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Localization Services for Online Common Operational Picture and Situation Awareness

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ABSTRACT Many operations, be they military, police, rescue, or other field operations, require localization services and online situation awareness to make them effective. Questions such as how many people are inside a building and their locations are essential. In this paper, an online localization and situation awareness system is presented, called Mobile Urban Situation Awareness System (MUSAS), for gathering and maintaining localization information, to form a common operational picture. The MUSAS provides multiple localization services, as well as visualization of other sensor data, in a common frame of reference. The information and common operational picture of the system is conveyed to all parties involved in the operation, the field team, and people in the command post. In this paper, a general system architecture for enabling localization based situation awareness is designed and the MUSAS system solution is presented. The developed subsystem components and forming of the common operational picture are summarized, and the future potential of the system for various scenarios is discussed. In the demonstration, the MUSAS is deployed to an unknown building, in an ad hoc fashion, to provide situation awareness in an urban indoor military operation.

INDEX TERMS Localization, mapping, networks, situation awareness.

I. INTRODUCTION

Urban situation awareness and especially localization information is important in many applications. Operations, such as search-and-rescue, military operations, urban combat, hostage situations, emergency situations, indoor fire, or earthquake damaged buildings, rely on localization information, as the map of the environment and location of targets in a possible unknown area is needed. Combining information from several subsystems is a key aspect in these perilous applications. Knowing where things are and combining several sources of information, enables context aware data gathering, analysis and decisions, and aid in situation awareness.

In this paper, a novel solution is presented, called Mobile Urban Situation Awareness System (MUSAS), which is an integrated system that provides localization services of several types to enable situation awareness with focus on an urban environment. The target use of the proposed MUSAS is an operation in an urban environment where locations of own field team members, persons and objects are of key importance. The operation environment is typically partly unknown, which require mapping and localization of objects.

A general use case scenario for the MUSAS is an operation in an urban environment as shown in Fig. 1. A field team performs some task based on the instructions from the mission leader and upper echelon. A common operational picture (COP) [1] of the situation is formed, by the COP server and the MUSAS operator managing the system, using data from several subsystems deployed in the field. The COP is relayed to all the parties involved: the field team, mission leader, and upper echelon, to assist them in performing their tasks. Field team members have a hand-held device for interfacing with the COP. The COP contains information of locations of objects and targets of the task, typically humans, overlaid on a map of the environment, to assist in situation awareness.

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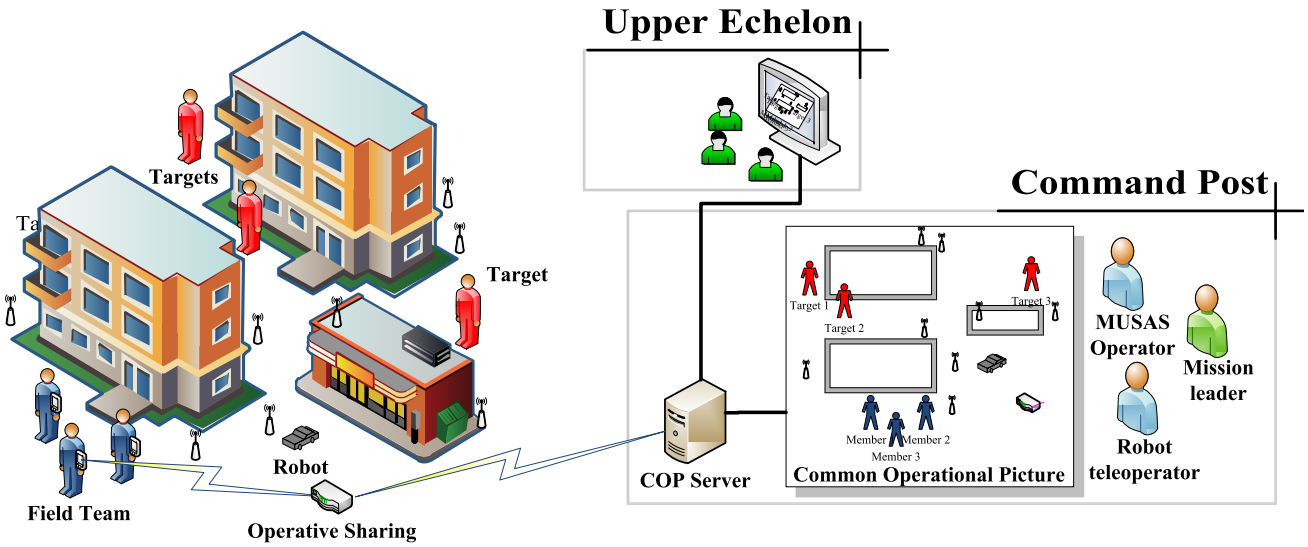


FIGURE 1. General use case example for the MUSAS and entities involved.

A. OBJECTIVES AND CONTRIBUTIONS

A key contribution of the MUSAS is providing a system for online localization based situation awareness using multiple localization and mapping methods. Compared to other similar systems, the MUSAS does not assume or rely on anything of the target environment. The MUSAS builds up its own infrastructure using Wireless Sensor Network (WSN) and Wireless Local Area Network (WLAN) technologies. It maps the unknown area and updates the knowledge as entities are localized. Location information of moving targets is tracked and updated to the COP model and all users. The system can operate both outdoors and indoors and has through wall observation capabilities.

The contributions of this work include describing the general design of an online system for producing and integrating information for a common operational picture, based on mapping an unknown environment and appending several localization information sources. A survey of existing solutions and relevant technologies are done. The subsystems are presented, including their technical details and relevant literature. An implementation is presented and the experiences from a test demonstration are discussed. Other issues related to situation awareness, such as data associating and clustering, object recognition and feature extraction, target identification and tracking, and prediction, are not considered.

In this section, the objectives of the MUSAS, related situation awareness solutions, and the contributions of this paper are described. In Section II, a general system description of a localization based situation awareness system is done, and feasible localization solutions suitable for the use case scenario are identified. The proposed MUSAS architecture and an overview of the implementation are presented in the following sections. In Section III, the robot system is described, including mapping an unknown area using simultaneous localization and mapping (SLAM) by the robot. In Section IV, the localization subsystems are described in more detail with the information they produce for making the COP. Wireless sensor node localization is treated in Section IV-A. Object localization has also been implemented, both for cooperating objects or persons, in Section IV-B, and for non-cooperating persons. For the non-cooperating case, radio tomography can be used, as presented in Section IV-C. In Section V the experiences from a test deployment and the use of the MUSAS in urban combat situations is described. Finally a short conclusion is given with some notes on the use of such systems in other scenarios. A technical report of the system with more detailed information on the implementation can be found in [2].

B. COMMON OPERATIONAL PICTURE

According to [3], situation awareness consists of several levels. The first level is perception or sensing. In the second level, comprehension is built from the observed data, as meaning is assigned to each piece of information and the relations between the components are inferred. In the third level, the situation implications are projected or predicted into the future. In this work only the first two levels are considered, where data is gathered by several entities and fused to some comprehensible picture of the situation. The task of the user is then to decide actions or predict the future based on the produced situation picture.

A common operational picture displays all gathered and combined data from several sources in a single presentation to the user [4]. The information is merged into a common frame of reference and visualized on a screen from where it is easy to comprehend the current situation. The main task of COP systems is thus to bring together data from different subsystems and present that into an overview for enabling situation awareness of a variety of users and different teams [1].

The early studies of COPs were carried out in the 1980's [4]. A major milestone is the development of a large group display to enable situation awareness in military command posts [3]. COPs have been successfully utilized in situations such as large scale natural disasters [5] and terrorist acts, where COPs have had a large impact on reducing human casualties.

A COP is often associated with geographical data, for instance in a combination with a Geographic Information System (GIS), as typical applications are tied to a possible large geographical area. Available maps, blue prints and floor plans can serve as a backdrop to pin the location based information to real-world coordinates and tie them to the environment.

C. SITUATION AWARENESS

Most of the situation awareness literature concerns military cases. The Joint Vision document from 2001 [6], highlights the importance of information superiority throughout the battlefield. Situation awareness of individual soldiers is an important issue, and different armies around the world are developing their future soldier concepts. The target is to create a soldier, who is not only a warrior, but also an active information creator and consumer. The report [7], summarizes some different programs. For example, the Future Soldier program is an international endeavor, led by the USA, to create a soldier of the 2030 [8]. An example of a networked system of systems is the Future Combat Systems (FCS) which links 18 different systems into an operating entity [9].

The Common Operating Picture Software/Systems (COPSS) for emergency management is presented in [10]. This system supports a four dimensional COP and focuses on Shared Situation Awareness (SSA) and supports multiple information sources. Research on a Small Unit Operations Situations Awareness System (SUO SASS) is presented in [11], which has similar aspects as the MUSAS, in terms of ad hoc networks and location services focusing on soldiers. The use of commercial-off-the-shelf (COTS) products in tactical environments is studied in [12]. Especially, an implementation in Android environment, similar to the MUSAS, is studied in [13].

D. SENSOR NETWORKS FOR EMERGENCY SITUATIONS

There are numerous wireless sensor network solutions envisioned for disaster and emergency situations where an infrastructure for data exchange is not readily available. In such scenarios, a WSN can be deployed in ad hoc fashion and provide the means for information exchange and other sensing purposes.

