUATING FIRETRACKER

FireTracker was evaluated in a field trial as described in the methods section. The main goal of the field trial was to understand how FireTracker affected and supported the smoke diving exercise self-evaluations, and to understand whether the data visualisations were useful for their training. In the field trial we first introduced FireTracker to the participants, and explained the purpose of the tool. One of the instructors was familiar with the tool, and had evaluated previous versions, the other three were new to FireTracker. Then we surveyed the site and building, and drew a floor plan to be used as the map by hand, as the particular building we used (an abandoned office building), didn't have a floor plan illustration available. The instructor who was previously unfamiliar with FireTracker set up the BLE beacons, and chose where to place them based on his understanding of how they worked.

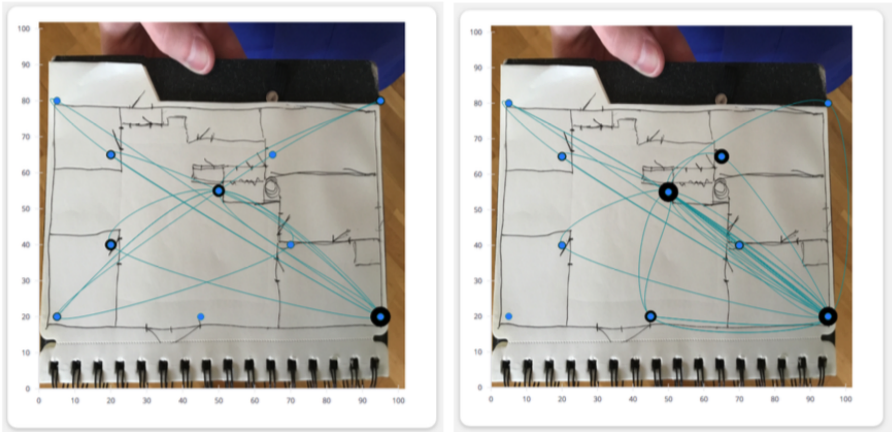
Four cycles of smoke dives augmented by FireTracker was carried out for the field trial. The cycles varied with smoke diver blinding method and equipment use, BLE beacon placement in the building, and on the roles assigned to the smoke diver (called "Smoke diver 1" and "Smoke diver 2"). Smoke diving always happens in pairs, and the tasks tied to the roles 1 and 2 are different; which smoke diver leads, which smoke diver searches rooms for missing persons whilst the other smoke diver pulls the firehose and so on. The first smoke dive was not carried out with smoke in the building, but by covering the helmet visors, which allowed the researchers to directly observe the smoke dive from within the building. The specifics of each cycle are presented in Table 1.

Results

This subsection presents the results from the field trial. The presentation of the results is divided between location tracking accuracy and value, and verbal feedback from smoke divers and instructors.

Table 1. Field trial exercise cycle

Exercise session	Equipment and blinding method	Number of participants
1	No smoke, helmet visors covered	Smoke divers: 2 Instructors: 2
2	Cold smoke, with full gear	Smoke divers: 2 Instructors: 2
3	Cold smoke, with full gear	Smoke divers: 2 Instructors: 2
4	Cold smoke, helmet only	Smoke diver: 1 Instructor: 1



(b) Smoke diver 1, exercise session 2 (c) Smoke diver 2, exercise session 2

Figure 5. Smoke dive tracks

Location tracking

As a test of the precision of the location tracks from the smoke diving, the field trial produced disappointing results. The tracks did not reflect the route chosen by the smoke divers, and made it seem like they were moving between locations to a high degree, whilst they actually were moving in a circular, clockwise pattern from right to left. The cause of the problem with the localisation was that the mobile phone intermittently picked up stronger signals from beacons that weren't the closest, producing tracks that did not reflect the path of the diver during the exercise. This happened because the location algorithm uses the beacon's known location on a map to position the user, and the user is deemed to be closest to the beacon with the strongest signal. There was also some "jumping" between beacons, resulting in a track that gave the appearance that the smoke divers walked back and to the same location.

One useful aspect of the tracking and smoke diving activity that FireTracker can be read from the tracks, can be seen in Figure 5, and can be related to the role distribution between the smoke divers. The figure shows the tracks from the second session of the exercises, for Smoke Diver 1 and 2. In the second session, both smoke divers walked the same route, but Smoke Diver 2 had the role of searching rooms, whilst Smoke Diver 1 pulled the firehose, and was more stationary when the pair was not advancing between the rooms. The track visualisations indicate more movement by Smoke Diver 2, which aligns with his role of entering and searching through each room.

