Toward a Rapidly Deployable Radio Tomographic Imaging System for Tactical Operations

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***Abstract*—The ability for special operations forces (SOF) to rapidly deploy a through-building tracking system upon arrival at a tactical operation, e.g., a hostage scenario, and thereby estimate the approximate locations of the people within the building has the potential to lower the risk of the operation and save lives. We study the feasibility of a rapidly deployed radio frequency (RF)-based tomographic imaging (RTI) system for use in tactical operations by Special Weapons and Tactics (SWAT) and other SOF, in which several low-power radio devices are placed around a building and used to image and track the motion of humans inside the building. Specifically, we identify and study the constraints of this application, such as the need for the sensor network to self-localize and self-calibrate with minimal input from the SOF. We implement and test, in a wide variety of experimental deployments, a real-time RTI tracking system which adheres to these constraints and provides valuable situational intelligence. We work in concert with local law enforcement and SWAT in order to obtain valuable feedback from end users. We show that our system is capable of providing useful tracking information (average errors of less than two meters) even when the self-localization results are inaccurate (up to three meters average error).**

I. Introduction

This paper describes progress in determining the feasibility of a new radio frequency (RF)-based technology for through-building surveillance, specifically, determining the positions of people inside a building using sensors placed only on the outside of the building. The enabling technology, RF tomographic imaging (RTI), uses a network of small, inexpensive wireless devices, placed around an area, to make measurements and estimate where people and objects are currently located in the area [10], [16], [20], [7], [12], [23], [8], [4], [6]. By using radio waves, the devices are able to image through walls, smoke, and other obstructions [19], [22], a major advantage over light and infrared. We introduce the fundamentals of RTI in Section II-A. The "see through walls" capability of RTI opens the door for many emergency response applications in which situational awareness is critical to save lives.

In this work we investigate the application of these technologies to a system for use in emergency response, specifically, for SWAT and military special operations forces (SOF). Consider the scenario of a SWAT team responding to a hostage situation. Upon arrival at the scene, golf-ball-sized RTI radios are placed, thrown, or tactically launched (from an M-32 or M203 launcher) around the building. Depending on the scenario, these might land on the ground, or be deployed so that they stick to the outside wall of the building. Once deployed, the radios communicate and form a mesh network. After the radios self-locate and form an accurate map of their own locations, they continuously measure received signal strength (RSS) on all of the pair-wise links in the network. The measurements are collected and processed in real-time to show the tracks and current locations of moving people and objects in the environment, as shown in Fig. 1. These data from our system represent significant situational intelligence which may help save lives during the course of the SWAT operation. For example, SWAT commanders could decide which part of the building is furthest from people and thus may be their safest point of entry.

This paper details feasibility studies for a robust, rapidly deployable, commercial RTI system. In contrast to experimental research tests in which sensors are hand-placed, mapped, and manually calibrated, in a tactically-deployed system, sensors must self-localize, self-calibrate, and the network must automatically form and start to measuring RSS.

The sensors must self-localize because many tactical operations are time-critical, and SOF cannot take the time to map the locations of the nodes. Additionally, precisely measuring

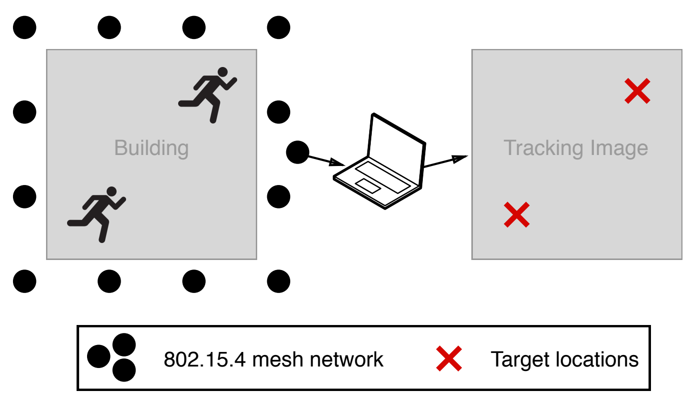


Fig. 1. System overview. Special operations forces arrive at a building, deploy mesh network nodes around the perimeter of the building, and estimate the locations of people moving inside.