In disaster scenarios, scalable and heterogeneous network solutions for situation management are required. DistressNet [14] provides such a solution and it offers: ad hoc wireless architectures for communication, data exchange to improve situation awareness, and collaborative acoustic sensing for human detection. The system has also multiple solutions for localizing the nodes with the purpose of topology-aware routing and congestion control.

The VigilNet [15] system targets military surveillance, exploiting sensor networks to track targets in areas of interest. The authors consider the setup and operation requirements of the network. In addition, the importance of node localization is considered and Global Positioning System (GPS) is used to fulfill the task. VigilNet targets long term operation and thus energy constraints have an essential role in the system design. On the contrary, the system presented in this paper is deployed for short time intervals and therefore, energy consumption of the nodes does not have to be considered in the system design.

Diamond and Ceruti [16] discuss a military COP model and system architecture for modern warfare. The use of commercial and COTS wireless devices, the diverse sensing possibilities of the devices, and data fusion of different information are seen as effective ways to improve situational awareness for military purposes. Such augments in situational awareness enable new combat paradigms for modern warfare. In contrast to the hypothetical investigation of [16], an actual implementation is presented in this paper.

E. MAPPING AND SEARCH-AND-RESCUE ROBOTICS

Reconnaissance and mapping of an unfamiliar area using a mobile robot, discussed in more detail in Section III, is indispensable, if it is unsafe for humans to enter. Mapping is needed to be able to navigate, operate, and localize the sensed information. The mapping of damaged buildings in an earthquake situation using both ground and aerial robots is presented by [17], where the mapping results of several robots are combined to produce a three dimensional map. Similar robots could be integrated in the MUSAS, with the addition of other subsystems, delivering various other information sources, such as localization of people and objects.

An EC project, Building Presence through Localization in Hybrid Telematic Systems (Pelote) [18], [19], studied the control of a human-robot team in a fire fighting scenario. The proposed solution consisted of a fire-fighter localization system [20], teleoperated robots [21] and an information fusion scheme to synthesize a common model from acquired data. One of the key contributions of the project was that it was experimentally shown that position information is critical in maintaining common situation awareness among the distributed team.

Similar to the MUSAS, Pelote emphasizes the importance of location based information. However, the MUSAS differs from Pelote in that it does not assume a priori information about the target environment. Furthermore, the MUSAS is built upon wireless sensor networks, which extend the range of applicable use case scenarios and enable new positioning possibilities, such as non-cooperative device free localization (DFL).

II. SYSTEM ARCHITECTURE

The target of the MUSAS is to provide a common operational picture for the command post, to the field team and share it

with the upper echelon. This is accomplished by combining information from several different subsystems into a single view. In this section, the general system design and components of the implemented MUSAS is presented. This section is concluded by a description on how the COP information is distributed and presented to the user to aid in situation awareness.

A. GENERAL SYSTEM OVERVIEW

A common operational picture is the visual representation of the up-to-date state of the operation. In this case, focusing on localization information of each entity. The COP includes, but is not limited to, the positions of targets and field team members, and the status of individual assets with respect to a common frame of reference, i.e. a map of the area.

To achieve a COP, information from several online localization systems, backdrop information, such as geographical data and operative information, must be integrated and distributed to all users, as summarized in Fig. 2. The COP server forms the COP model based on inputs provided by all subsystems, and it shares the resultant model with the upper echelon and with the field team using the operative sharing subsystem. The backdrop information subsystem provides basic information related to the operation and the environment. Based on the localization systems, online situation and localization information are formed, and updated the COP model to the current state of the situation. The operative sharing subsystem allows transferring and displaying the generated COP model to the field team, and conveying status updates from the field team to the COP server. Similarly, the upper echelon subsystem provides means for conveying the COP model to the command post, and delivers executive commands to the COP server.

B. INFORMATION SHARING AND INTEGRATION

The COP model must support integration of data gathered from multiple sources. In the MUSAS, various types of information are provided by different subsystems such as mapping information from the robot, and position based content from the team member and target localization subsystems as shown in Fig. 2. Transferring information from the individual subsystems to the COP server and sharing the up-to-date COP model with the upper echelon and users requires a sophisticated networking paradigm. The networking demands can be conveniently fulfilled by abstracting the network away and utilizing a distributed object system architecture. This solution abstracts the underlying technologies to independent functional entities and the integration of the subsystems is done by using a common data sharing framework.

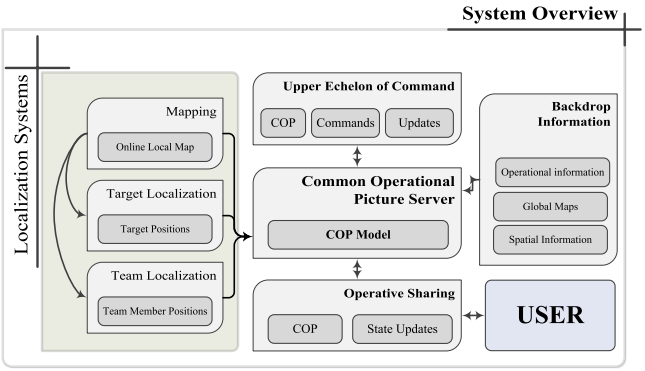


FIGURE 2. General localization based common operational system overview.

Interactions among distributed object systems is generally enabled by utilizing object-oriented middleware, such as Common Object Request Broker Architecture (CORBA), Remote Method Invocation (RMI) [22] and Internet Communication Engine (ICE) [23]. Middleware, such as CORBA and ICE simplify the development of a distributed system. In addition, they allow independent development efforts of the subsystems, as they support multitudes of operating systems and programming languages.

Considering the diverse requirements of the MUSAS subsystems and the time constraints of data integration and sharing, ICE emerges as the best alternative. This particular middleware architecture is augmented by several services, including a publisher-subscriber topic based event distribution system called IceStorm. Using the IceStorm service, information exchange among the subsystems can be implemented as asynchronous event invocations in topic subscribers. The COP server and subsystems are thus interfaced by abstracted topics defined in and managed by IceStorm.

A fundamental need for a system supporting spatial situation awareness is a subsystem for binding the information from various sources to real world locations. Part of the integration process is associating and combining the position information from the individual localization subsystems to geographic information. Geographic layers, such as maps and blueprints, provide a global coordinate system for the various subsystems. Thus, the location information of the subsystems is inserted into the COP model and delivered to the users in conjunction with the geographic information.

Geographic Information System is one of the well-studied comprehensive solutions, which offers a closed infrastructure and a variety of functions for this purpose. GIS provides means to present the information in layers to aid visual cognition. Further, GIS offers a framework for integrating positioning information generated by the other localization subsystems. By using this framework, the COP server is able to increase the abstraction level of individual objects. The information of individual subsystems is not anymore an object with x- and y-coordinates that are bound to its local coordinate system. Rather, it has a location based on real world coordinates and a certain type, symbol and additional information provided by the COP model.

C. SYSTEM TECHNOLOGIES AND OPERATION

The selected technologies for each subsystem in the MUSAS are depicted in Fig. 3, with brief motivation of the selections in this subsection. Further details are given in Section IV.

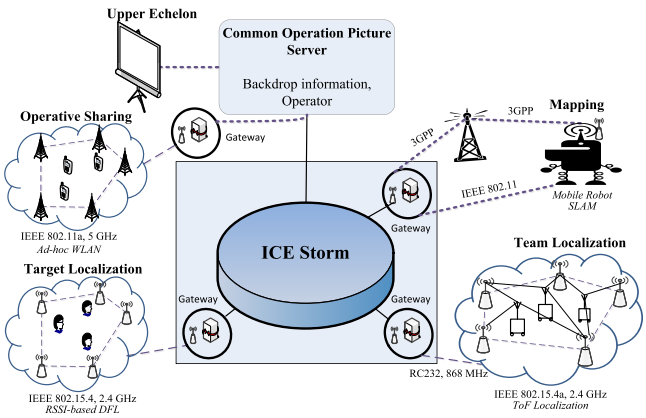


FIGURE 3. The MUSAS system implementation and the utilized technologies.

A common operational picture requires an accurate and up-to-date map of the operating environment, with a common notion of reference and direction. Since, in most of the considered scenarios, this knowledge is not available a priori, a mobile robot, which can generate the map while localizing itself is the most suitable solution among the alternatives, as demonstrated in Pelote [19]. Thus, in the MUSAS, a mobile robot, which is capable of simultaneous localization and mapping, is utilized to generate the map of the environment.

Wireless Sensor Networks can be successfully used to measure spatially distributed data, as a large number of nodes can be distributed in the area of interest. Therefore, an ad hoc WSN is a suitable solution employed in the MUSAS, where relying on existing infrastructure is not possible, due to several reasons, such as damaged and potentially unreliable existing systems.

The target and team localization subsystems aim at estimating the location of assets in the monitored environment. Despite the fact that both systems can be implemented based on visual or radar sensors, the limitations imposed by the cluttered environment and the cost, leverage radio based localization systems. Therefore, the proposed system is built on top of low-cost wireless networks.

An IEEE 802.15.4 network is employed for localizing non-cooperative targets using radio tomographic imaging [24], [25]. The IEEE 802.15.4 nodes are localized using the mobile robot to enable ad hoc deployment. The robot is connected by a versatile multi-radio gateway to support remote operation. For localizing team members, wearable sensors based on IEEE 802.15.4a, time of flight, and inertial sensors are used. To share the COP information to the users, an ad hoc IEEE 802.11a network is used. Gateways for each network are connected together with a wired local area Ethernet network and the ICEStorm publish-subscribe service is used to pass information to the COP server and the other subsystems.