Feedback from smoke divers and instructors

The smoke divers were asked questions about whether the visualizations gave them more information about the exercise and their own performance, and how it contributed to the internal evaluation of the exercise, in separate semi structured interviews. The evaluation with the smoke divers focused on wearing the mobile phone, tracking, and the resulting visualisations. The smoke divers both highlighted that FireTracker didn't require much from them, and that they concentrated on their routines during the exercise, which is in line with our goal for FireTracker to be pervasive to the exercise whilst tracking. They both gave the feedback that the tracks were too imprecise to be of value. One of the smoke divers found the presentation of the movement (as movement between the blue dots) a little confusing, and would have preferred a footpath-like track of his movement. *It (FireTracker) would have helped me appreciate more about my movement in the building. But I would have preferred a tail (visualisation). That would have made it easier for me to see where I had been. I would have understood more easily. Almost like playing* *a movie, one and one dot appearing. And preferably in two colours, one for me and one for (colleague).* They both gave the feedback that the data visualisations would have been very useful if they had been more precise. The smoke divers SUS results were 67,5 and 57,5, both below the accepted score of 68.

The evaluation with the two instructors was focused on use of the administration tool, in addition to the tracking app and visualisations. They found that it was easy to use, and the instructor who had never used it before reported that "*I didn't need a manual, I figured out how to use it after a couple of minutes*". Both reported that the data would be very useful in exercise evaluation, but were currently too imprecise, and they wouldn't be able to identify errors in the smoke diver movement with the current level of granularity. One of the instructors made a similar comment to one of the smoke divers; that he would have preferred to have the localisation nodes in the visualisations appear in the same order they were visited, rather than all at once.

Regarding expectations to how they could use FireTracker, the chief training instructor responded that he sees it as a tool for inspecting or verifying the activity of the smoke divers, and as a starting poing for a discussion with the smoke divers: *It would be very good for learning about their (the smoke divers) search patterns, to see if it matches the theory. They are supposed to make a plan before entering, and with this tool you can check if they follow it. Did they follow the wall to the right, or turn around? If so, why? It would be a very useful tool for that.* He also had the idea that they could place artefacts in the house, such as training dolls and similar items, and match the track visualisation against the artefacts in the evaluation. He also thought it would be useful for the smoke divers themselves to see their own data. The other instructor commented that it would improve their basis for providing feedback to the smoke divers, and that data from one team could increase the training value to the teams that waited outside (buildings are searched sequentially by teams of two, and when one team runs out of air they exit, the next team takes over). The total SUS score for the instructors were 82,5 and 90, although they underscored that they answered under the assupmtion that the data had been precise.

Discussion

Beacon precision: As part of an infrastructure of a system to support indoor localisation not tied to one specific place, the beacons used in our study, in the way we have used them, currently seem to provide too imprecise data to support precision tracking. The beacon signal strength that our algorithm build on was affected by a number factors such as mobile phone make and obstruction of physical objects, resulting in unpredictable data. During development we experimented with several ways of increasing precision, such as manipulating the signal strength in digital and physical ways, and different types of placement. This finding is in line with (Fischer and Gellersen 2010), who describes the accuracy of indoor positioning systems along the two axis of precision and portability, where an increase in portability leads to less precision and vice versa. One of the main design requirements behind the development in this study, was that the localisation technology needed to work in conditions (i.e. buildings) that were unknown beforehand.

Capturing non-movement: As discussed in the section on FireTracker infrastructure, the study started with the goal of capturing smoke divers indoor movement during exercises. The goal was to improve and create new opportunities for discussions between smoke divers and instructors in the post exercise evaluations, and was based on the observation that their movement and search patterns are set according to standards and competencies, yet there are limits on observation. Following observation of a full scale smoke diving exercise, and the following evaluation session, at an early stage in the development process, we realised that there were additional important aspects of non-movement as well. During the evaluation session, they discussed events that had caused pauses in the search, because this was when there were situations and problems to solve. Or in other words, a search without stops, would be "everything as normal". We saw the opportunity to uncover further aspects of the smoke diving activity using the gyroscope and accelerometer. The imagined scenario was that when a search pauses, we could provide metrics on their pyshical activity levels, which could enhance discussions about why the momentary stop in the search took place. Our current version displays these data as "yes" or "no" to walking and head movement at each location, and future versions will display these data in more detail, indicating amounts of steps and head movement.

Conclusions

The field testing of FireTracker during a training exercise revealed that both the instructors and the firefighters thought the tool was very useful. The smoke divers found the performance data on their activity interesting, and the instructors appreciated the idea behind the visualisations and found the system very easy to use, although the localisation tracks were to imprecise with our current version of FireTracker. Further development of the tool will include better quality visualisations and localisation precision, and the investigation of the use of learning analytics to identify patterns of good and bad movement so that they can be flagged to the instructors and firefighters.

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