This material is based upon work supported by the National Science Foundation under Grant Nos. #0748206 and #1256633.

the node locations may put SOF personnel at risk.

The network must self-calibrate regardless of the number of people already present within the building being monitored. Previous RTI methods [19], [22] have required empty-building calibration measurements in order to generate accurate tracking results, but empty-building calibration measurements may not be possible in many tactical operations. Additionally, since our system can measure RSS on multiple wireless channels, a part of the self-calibration process involves deciding which channels represent the best source for tracking measurements in real-time.

We show that these capabilities are feasible, that robust localization performance can be achieved, and that a complete system with these capabilities would be very compelling for end users. In summary, a through-building surveillance system with the capabilities we demonstrate are feasible would be used by SWAT and other SOF, and would help save lives.

Specifically, our paper describes the following achievements towards a complete RTI tracking system that could be operated and used by SOF:

- We implement in real-time *kernel distance-based radio tomographic imaging* (KRTI), an RTI method that has improved performance compared to previously reported attenuation-based RTI [18] and variance-based RTI (VRTI) [19], [22]. We describe KRTI and its performance in Sections II-A and IV-A.
- Since sensors must self-localize using a combination of GPS, received signal strength (RSS) measurements, and minimal user input, before they can estimate the positions of people in the environment, we study the effects of poor self-localization on tracking performance. Surprisingly, we find that the performance of KRTI degrades gracefully as the sensors' self-localization errors increase. This result is discussed further in Section IV-B.
- We implement and test a particular sensor self-localization method, called distributed weighted multi-dimensional scaling (dwMDS) [1], [2] that combines GPS, RSS, and building layout information for sensor self-localization. We describe dwMDS in Section II-B and show in Section IV-B that our experiments yield an average sensor self-localization accuracy of about 1.5 meters.
- We implement two types of sensor self-calibration. First, the KRTI system must know the histogram of RSS values on each link. We show this can be calculated in real-time from RSS data, without requiring any "empty-building" calibration. Empty-building calibration is impossible in emergency response applications, but has been used in most previous research [10], [18], [17]. Second, we choose upon deployment the best frequency channel for each link according to its fade-level. These two self-calibration methods are discussed in Section II-C.
- We examine the use of directional antennas for through-building KRTI. We find that equipping sensors with directional antennas, compared to omni-directional antennas, reduces average tracking error further, by as much as 22%. This result is described in Section IV-C.
- Finally, we study the effects of using different sized networks for KRTI and find that the number of sensors can be dramatically reduced compared to the 30 or more used in previous research [18], [22]. With only ten sensors, accurate localization (less than 1 meter RMSE) can be achieved. This development is described in Section IV-D.

In summary, we show that a tactically deployed RTI system with a small number of sensors can perform sensor self-localization with minimal input from end users, can self-calibrate, and still provide high accuracy localization and tracking of people in a variety of experimental deployments. In addition, we collaborate extensively with local SWAT order to get feedback on system deployment and usability. End user observations of a testbed deployment are described in Section IV-E.

II. Methodology

In this section we introduce the RTI method we implement to produce the images used to track human motion. Next, we discuss the method we use to allow the nodes to self-localize. Finally, we discuss network self-calibration.

A. Radio Tomographic Imaging Implementation

Several methods for RTI-based location tracking have been introduced over the past few years [21], [15], [9], [12]. In [18], the authors measure the average RSS on each link while the tracking area is empty and then determine where a people are in the network based on changes in the RSS values for each link. In [19], the authors monitor the variance of the RSS on each link in order to localize motion in the network. This method has the benefit that it does not require offline calibration, but it cannot detect stationary targets.

Recently a new RTI method, kernel distance radio-tomographic imaging (KRTI) [23], [13], was introduced which detects stationary and moving targets without the need for offline calibration. KRTI uses a kernel distance metric to quantify the difference between two histograms of RSS measurements for each link in order to track people within the network. Using histograms of RSS measurements combines the benefits of the methods presented in [18] and [19], quantifying changes in both the mean and the variance of RSS measurements for each link. An example of the images generated with KRTI and used for tracking is shown in Fig. 2. The hot point in the image represents the position of the person being tracked.