The proposed solution is composed of different wireless communication technologies, some of which may operate on the same frequency band. Therefore, to not interfere with one another, the medium access of these technologies must either be synchronized, or they must be operated in non-overlapping frequencies. In the proposed system, the latter is mostly employed. Subsystem with overlapping frequencies, communicates in turns.

Many of the localization subsystems utilize location information from the other subsystems as depicted in Fig. 4. As an example, radio tomographic imaging requires that the location of the nodes are known. However, in most of the considered use-case scenarios, the node locations are not known a priori. One solution to this problem is to use the robot as a mobile beacon to locate other nodes of the network as described in Section IV-A. Another solution is to equip the robot with a node deployment system and distribute the nodes in desired positions as the robot explores the environment. It is to be noted that these two solutions are not complementary and can be used side by side. In the MUSAS, both options are utilized.

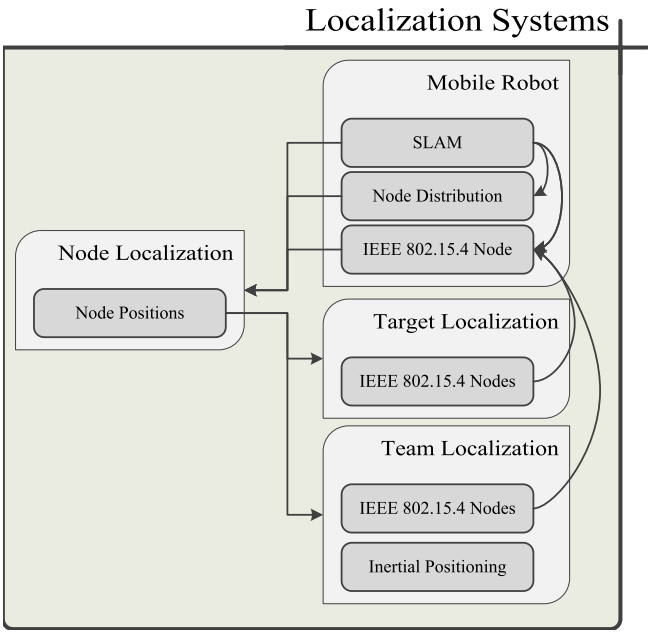


FIGURE 4. Localization systems information flow.

D. COMMON OPERATIONAL PICTURE SERVER

The main task of the COP server is to produce the COP model, which includes all information that is significant for supporting situation awareness. The COP server encapsulates multiple functions, such as hosting relevant backdrop information, geographical information system, as well as publishing the formed COP. These entities are presented in Fig. 5, which is a detail view of the COP server block in Fig. 2. The COP server hosts also multiple services needed by the system, such as information sharing and operative sharing services. A command and control application is running as a front end application for the COP server, which provides a user interface for the command post operator.

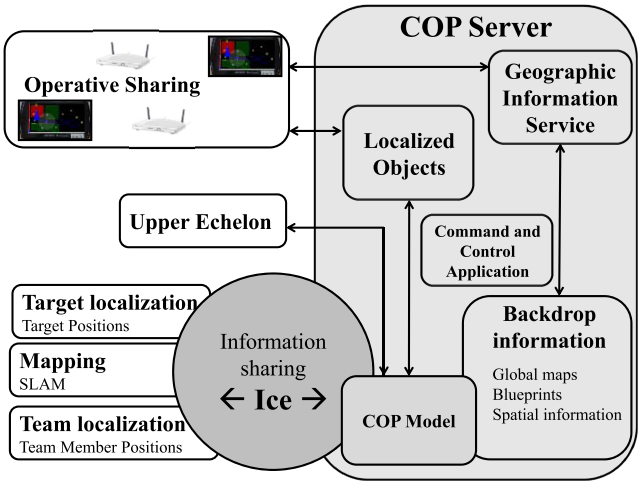


FIGURE 5. COP server framework.

E. PRESENTATION

The COP is presented to the mission leader and upper echelon on a large group display, whereas the field team members are shown a scaled down version in a hand-held device. In either case, a user can zoom in and inspect detailed information associated with a region or object of interest.

The COP presented to the mission leader and the MUSAS operator is shown in Fig. 6. In the depicted scenario, the robot is heading forward in a corridor of an unknown building, simultaneously updating a SLAM generated map. The MUSAS operator identifies the blueprint of the environment and marks it appropriately. The color of the rooms can be changed according to the situation. Additionally, rooms, objects and events can be marked with appropriate NATO APP6B symbols and other polygon shapes, all referencing to local coordinates or real world coordinates (MGRS, WGS84). It is also possible to display the map partially transparent on top of a satellite map, to match it with the surroundings. This mode reveals shapes of the terrain and different targets such as monuments hidden in a forest, improving the situational perception.

The mobile application for the field team members, shown in Fig. 7, is created on an Android platform. Android is chosen because it allows easy deployment on new devices using the same operating system, and makes it possible to use a wide range of COTS products. The application is designed to be as simple as possible for a field team member to perceive the current operational picture. The hand-held application contains only a selected set of features which are presented in Table 1. Common use cases are moving the map, zooming the map, and adding a new object. Every feature is available by using only one hand, including opening the carrying pouch, where it is attached on the torso of the field team member.

F. OPERATIVE SHARING

Sharing the COP information to hand-helds of the field team members is accomplished by using a mobile IEEE 802.11a (WLAN) based ad hoc capable, battery powered, access point network. The network, depicted in Fig. 8(a) and Fig. 3, enables flexible deployment and independence from external infrastructure. No special configuration is needed for the network and it acts as a normal WLAN network for the hand-held devices. The access point, pictured in Fig. 8(b), can automatically connect and join to the existing network access points in the field. When deploying the system, it can be placed anywhere, because it is battery driven. Furthermore,

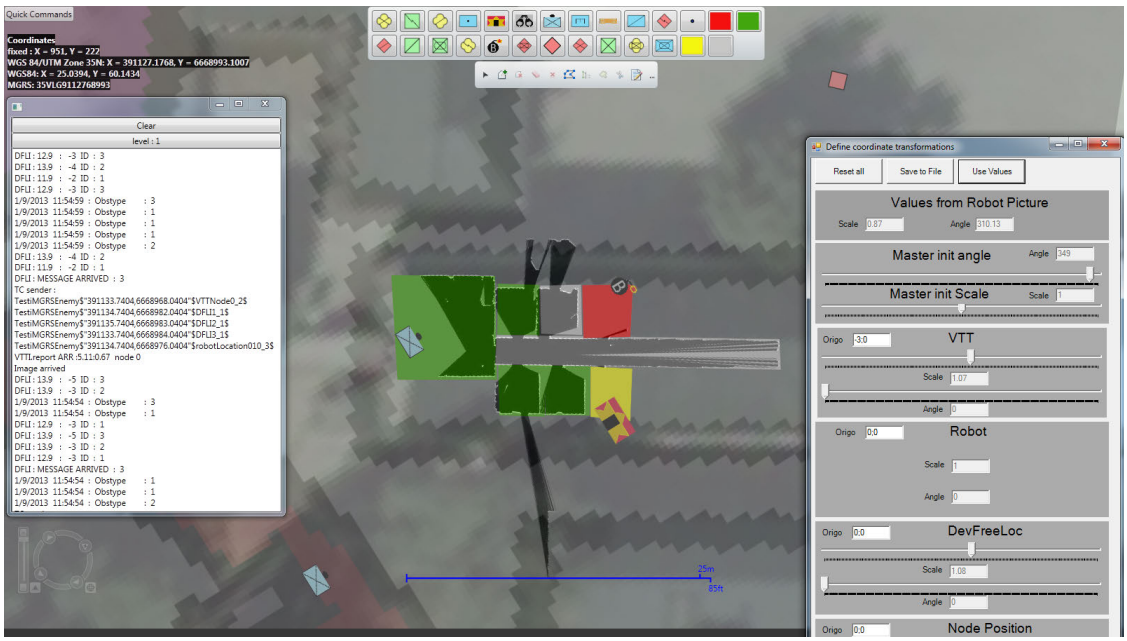


FIGURE 6. Command and control server application user interface.

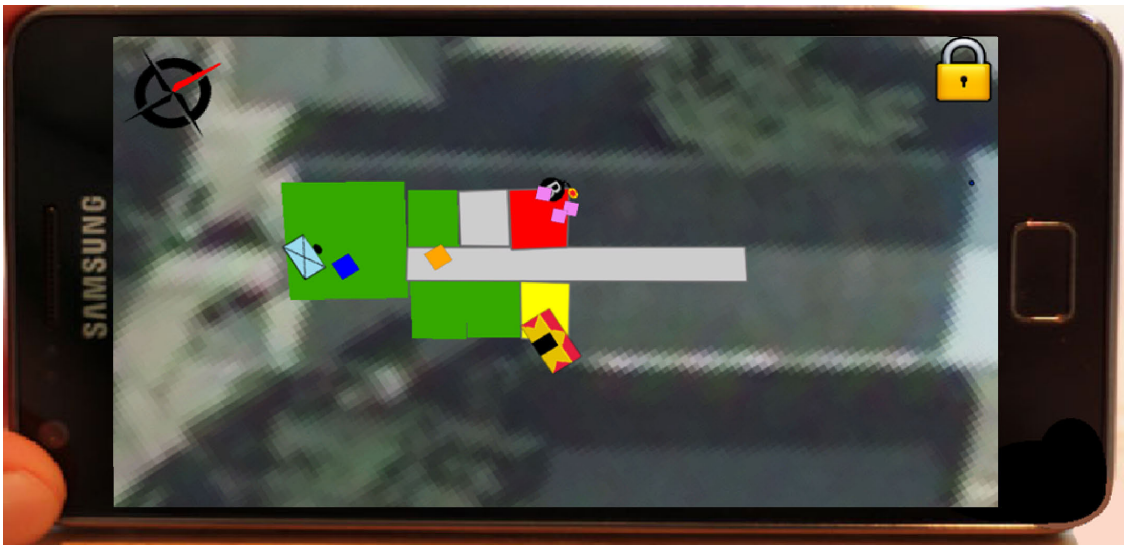


FIGURE 7. Hand-held device graphical user interface for assisting in situation awareness of field team members.

to expand the coverage, existing access points can be moved or new access points can be added.