In KRTI, a long-term histogram is used as a baseline, while a short-term histogram is used to track recent changes in RSS on each link. When applied to these two histograms for a given link, the kernel distance metric is an indicator of motion on or near the link. The results we present in this work rely on KRTI in order to perform tracking because it is well-suited to hostage and barricade situations, in that it does not require empty-building calibration measurements and is capable of running in real-time. We note that a background subtraction method like the one presented in [3] is also capable of determining

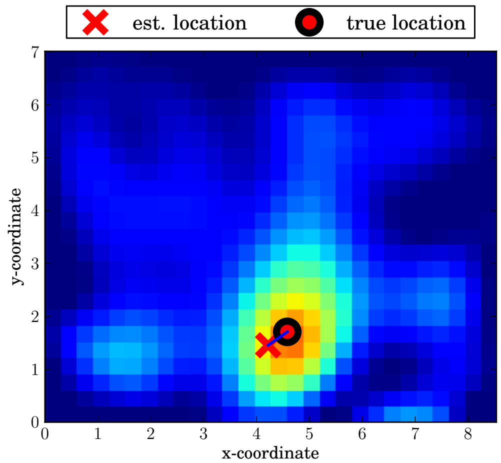


Fig. 2. Example image for multi-channel KRTI.

these distributions without empty-building measurements, but includes more computational complexity.

B. Sensor Network Self-Localization

The proposed tracking system requires knowledge about the relative locations of the radio transceivers deployed around the building within which the human targets are to be tracked. More precise node localization leads to more accurate tracking, which would be valuable to end users like SWAT. Since a SWAT team may not have the time or be willing to put their personnel at higher risk in order to precisely measure out the node locations, the nodes should self-localize and begin to track people within the network with little or no help from the team deploying the system.

There are several methods in the literature for localizing radios. They typically use the time of arrival (TOA) or received signal strength (RSS) of radio transmissions in order to estimate inter-node distances [11]. An ordination technique like multi-dimensional scaling (MDS) [2] can then be applied to find a map of sensors that best fits the measured inter-node distances.

In this work, we implement and augment a type of MDS called distributed weighted multi-dimensional scaling (dwMDS) [2], an ordination method which, given a noisy set of inter-point distances, attempts to find the most likely arrangement of these points. In our case, these points correspond to the locations of the network nodes, and the inter-point distances are estimated using the maximum-likelihood estimator (MLE) for the large-scale path loss model in [14] and the RSS measurements made by the nodes. In order to mitigate the effects of fading error on the RSS measurements for each link, we use the average RSS over five channels for each link.

The dwMDS cost function is

$$S = 2\sum_{i\neq j} w_{ij}(\delta_{ij} - d_{ij}(X))^2 + \sum_i r_i \|\mathbf{x}_i - \bar{\mathbf{x}}_i\|^2, \qquad (1)$$

where δ_{ij} is the estimated distance between nodes i and j, $d_{ij}(X)$ is the distance between nodes i and j for the node location matrix X, w_{ij} is a weighting factor which represents the quality of the distance estimate, x_i is the ith node location, $\bar{x_i}$ represents an *a priori* estimate of the ith node location, and r_i is a weight that represents the quality of the *a priori* estimate. The $\bar{x_i}$ could come, for example, from GPS receivers attached to the nodes or from coarse location estimates contributed by the end user. The cost function is then minimized over the node location matrix X.

We envision that the user interface might include a method for the users to mark (for example, by tapping on a touch-screen) the approximate node locations ($\bar{x_i}$) on a map or aerial image, similar to those provided by Google Maps. Building shapes could be directly inferred from the satellite imagery using edge detection. In addition, end users like SOF have access to building plans, which could also function as input to the software interface. We leave the design of the user interface for future work, but note that the shape of the building around which the nodes are deployed further constrains the locations of the nodes. We augment the dwMDS cost function in order to include the building shape constraint

$$S = 2\sum_{i\neq j} w_{ij}(\delta_{ij} - d_{ij}(X))^2 + \sum_i r_i \|\mathbf{x}_i - \bar{\mathbf{x}}_i\|^2 + a\sum_i \|x_i - p\|^2, \qquad (2)$$

where p is the nearest point on the perimeter to x_i and a is a weighting factor that represents the quality of the perimeter information.