III. ONLINE INFORMATION ACQUISITION USING A MOBILE ROBOT

To operate in an unknown environment, reconnaissance to collect data and map the area is necessary. The map information, discovered objects, and other information are localized to the local map coordinates and further to global coordinates. For mapping and reconnaissance purposes, the MUSAS uses a mobile robot with SLAM capabilities. In this section, a short description of the mobile robot system is presented. The system components required for control, and how the location information provided by the robot is used in the system, is described.

A. OVERVIEW

A mobile robot features many benefits in the use cases of the MUSAS. Most importantly, it can be deployed to gather information about an unknown situation without risking human lives and the robot is in a central role in creating a common frame of reference for the system.

The remote-controlled robot, shown in Fig. 9, is used as an exploring scout. The robot builds a metric map of the environment while localizing itself against the map. The robot is a tracked platform, weighting approximately 100kg and carries along 100Ah of energy as well as sensors and sufficient computation power. Further details about the robotic system can be found in [26]. In the MUSAS, a laser range finder and dead reckoning for creating the map are used. A camera with a pan-tilt-unit is provided for the teleoperator. In addition, the robot is equipped with a communication subsystem, which enables communication with the robot practically in all environments, without the need for an existing infrastructure.

To build up the localization and sensing infrastructure, treated in Section IV, the teleoperator can deploy wireless sensors into strategic places in the environment, using a wireless sensor node distribution subsystem integrated to the robot. The node deployment is controlled over ICEStorm. Whenever a node is deployed, the information, including the known location of the deployed node, is published to ICEStorm with a timestamp. Further, the robot communicates with the rest of the wireless network, and localizes nodes with unknown positions, deployed by other means, as explained in Section IV-A.

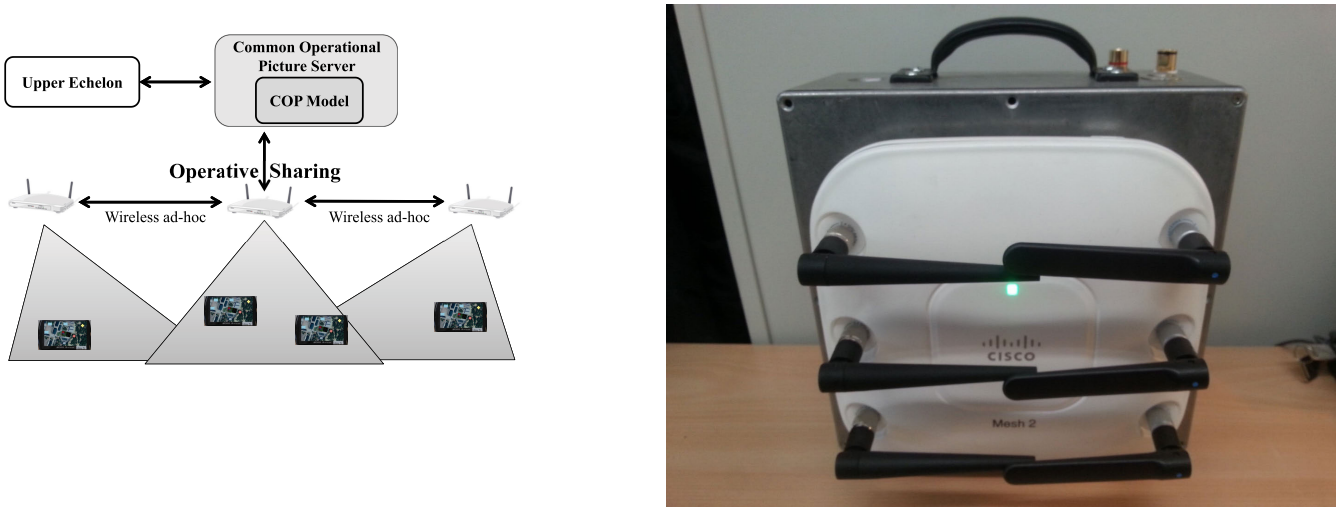
B. COMMUNICATION AND CONTROL

The robot is controlled by teleoperating from the command post. The laser range finder data, the image from the camera, the calculated position and the constructed map of the area is sent to the teleoperation station display shown in Fig. 10. The calculated position of the robot and the constructed map is distributed from the teleoperation station to the COP server by using ICE, as shown in Fig. 3.

As a communication link between the robot and the teleoperation station, two multi-interface routers are used. The routers are especially designed for critical applications where broadband and reliable connectivity and largest possible coverage is needed. They have multiple different kinds of radio terminals, such as 3G HSPA, CDMA450/2000, WiMAX, Wi-Fi, LTE, Flash-OFDM, TETRA (Trans-European Trunked Radio, a radio specifically designed for use by government agencies and emergency services) or satellite, which can be used depending on the situation. The router monitors continuously all installed Wide Area Network (WAN) radios and switches to another radio if one fails or the quality of service is below a user specified threshold. In addition, the routers support virtual private networking, which enables secure and seamless connection, independent of the used radio technology.

TABLE 1. Hand-held device functions.

Feature	Options
Map	Satellite or Raster
User views	Targets, team members, events, rooms (with colors), and compass
Marking objects	Event, Hostile, Unknown, Neutral
Gestures	Pinch - Zoom map Pinch + Rotate - Rotate map Short press - North up Long press - Select satellite or raster map
Compass	Displays North



(a) (b)

FIGURE 8. Operative Sharing (a) connecting the COP server and the field team member hand-helds using an ad hoc WLAN. (b) WLAN access point with batteries.

As a communication architecture, GIMnet [27], [28], which is a service-based communication middleware for distributed robotic applications, is used. From an application point-of-view, GIMnet provides a virtual private network where all participating nodes may communicate point-to-point using simple name designators for addressing. Using the multi-interface routers and the communication architecture, the system provides the possibility to seamlessly control the robot from virtually any remote location. The setup is mostly the same as in [29].

C. SIMULTANEOUS MAPPING AND TRACKING

Simultaneous localization and mapping, is a well-studied field, and there are several approaches for solving it [30]–[32]. Here, the requirements are to map an arbitrary environment in real time, without changing the frame-of-reference during mapping. Because of these requirements, the problem is approached using a grid-based mapping and tracking (or Maximum Likelihood SLAM) method. The approach incrementally builds an occupancy grid through two steps: 1) Tracking, which maximizes the observation likelihood given the map, and 2) mapping, which fuses the observation with the map into the pose provided by the tracking step. This approach does not employ a loop-closing mechanism, and therefore is referred to as mapping and tracking, in order to distinguish it from a full SLAM solution.

FIGURE 9. The mobile robot unit used for exploring, mapping and node localization in the MUSAS.

The mapping step is a trivial occupancy update step using known pose and laser scanner data with a line model [33]. The tracking step uses a globally optimal search algorithm introduced in [34] for finding the best pose in the map. The search algorithm branches the pose space, with an objective to minimize the point distance to occupied map cells. The solution is bound by using an efficient approximation of the upper and lower bounds of the objective. The algorithm has

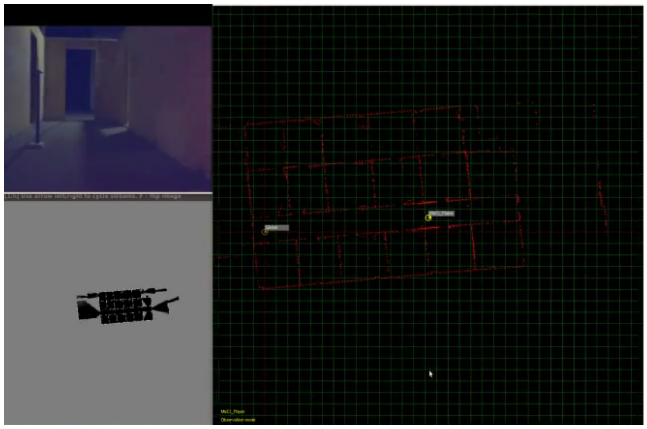


FIGURE 10. Teleoperation view for mobile robot.

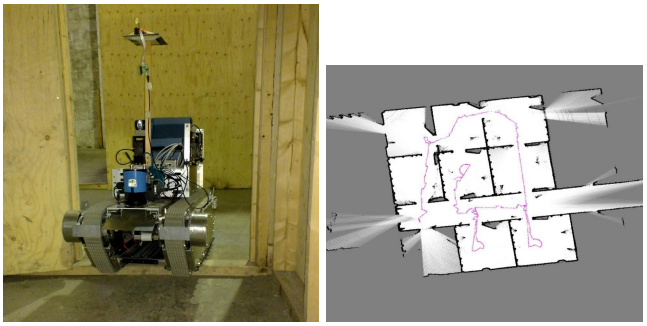


FIGURE 11. (a) The robot in the test environment. (b) An example map from the test scenario.

been shown to provide robust, sub-resolution pose estimates even with very large search spaces [34] and being able to map accurately even in the presence of large loops [29]. In this use-case, the map is incrementally built, and thus the search space is relatively small. The robot mapping and tracking inside the target area is shown in Fig. 11(a).