Another possible way to improve network self-localization is to use nodes that include GPS capability. Current commercial GPS devices are capable of localizing to as little as 2 m within 30 s of deployment, and are inexpensive thanks to the rise of the mobile phone. The GPS-based node locations may be used as *a priori* information in (2) or in addition to it. In fact, if GPS can reliably localize to 2 m and the end user only requires coarse target tracking, RTI might be performed using the GPS measurements alone. It is important to note that GPS receivers require unobstructed views of the sky to accurately localize, so we may not be able to rely on GPS in situations where the nodes are not exposed to the sky.

C. Sensor Network Self-Calibration

The tracking system must also establish baseline RSS distributions for each link in order to quantify changes in RSS and localize motion. Since it is not possible for end users to remove the antagonists or hostages from a building in order to perform calibration measurements, these distributions must be estimated online. For multi-channel KRTI, it is also necessary to decide which frequency channels to use. We describe our methods for online baseline RSS estimation and channel selection below.

Baseline RSS estimation: KRTI relies on keeping two histograms of RSS measurements for each link in the network and comparing those distributions in order to determine whether or not people are moving near each link. Self- calibration after deployment occurs in real-time by continuously calculating the long-term histogram and using it as a baseline for detecting human motion. The long-term histogram converges to what would be seen in a calibration to be useful for finding both moving and stationary people in the building. The convergence speed is adjustable, but we find that good performance is achieved with parameters that require about 30 s for convergence. According to our end user contacts, most barricade scenarios last long enough (sometimes multiple days) to allow such a convergence time. We note that people must move periodically in order for our tracking system to locate them. If they remain stationary for a period of time beyond the memory of both histograms, they will disappear from the tracking image.

Channel Selection: We leverage frequency diversity in our test system and demonstrate through multiple experiments that it improves tracking performance. The fading experienced by each link in the network is frequency selective, i.e., the RSS is different due to the different constructive or destructive combinations of the multipath components as a function of frequency. Transmitting on multiple channels makes it more likely that a channel will be found on which each link can be used reliably for RTI.

The best channels for RTI are those in an anti-fade, because the RSS on these channels are typically strongly affected only when a human target is blocking the line between the two nodes of the link, and not when she is moving at other positions [17]. In other words, anti-fade links are the most spatially informative [6], [5]. For each link, we choose the channel with the highest average RSS, because these channels are most likely to be in an anti-fade. There are other options for combining information from multiple channels, e.g., using the best n channels, but we leave the exploration of these options for future work. For multi-channel KRTI, we allow an additional 30 s for channel selection, leading to a total of 60 s for calibration and channel selection.

III. Experiments

In this work, we present results both from real-time experiments as well as experiments that were used in post-processing for analysis of system design. We perform experiments at the following sites (the building layouts are presented in Fig. 3):

- **Site A**: A 110 square meter single floor of a modern home in a typical suburb, comprised of four rooms and a bathroom. (33 nodes deployed)
- **Site B**: A 50 square meter building comprised of 2 rooms. (34 nodes deployed)
- **Site C**: A 55 square meter living space comprised of a single room. (36 nodes deployed)

In each case, Texas Instruments CC253X-based nodes are deployed as uniformly as possible around the perimeter of the building and data are collected using 8 dBi directional and omni-directional antennas while a human target follows planned routes throughout the building. The tracking data are analyzed in post-processing to determine the accuracy of the system. We study the tracking performance when fewer nodes are used to surround each location by using RSS measurements made at a subset of the nodes from each deployment. Additionally, we study the effects of poor node self-localization by adding noise to the known locations of the nodes.