Fig. 11(b) provides an example map from the test scenario. The map is built in real-time by the robot and shows an exploration through eight rooms. The map is published to the other subsystems using ICEStorm as an image every 10 seconds. The map is then used in the command post and overlaid with the a priori map and global geographical information in the COP server. The map is also provided to the robot operator in order to help in keeping spatially oriented while driving the robot, as shown in Fig. 10. The pose of the robot is published to ICEStorm continuously, for the other subsystems, specifically the robot operator and the node localization system.

IV. SYSTEMS FOR LOCALIZATION

Localization of wireless nodes in Wireless Sensor Networks has been researched extensively, because in spatially distributed systems, sensor data is only meaningful if the location of its origin is known. In the MUSAS, not only node locations are needed, but also locations of field team members, targets and other objects and events, as well as their position in relation to a map. The following subsections briefly present the localization subsystems of the developed MUSAS and explain their technical details and how they produce the required localization information. The interactions of the localization subsystems are described in Section II-C.

A. NODE CALIBRATION AND LOCALIZATION

Due to the ad hoc nature of emergency and rescue situations, the localization systems used in the MUSAS cannot depend on pre-installed infrastructure in the target site. Thus the WSNs used have to be deployed ad hoc. In the most general case, nodes will be placed in random or unknown positions. Once the network has been deployed, the task is then to estimate the position of the nodes, such that the information measured through their sensors can be associated to the known locations.

There are many existing localization methods for WSN [35]. In this work, a maximum likelihood (ML) algorithm based on radial received signal strength (RSS)-distance models is used. Using RSS as a primary source of information for localization has advantages and drawbacks. First, the circuitry to measure RSS is low-cost and most of the radio chips on the market provide an RSS indicator. On the other hand, RSS can be significantly affected by obstacles, and as a consequence, localization using RSS is known to be considerably inaccurate in cluttered environments. However, this sensitivity can be exploited to detect and track objects or persons by monitoring changes in the RSS as is done in Section IV-C. Thus, the same source of information can be used to both locate nodes and track people.

In contrast to RSS-distance model based methods, time based methods using radio signals, such as ultra wide band radios, are less sensitive to the presence of obstacles and gives more accurate position estimates [36]. However, they require expensive circuitry to measure time. Additionally, ranging using time based methods requires dedicated time slots, which can be a limiting factor for tracking [37].

In order to effectively localize the nodes deployed in unknown positions, the MUSAS uses the robot as a mobile beacon. While the robot is exploring the environment, it is communicating with the nodes of the WSN. The robot position is known at all times, and therefore every RSS measurement can be associated to a unique beacon position. Each of the measurements can then be thought of as coming from a fixed beacon placed at the position of the robot at the measurement instant [38]. The advantage of a moving beacon with respect to a limited number of fixed beacons, is that the amount of measurements can be much larger and richer, which allow the localization algorithms to produce more accurate position estimates.

The performance of the localization algorithm depends strongly on the ability of the model to make good predictions of the RSS. In cluttered environments, the RSS can vary significantly, and thus the RSS is modeled as a random

variable. Perhaps the most used RSS-distance model is the log-normal model, which describes the RSS as a normally distributed variable with a mean, decaying proportionally to the logarithm of the distance and with a variance characterizing the variability of the observed RSS [39]. The decaying factor and the standard deviation are well known to depend strongly on the particular environment, and need thus to be estimated. However, the local inhomogeneity of the environment and the hardware differences among the nodes influence significantly the model parameters, which in turn have a strong negative effect on the localization accuracy [40]. Thus, instead of using one model for all the nodes, each node has its own model whose parameters are tuned specifically for that node and the environment.

Because the MUSAS is designed for ad hoc situations, it is not possible to assume the availability of models calibrated a priori or to calibrate the models before the operation. Therefore, algorithms that calibrate the model simultaneously as the node locations are being estimated are needed.

The problem of simultaneous node localization and model parameter estimation can be posed using ML or least-squares (LS) principles, leading in general to a nonlinear optimization problem. The problem can then be solved using any standard nonlinear optimization techniques, such as grid based or Newton-Raphson based. When using the log-normal model, the dependency on the model parameters is linear. Recognizing that the ultimate goal is position estimation, the model parameters can be seen as nuisance parameters, which can be eliminated using the principle of separable least squares [41]. Thus, the search space is reduced to the coordinates of the nodes.

Another conceptually simple approach for simultaneous localization and model calibration is a recursion consisting of 2 steps: starting from an initial guess on the model parameters, first estimate the positions of the nodes. Then, using the estimated positions, re-estimate the model parameters, and start the cycle again. This idea has been proposed in [42] using fixed beacons. In [38] the same principle is exploited using a robot as a mobile beacon to locate the nodes of a WSN in three different environments. With the system used in the MUSAS, a mode localization accuracy of 47 cm was achieved in a large uncluttered space and approximately 1 meter accuracy in a semi-open lobby and a typical office environment [38].

B. TEAM LOCALIZATION SYSTEM

During operation, it is beneficial to know where own team members are located at any given time. This information can be used in operative planning and execution to increase effectiveness and direct the operation where necessary. For the MUSAS, a team localization system exploiting wearable sensors is developed to produce location information of own team members. In addition, the developed system also provides information about the physical state of the person who is wearing the sensor.

Localization of people has been studied extensively, and various different technologies have been proposed [43]–[47]. Commercially ready solutions for outdoor localization already exist such as GPS and GLONASS. On the contrary, indoor localization is more challenging since line-of-sight to GPS satellites is not available and readily available solutions fulfilling the MUSAS requirements do not exist. In most use-case scenarios of the MUSAS, the team operates both indoors and outdoors. Therefore, the proposed system is designed to have a set of complementary positioning technologies that enable localization in versatile urban environments.

The developed system is based on wearable wireless sensor nodes, which are installed on the clothing and equipment of the team members. Outdoors, the location estimates are provided by GPS. Indoors, the localization is carried out by exploiting either inertial navigation, radio based solutions or both simultaneously. Physical condition monitoring is

(a) (b)

FIGURE 12. **(a) The architecture of the team localization system. (b) Wearable sensor node installation on a soldier.**

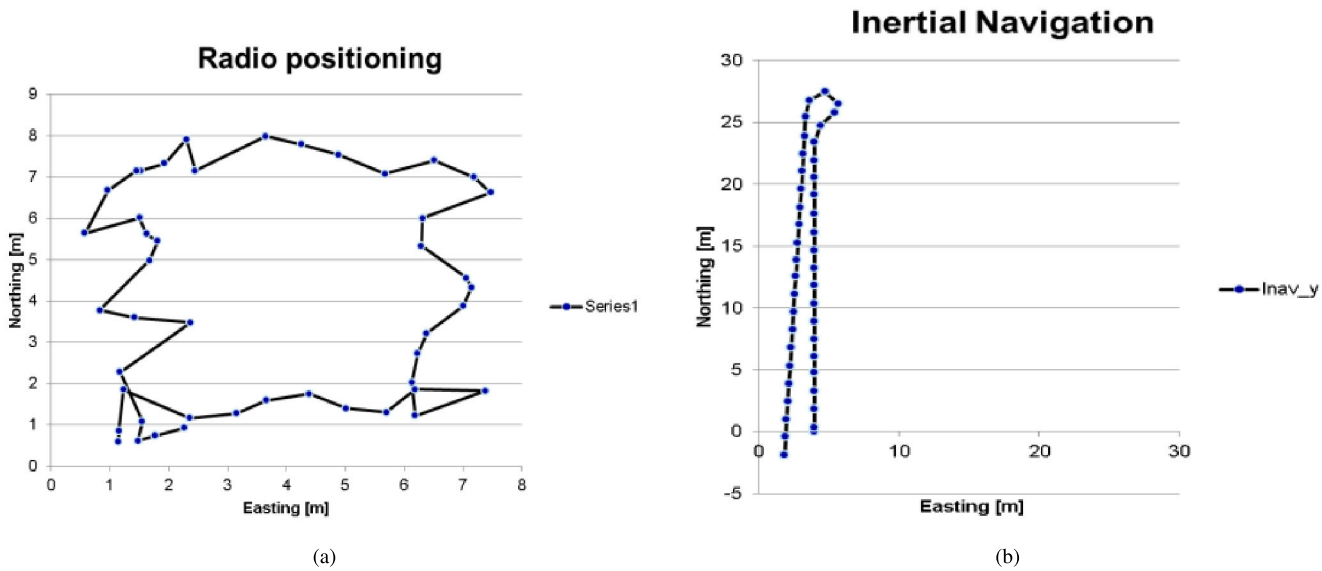


FIGURE 13. **(a) Radio and (b) Inertial navigation in deployment environment.**

implemented by an inertial based activity recognition algorithm that is able to classify some common activities during operation such as: walking, standing, ascending or descending stairs. The algorithm provides the general intensity level of the current activity.