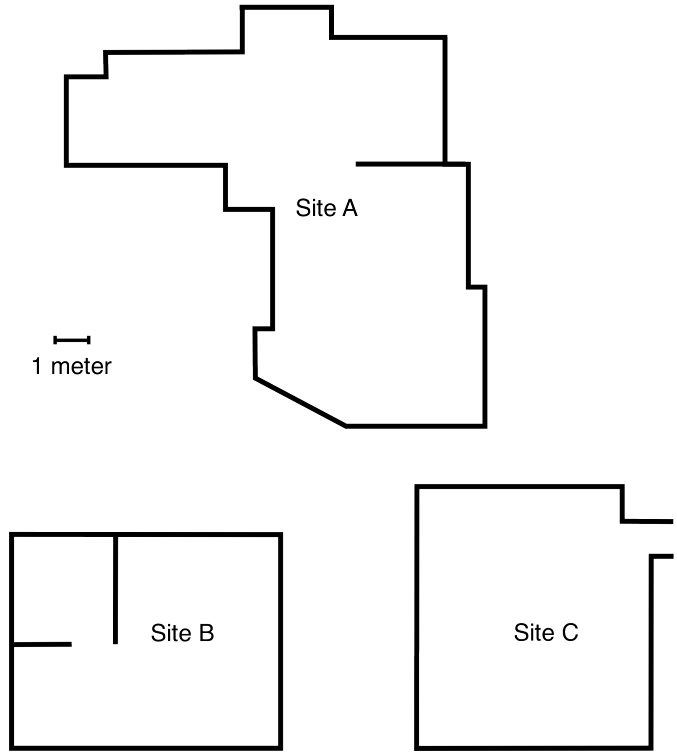


Fig. 3. Experiment sites

A. Tracking

Before pursuing our research objectives relating to self-localization and self-calibration, we first evaluate the tracking performance of a system when the node locations are known exactly for each of the three experiments. Knowing the performance with exact node locations is important as a baseline for evaluating the effect of automatic configuration on tracking accuracy during rapid deployment.

B. Node Self-Localization

In order to test the accuracy of node self-localization methods like dwMDS, we precisely record the positions of each node during each deployment. During the calibration phase immediately after each deployment, we apply dwMDS in order to estimate the relative locations of the nodes.

We are also interested in the performance of our tracking system in the presence of imperfect knowledge of the node locations. In order to understand the effects of poor node self-localization, we simulate the circumstance by adding Gaussian noise to the true node locations and comparing the corresponding tracking results to those we achieve with the correct node locations.

C. Antenna Type

The use of better radio hardware may improve the performance of an RTI tracking system. For example, we are interested in determining whether or not the use of directional antennas results in better tracking performance. Previous research of RTI [18], [19] has relied primarily on omni-directional antennas, which radiate more energy away from the tracking area than they do into it. We expect that the more focused gain pattern of the directional antennas should maximize the amount of power being radiated through the building, as opposed to away from it or around it, leading to a more connected network, a higher average fade level, and better tracking performance. Maximizing the power radiated into the building is especially important in through-building imaging, where the signal may need to propagate through multiple exterior and interior walls.

In order to examine the benefits of directional antennas for our application, we first perform each experiment with radios that include a PCB microstrip inverted-F antenna with an omni-directional gain pattern. We then repeat the experiment using circularly polarized 9 dBi directional antennas. In each case, we set the transmitted power for our radios to the maximum power allowed by the hardware in order to increase network connectivity as much as possible.

D. Network Size

It is important to understand the trade-off between the number of nodes in the RTI network and the corresponding tracking accuracy, because the tracking system must offer a fast and simple deployment in order to be useful to the end users. In some barricade scenarios the hostile targets may be armed, making it dangerous for SOF to spend time setting up nodes around the perimeter of the building. In these cases, smaller networks may allow for safer deployments and still offer useful tracking data. For example, using 30-40 nodes may allow for tracking a person to within 0.3 m of their true location, but the end user may wish to sacrifice some accuracy in order deploy the system quickly in a dangerous situation, e.g., using 10 nodes and accepting a tracking error of 1 m.

We examine the tracking performance for networks which include 10 to 36 nodes. At each experimental deployment, the nodes are placed around the perimeter of the building in an approximately equally spaced pattern.

E. Collaboration with End Users

In order understand the constraints of the potential end users of our system, we collaborate with one of Utah's largest SWAT operations, the Unified Police Department in Salt Lake City. The purpose of our collaboration is to obtain explicit feedback about our proposed system, whether it would actually help in tactical operations, and what physical constraints need to be addressed in order for such a system to become important and useful to end users.