The team localization system, shown in Fig. 12(a), uses inertial navigation and radio based ranging for localization in indoor environments. Ranging is optional and utilized only if radio positioning base stations are deployed in the environment. Each wearable sensor node has an embedded microcontroller based computing unit for running the localization algorithms, radios for data transmission and ranging, and an IMU (Inertial Measurement Unit) with a 3D gyroscope, magnetometer and acceleration sensors for inertial navigation. The wearable sensors are installed on the back of the person as shown in Fig. 12(b), the antennas and IMU on the shoulders, and the acceleration sensors are placed on the right and left boots. Nanotron 2.4 GHz, IEEE 802.15.4a short range radios are used for radio based ranging and relative distance measurement between team members. Wireless communication with the MUSAS is performed using the RC232, 868 MHz RC1180HP long range radios. The wearable sensors are described in more detail in [48].

Inertial navigation of the system is based on estimating the step length using acceleration data gathered from the boots. This information is combined with heading information provided by the gyroscope and magnetometer. Radio based localization relies on time-of-flight (TOF) based distance measurements to fixed base stations, with known locations.

Both localization methods have been implemented separately in the proposed system. The accuracy of the radio-based localization system depends on the used positioning algorithm and the operating environment. Highest accuracy is achieved in unobstructed environments and in line-of-sight conditions. The accuracy decreases in cluttered environments where multipath propagation is common. Inertial navigation is bound to drift during operation and needs regular position and heading corrections. Radio based positioning does not drift, and in future developments, the inertial navigation drift will be compensated by data fusion algorithms taking benefit of GPS or radio based positioning estimates, when available.

Fig. 13 shows some test results gathered during the deployment. Using radio positioning, a test walking trip is done near the walls inside a room approximately $90m^2$. The radio positioning base stations are installed at the corners of the room. The radio based system is capable of localizing a person with an accuracy of 2 m. In the inertial navigation test, a back and forth route was done in a corridor. In the activity recognition test, a stair case was walked, first downstairs and returning back to the start position, as indicated in Fig. 14. The activity recognition algorithm classifies different types of activities. The current type of activity is indicated in color in the end user interface.

C. DEVICE FREE LOCALIZATION

The MUSAS requires localizing targets in the operation area, rendering a need for utilizing a non-cooperative positioning technology that can operate in various ambient conditions. Device-free localization (DFL) is an emerging technology based on RSS measurements of a dense wireless network. DFL fulfills the target localization requirements of the MUSAS, since it is independent of ambient conditions such as lighting, temperature, humidity, etc., it can operate in

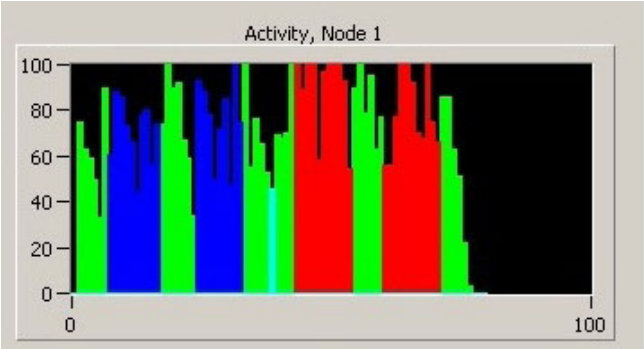


FIGURE 14. Activity recognition test results (green=level walk, blue=descending the stairs, red=ascending the stairs).

obstructed environments, and it can be used in through-wall scenarios. Most notably, this technology does not require that the targets to be localized carry any device.

DFL is based on the fact that wireless communication is affected by people [49], [50], which can be observed in RSS measurements of low-cost wireless devices [51]. Generally, a change in RSS is observed when the link line of two communicating nodes is blocked. Further, the presence of a person causes correlated changes in nearby links, enabling a collaborative localization effort. Since the radio is used for extracting localization information, these systems are referred to as radio frequency (RF) sensor networks [52].

One approach to RSS-based DFL is to estimate the changes in the propagation field of the monitored area, and then form an image of this field, a process referred to as radio tomographic imaging (RTI) [24], [25]. The formed image can then be used to infer the locations of people within the deployed wireless network as shown in Fig. 15(a). Use cases of the MUSAS, set strict demands on the used wireless sensor network and the RSS-based DFL system operation. In the following, these demands are addressed and the applied solutions introduced.

A network monitoring and management framework is essential to manage a WSN as argued by Tolle et. al. [53]. In addition, numerous works have shown that the communication conditions vary significantly over time [54], making network management mandatory to ensure functionality in the long-run. Network management serves two purposes in RSS-based DFL: first, the network can be configured easily, reducing the deployment time; second, it offers the possibility to adapt to changing communication conditions, for instance, the network can change the frequency channel of operation if needed. For these reasons, a network monitoring and management framework is designed and utilized for the purpose of the MUSAS [55].

Similarly, as in the case of the node localization system, the locations of the sensors and RSS-based DFL could be calculated simultaneously as proposed in [56]. However, the MUSAS, take advantage of the robot and the proposed solutions in Section IV-A for obtaining the node locations, and then performs DFL using the known positions of the nodes.

Most RSS-based DFL algorithms require that the RSS statistics are known when the link line is not obstructed by a person. In the current case, there is no possibility for empty-area calibration, thus the system must learn the RSS statistics while running and adapt to the changing environment. Several possibilities exist: first, methods that do not require calibration could be applied [57]; second, online algorithms capable of learning the RSS-statistics when the link is not affected by a person could be used [58], [59]; or third, methods for online calibration could be applied [60], [61]. The methods proposed in [61] are used in the MUSAS.

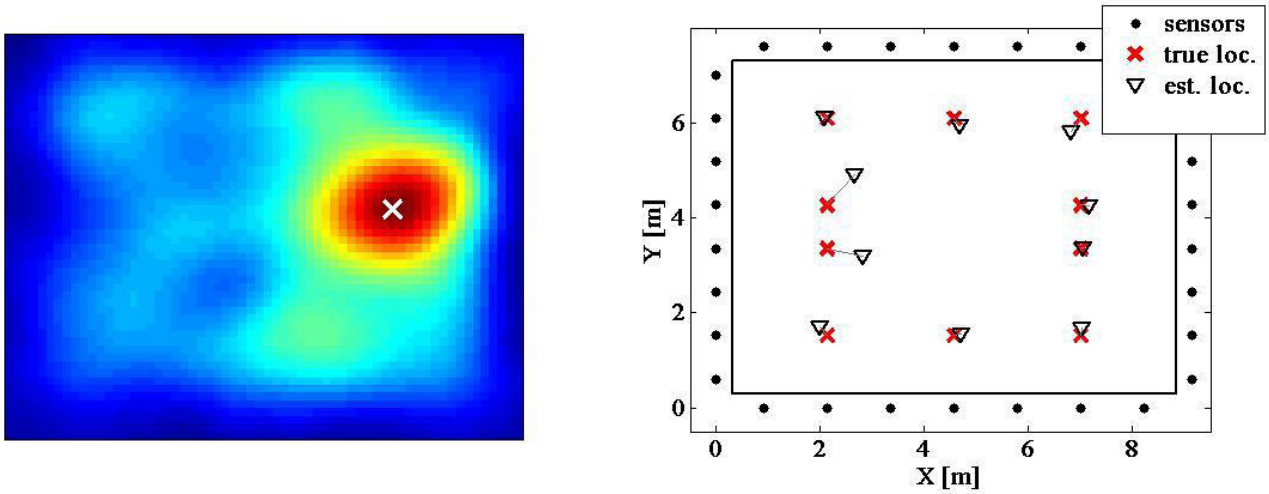
In an urban environment, it is not always possible to deploy sensors inside the same space where the targets are located. Therefore, through-wall localization capability is desired, which is enabled by the RF-based approach. Previous DFL attempts in through-wall scenarios have used variance-based RTI (VRTI) [57], [62]. However, VRTI is not able to localize a stationary target, since it is based on a windowed variance of the RSS. Kernel distance-based RTI (KRTI) has been demonstrated to localize both stationary and moving targets, even through walls of a building [63]. In the MUSAS, the algorithms presented in [64] are exploited, where a multi-scale spatial model and a novel measurement model are utilized. The results demonstrate high accuracy localization (0.3 m) in a through-wall environment as shown in Fig. 15(b).

It is often required to localize and track multiple targets. In [65]–[67], particle filters are used to track multiple targets simultaneously. However, these works assume that the number of targets is known a priori and that the target trajectories do not intersect. These systems struggle also in estimating the locations in real-time, because of the complexity of particle filters. The above drawbacks are addressed in [68], in which machine vision algorithms are adapted for the purpose of imaging-based DFL, and exploited in the MUSAS. The algorithms are able to estimate the number of people correctly 97% of the time. Furthermore, experiments demonstrate that the system is capable of tracking up to four targets with intersecting trajectories with an average error of 0.55 m or lower in a cluttered indoor office.

V. TEST DEPLOYMENT IN AN URBAN HOSTAGE SITUATION

The implemented MUSAS system was tested, demonstrated and evaluated in an urban military training facility at Santahamina, Finland, in November 2012 as described in this section. The experiment was conducted in a testing yard, consisting of a plywood maze for training troops in urban area warfare. A platoon of soldiers, specialized in urban area warfare, served as a field team and as hostile forces, targets. The evaluation case was a hostage situation, where hostile forces and hostages resided in an unknown indoor environment.

In this event, the system formed a COP using a mobile robot, the device-free localization system, and the wearable sensor nodes. The network was built and localized automat-



(a) (b)

FIGURE 15. (a) The estimated RF propagation field image. The estimated distribution coincides with the true location of the person (white cross). (b) The position estimates obtained with RSS-based DFL in a through-wall scenario.

ically as the troops advanced inside the building. During the test a WLAN infrastructure network of approximately 300 × 600 meters was achieved, including the interior of the building, by using only four access points. The soldiers were able to carry the hand-held devices and expand the WLAN network when needed. The robot used two different 3G connections for the remote operator, to ensure connection during the operation. 20 IEEE 802.15.4 sensor nodes where used for DFL. The robot deployed 5 nodes inside the building during the demonstration. Three team localization beacon nodes were used to localize the field team.

The indoor environment map was built online as the robot mapped the building. The MUSAS produced real-time results and delivered information to the field team, including the map, the locations of individual solders and other localized objects and relevant information. In the COP model, rooms were colored red if hostile elements were in a room. After the space was cleared out of danger, the color was changed to green.

Attaching the mobile devices to the soldier's equipment and using it during action were evaluated. Two options were studied: attachment to the left hand (for a right-handed user) and to the upper left torso, using a specific pouch. The first impression was that the hand attachment was better, but the torso attachment proved more reliable. The device is vulnerable when used in the hand, consuming more of the user's attention and also possibly preventing other activities during battle. The torso attachment is slightly more difficult to reach, but, on the other hand, the device is well protected and unobtrusive. After some training, the soldiers got used to carrying and using the device attached to the torso. Later, the mobile device will probably be developed to fit to this attachment more effectively. The soldiers also used glows, specially designed for tactical use with touch screen capability.

During the tests it was recognized that it is inconvenient for the soldier to operate the hand-held device displaying the COP when in action. For this reason, the device was only used for supporting situation awareness, not for active use, such as marking discovered objects to the COP model. During the tests, a short movie was shot [69], which explains the operational concept of the MUSAS. The users gave good feedback about the usability of the mobile devices and also on the speed of the system. In further test the system can be used to evaluate the use of a common operational picture for situation awareness in critical tasks and operations.

VI. CONCLUSIONS

The presented framework provides a novel and scalable solution for creating, hosting and delivering a common operational picture in a multisensory environment focused on localization and position based information in an urban environment. The proposed system is demonstrated by the implemented MUSAS and tested in a realistic urban environment in a military hostage situation.

Compared to other similar systems, the MUSAS focuses on multiple localization services and localized information presentation. The system can be deployed in search-and-rescue and earthquake disaster situations to map the environment and localize people. It has also applications in police hostage situation, indoor fire-fighting scenarios and military operations.

The next step in research is to use a distributed server architecture [70] and distributed computation, to increase modularity and robustness of the overall system. The MUSAS has the architectural solutions which enable distribution of vital services throughout the network and subsystems. Future plans for development include also the implementation of a 3D environment model for localization, as well as improved views for the Android devices.

REFERENCES

[1] M. D. McNeese, M. S. Pfaff, E. S. Connors, J. F. Obieta, I. S. Terrell, and M. A. Friedenberg, "Multiple vantage points of the common operational picture: Supporting international teamwork," in *Proc. 50th Annu. Meeting Human Factors Ergonom. Soc.*, 2006, pp. 467–471.

[2] R. Virrankoski, "Wireless sensor systems in indoor situation modeling II (WISM II)," Dept. Comput. Sci., Univ. Vaasa, Vaasa, Finland, Tech. Rep. 188, 2013.

[3] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," *J. Human Factors Ergonom. Soc.*, vol. 37, no. 1, pp. 32–64, 1995.

[4] R. S. Hager, "Current and future efforts to vary the level of detail for the common operational picture," Naval Postgraduate School, Monterey, CA, USA, 1997.

[5] A. Deschamps, D. Greenlee, T. J. Pultz, and R. Saper, "Geospatial data integration for applications in flood prediction and management in the Red River Basin," in *Proc. Geosci. Remote Sens. Symp.*, vol. 6. Jan. 2002, pp. 3338–3340.

[6] U. G. P. Office, *Joint Vision 2020*. Washington, DC, USA: Government Printing Office, 2001.

[7] (2012). *Programmes at a Glance* [Online]. Available: http://www.soldiermod.com/volume-10/pdfs/articles/programmes-overview-may-2013.pdf

[8] A. Taylor, *Future Soldier 2030 Initiative*. New York, NY, USA: US Army RDECOMM, 2009.

[9] R. Dietterle, "The future combat systems (FCS) overview," in *Proc. Military Commun. Conf.*, vol. 5. Oct. 2005, pp. 17–20.

[10] R. Balfour, "Next generation emergency management common operating picture software/systems (COPSS)," in *Proc. LISAT*, May 2012, pp. 1–4.

[11] L. J. Williams, "Small unit operations situation awareness system (SUO SAS): An overview," in *Proc. Military Commun. Conf.*, vol. 1. Oct. 2003, pp. 13–16.

[12] V. Kaul, C. Makaya, S. Das, D. Shur, and S. Samtani, "On the adaptation of commercial smartphones to tactical environments," in *Proc. Military Commun. Conf.*, Nov. 2011, pp. 7–10.

[13] N. Suri, L. Pochet, J. Sterling, R. Kohler, E. Casini, J. Kovach, *et al.*, "Middleware, and applications for portable cellular devices in tactical edge networks," in *Proc. Military Commun. Conf.*, Nov. 2011, pp. 7–10.

[14] S. M. George, W. Z. C. H. Myounggyu Won, Y. O. L. A. Pazarloglou, R. Stoleru, and P. Barooah "Distressnet: A wireless ad hoc and sensor network architecture for situation management in disaster response," *IEEE Commun. Mag.*, vol. 48, no. 3, pp. 128–136, Mar. 2010.

[15] T. He, S. Krishnamurthy, L. Luo, T. Yan, L. Gu, R. Stoleru, *et al.*, "Vigilnet: An integrated sensor network system for energy-efficient surveillance," *ACM Trans. Sensor Netw.*, vol. 2, pp. 1–38, Feb. 2006.

[16] S. M. Diamond and M. G. Ceruti, "Application of wireless sensor network to military information integration," in *Proc. 5th IEEE Int. Conf. Ind. Informat.*, vol. 1. Jun. 2007, pp. 317–322.

[17] N. Michael, S. Shen, K. Mohta, Y. Mulgaonkar, V. Kumar, K. Nagatani, *et al.*, "Collaborative mapping of an earthquake-damaged building via ground and aerial robots," *J. Field Robot.*, vol. 29, no. 5, pp. 832–841, Sep./Oct. 2012.

[18] F. Driewer, H. Baier, K. Schilling, J. Pavlicek, L. Preucil, N. Ruangpayoongsak, *et al.*, "Hybrid telematic teams for search and rescue operations," in *Proc. IEEE Int. Workshop Safety, Security, Rescue Robot.*, May 2004, pp. 2–4.

[19] M. Kulich, J. Kout, L. Preucil, R. Mazl, J. Chudoba, J. Saarinen, *et al.*, "PeLoTe—A heterogeneous telematic system for cooperative search and rescue missions," in *Proc. IEEE/RSJ IROS*, Sep. 2004, pp. 1–8.

[20] J. Saarinen, S. Heikkila, M. Elomaa, J. Suomela, and A. Halme, "Rescue personnel localization system," in *Proc. IEEE Int. Workshop Safety, Security Rescue Robot.*, Jun. 2005, pp. 218–223.

[21] N. Ruangpayoongsak, H. Roth, and J. Chudoba, "Mobile robots for search and rescue," in *Proc. IEEE Int. Workshop Safety, Security Rescue Robot.*, Jan. 2005, pp. 212–217.

[22] J. Lee, "Enabling network management using Java technologies," *IEEE Commun. Mag.*, vol. 38, no. 1, pp. 116–123, Jan. 2000.

[23] M. Henning, "A new approach to object-oriented middleware," *IEEE Internet Comput.*, vol. 8, no. 1, pp. 66–75, Feb. 2004.

[24] N. Patwari and P. Agrawal, "Effects of correlated shadowing: Connectivity, localization, and RF tomography," in *Proc. Int. Conf. IPSN*, 2008, pp. 82–93.

[25] J. Wilson and N. Patwari, "Radio tomographic imaging with wireless networks," *IEEE Trans. Mobile Comput.*, vol. 9, no. 5, pp. 621–632, May 2010.

[26] M. Matusiak, J. Paanajärvi, P. Appelqvist, M. Elomaa, M. Ylikorpi, and A. Halme, "A novel marsupial robot society: Towards long-term autonomy," in *Proc. 9th Int. Symp. DARS*, Nov. 2008, pp. 523–532.

[27] J. Saarinen, A. Maula, R. Nissinen, H. Kukkonen, J. Suomela, and A. Halme, "GIMnet—Infrastructure for distributed control of generic intelligent machines," *Provider (Server)*, vol. 586, no. 29, pp. 525–530, 2007.

[28] A. Maula, M. Myrsky, and J. Saarinen, "GIMnet 2.0-enhanced communication framework for distributed control of generic intelligent machines," in *Proc. 1st IFAC Conf. Embedded Syst., Comput. Intell. Telemat. Control*, 2012, pp. 62–67.

[29] M. Myrsky, A. Maula, J. Saarinen, and I. Kankkunen, "Teleoperation tests for large-scale indoor information acquisition," in *Proc. Comput. Intell. Telemat. Control Embedded Syst.*, vol. 1. 2012, pp. 13–18.

[30] M. W. M. G. Dissanayake, P. Newman, S. Clark, H. Durrant-Whyte, and M. Csorba, "A solution to the simultaneous localization and map building (SLAM) problem," *IEEE Trans. Robot. Autom.*, vol. 17, no. 3, pp. 229–241, Jun. 2001.

[31] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: Part I," *IEEE Robot. Autom. Mag.*, vol. 13, no. 2, pp. 99–110, Jun. 2006.

[32] T. Bailey and H. Durrant-Whyte, "Simultaneous localization and mapping (SLAM): Part II," *IEEE Robot. Autom. Mag.*, vol. 13, no. 3, pp. 108–117, Sep. 2006.

[33] H. P. Moravec, "Sensor fusion in certainty grids for mobile robots," *AI Mag.*, vol. 9, no. 2, pp. 61–74, 1988.

[34] J. Saarinen, J. Paanajïärvi, and P. Forsman, "Best-first branch and bound search method for map based localization," in *Proc. IEEE/RJS Int. Conf. Intell. Robot. Syst.*, Sep. 2011, pp. 59–64.

[35] F. Seco, A. R. Jimenez, C. Prieto, J. Roa, and K. Koutsou, "A survey of mathematical methods for indoor localization," in *Proc. IEEE Int. Symp. Intell. Signal Process. WISP*, Aug. 2009, pp. 9–14.

[36] N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, and R. J. O'Dea, "Relative location estimation in wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 51, no. 8, pp. 2137–2148, Aug. 2003.

[37] G. E. Garcia, L. Muppirisetty, and H. Wymeersch, "On the trade-off between accuracy and delay in cooperative UWB navigation," in *Proc. IEEE WCNC*, Apr. 2013, pp. 1603–1608.

[38] J. Vallet, O. Kaltiokallio, M. Myrsky, J. Saarinen, and M. Bocca, "Simultaneous RSS-based localization and model calibration in wireless networks with a mobile robot," *Proc. Comput. Sci.*, vol. 10, pp. 1106–1113, Aug. 2012.

[39] S. Seidel and T. Rappaport, "914 MHz path loss prediction models for indoor wireless communications in multifloored buildings," *IEEE Trans. Antennas Propag.*, vol. 40, no. 2, pp. 207–217, Feb. 1992.

[40] J. Vallet, O. Kaltiokallio, J. Saarinen, M. Myrsky, and M. Bocca, "On the sensitivity of RSS based localization using the log-normal model: An empirical study," in *Proc. 10th WPNC*, 2013, pp. 1–6.

[41] F. Gustafsson and F. Gunnarsson, "Localization in sensor networks based on log range observations," in *Proc. 10th Int. Conf. Inf. Fusion*, Jul. 2007, pp. 1–8.

[42] R. Zemek, D. Anzai, S. Hara, K. Yanagihara, and K.-I. Kitayama, "RSSI-based localization without a prior knowledge of channel model parameters," *Int. J. Wireless Inf. Netw.*, vol. 15, nos. 3–4, pp. 128–136, 2008.

[43] A. Amanatiadis, D. Chrysostomou, D. Koulouriotis, and A. Gasteratos, "A fuzzy multi-sensor architecture for indoor navigation," in *Proc. IEEE Int. Workshop IST*, Jul. 2010, pp. 452–457.

[44] H. Muller, C. Randell, and A. Moss, "A 10 mW wearable positioning system," in *Proc. 10th IEEE ISWC*, Oct. 2010, pp. 47–50.

[45] S. Holm, "Hybrid ultrasound–RFID indoor positioning: Combining the best of both worlds," in *Proc. IEEE Int. Conf. RFID*, Apr. 2009, pp. 155–162.

[46] R. Tenmoku, M. Kanbara, and N. Yokoya, "A wearable augmented reality system for navigation using positioning infrastructures and a pedometer," in *Proc. 2nd IEEE/ACM ISMAR*, Oct. 2003, pp. 344–345.

[47] S. Lee, B. Kim, H. Kim, R. Ha, and H. Cha, "Inertial sensor-based indoor pedestrian localization with minimum 802.15.4a configuration," *IEEE Trans. Ind. Informat.*, vol. 7, no. 3, pp. 455–466, Aug. 2011.

[48] M. Korkalainen, P. Tukeva, M. Lindholm, and J. Kaartinen, "Hybrid localization system for situation awareness applications," in *Proc. 3rd WOWCA*, Apr. 2012.
[49] H. Hashemi, "The indoor radio propagation channel," *Proc. IEEE*, vol. 81, no. 7, pp. 943–968, Jul. 1993.
[50] H. Hashemi, "A study of temporal and spatial variations of the indoor radio propagation channel," in *Proc. 5th IEEE Int. Symp. Pers., Indoor Mobile Radio Commun., Wireless Netw., Catch. Mobile Future*, vol. 1. Sep. 1994, pp. 127–134.
[51] K. Woyach, D. Puccinelli, and M. Haenggi, "Sensorless sensing in wireless networks: Implementation and measurements," in *Proc. 4th Int. Symp. Model. Optim. Mobile, Ad Hoc Wireless Netw.*, 2006, pp. 1–8.
[52] N. Patwari and J. Wilson, "RF sensor networks for device-free localization: Measurements, models, and algorithms," *Proc. IEEE*, vol. 98, no. 11, pp. 1961–1973, Nov. 2010.
[53] G. Tolle and D. Culler, "Design of an application-cooperative management system for wireless sensor networks," in *Proc. 2nd Eur. Workshop Wireless Sensor Netw.*, 2005, pp. 121–132.
[54] A. Cerpa, J. Wong, L. Kuang, M. Potkonjak, and D. Estrin, "Statistical model of lossy links in wireless sensor networks," in *Proc. 4th Int. Symp. Inf. Process. Sensor Netw.*, 2005, pp. 81–88.
[55] H. Yigitler, O. Kaltiokallio, and R. Jäntti, "A management framework for device-free localization," in *Proc. IEEE IJCNN*, Aug. 2013.
[56] X. Chen, A. Edelstein, Y. Li, M. Coates, M. Rabbat, and A. Men, "Sequential Monte Carlo for simultaneous passive device-free tracking and sensor localization using received signal strength measurements," in *Proc. 10th Int. Conf. IPSN*, 2011, pp. 342–353.
[57] J. Wilson and N. Patwari, "See-through walls: Motion tracking using variance-based radio tomography networks," *IEEE Trans. Mobile Comput.*, vol. 10, no. 5, pp. 612–621, May 2011.
[58] Y. Zheng and A. Men, "Through-wall tracking with radio tomography networks using foreground detection," in *Proc. IEEE WCNC*, Apr. 2012, pp. 3278–3283.
[59] A. Edelstein and M. Rabbat, "Background subtraction for online calibration of baseline RSS in RF sensing networks," *IEEE Trans. Mobile Comput.*, vol. 99, p. 1, 2012, doi: http://doi.ieeecomputersociety.org/10.1109/TMC.2012.206
[60] O. Kaltiokallio, M. Bocca, and N. Patwari, "Follow @grandma: Long-term device-free localization for residential monitoring," in *Proc. IEEE 37th Conf. LCN Workshops*, Oct. 2012, pp. 991–998.
[61] M. Bocca, O. Kaltiokallio, and N. Patwari, "Radio tomographic imaging for ambient assisted living," in *Evaluating AAL Systems Through Competitive Benchmarking* (Communications in Computer and Information Science), vol. 362, S. Chessa and S. Knauth, Eds. Berlin Heidelberg, Germany: Springer-Verlag, 2013, pp. 108–130.
[62] Y. Zhao and N. Patwari, "Noise reduction for variance-based device-free localization and tracking," in *Proc. 8th Annu. IEEE Commun. Soc. Conf. SECON*, Jun. 2011, pp. 179–187.
[63] Y. Zhao, N. Patwari, J. M. Phillips, and S. Venkatasubramanian, "Radio tomographic imaging and tracking of stationary and moving people via kernel distance," in *Proc. 12th Int. Conf. Inf. Process. Sensor Netw.*, 2013, pp. 229–240.
[64] O. Kaltiokallio, M. Bocca, and N. Patwari. (2013, Feb.). *A Multi-Scale Spatial Model for RSS-based Device-Free Localization* [Online]. Available: http://arxiv.org/abs/1302.5914
[65] J. Wilson and N. Patwari, "A fade-level skew-laplace signal strength model for device-free localization with wireless networks," *IEEE Trans. Mobile Comput.*, vol. 11, no. 6, pp. 947–958, Jun. 2012.
[66] F. Thouin, S. Nannuru, and M. Coates, "Multi-target tracking for measurement models with additive contributions," in *Proc. 14th Int. Conf. Inf. Fusion*, 2011, pp. 1–8.
[67] S. Nannuru, Y. Li, M. Coates, and B. Yang, "Multi-target device-free tracking using radio frequency tomography," in *Proc. 7th Int. Conf. ISSNIP*, 2011, pp. 508–513.
[68] M. Bocca, O. Kaltiokallio, N. Patwari, and S. Venkatasubramanian, "Multiple target tracking with RF sensor networks," *IEEE Trans. Mobile Comput.*, vol. PP, no. 99, p. 1, 2013, doi: 10.1109/TMC.2013.92.
[69] (2013, Apr.). *Finnish Combat Camera Team* [Online]. Available: http://www.youtube.com/watch?v=9v1fFIHRWGE
[70] J. Timonen, "Distributed information system for tactical network," in *Proc. 3rd Workshop Wireless Commun. Appl.*, Vaasa, Finland, Apr. 2012.

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