We organize an extensive through-building tracking demonstration day for members of the SWAT team and other law enforcement agencies in order to deploy our tracking system around a home in Salt Lake City and simulate hostage and barricade scenarios while law enforcement officers offer valuable feedback about system deployment and performance.

IV. RESULTS

We present the major results from our experimental deployments below. We discuss general tracking results in Section IV-A, self-localization results and the corresponding effects on tracking performance in Section IV-B, a comparison of tracking performance for directional and omni-directional antennas in Section IV-C, and the effects on tracking performance of using fewer nodes in Section IV-D. Finally, we discuss the feedback from local SOF after a real-time demonstration of the system in Section IV-E.

A. Tracking

At Site A, with exact locations of nodes known, an average tracking error of approximately 1.1 meters was achieved with 33 nodes over 110 square meters. At Site B, an average tracking error of 0.46 meters was achieved with 34 nodes over 50 square meters. At Site C, an average tracking error of 0.54 meters was achieved with 36 nodes over 55 square meters. Some tracking results for Sites A and B are depicted in Fig. 4.

We expect that with a higher density of nodes per unit area, we should see a lower average tracking error, and this can be seen in the results presented in Table I. As seen in Fig. 6, Sites B and C, which are approximately the same size and have similar node-to-area ratios, show similar average tracking results. Site A, which represents a larger area and is covered with less nodes, shows slightly higher average tracking error.

While these tracking results would be beneficial according to our SOF contacts, they are achieved using near-perfect knowledge of the node locations, which SOF may not have access to in most scenarios. The sequel discusses node self-localization results.

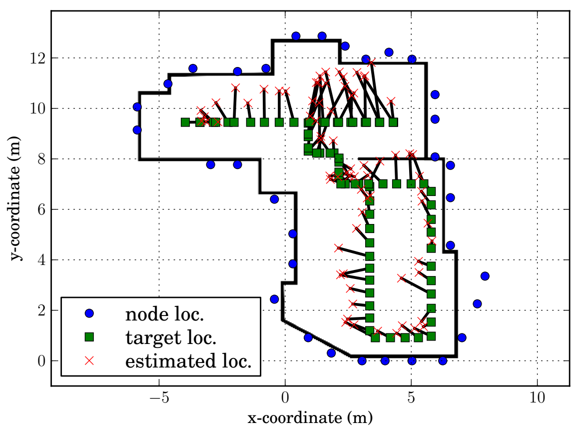
B. Self-Localization

In Fig. 5(a), we show the dwMDS results for Site A without any *a priori* information about the node locations ($r_i = 0$ for all i in (1)), which yield an average error of 3.3 m. The reason for the high average error is the rich multipath environment of the building, which leads to small-scale fading, and the failing of the large scale path loss model. We will show that we can still achieve acceptable human target tracking results with this level of error in the network self-localization, but we can improve the self-localization by including some information from the end user about the deployment, specifically, *a priori* estimates of the node locations and building perimeter shape.

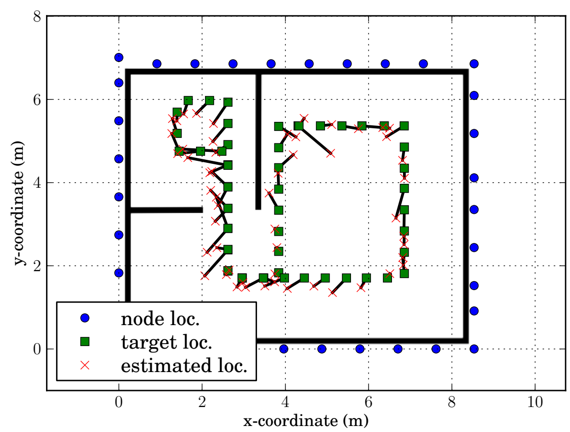
Fig. 5(b) shows the results of dwMDS for Site A with coarse (2 m average error) *a priori* node locations and the augmented cost function (2). In (2), this means that $r_i > 0$ and $a > 0$,

	Site A	Site B	Site C
10-node system	1.27 m	1.19 m	0.89 m
20-node system	1.22 m	0.70 m	0.68 m
30-node system	1.01 m	0.49 m	0.58 m
Random estimator	6.0 m	3.6 m	3.8 m

TABLE I
AVERAGE TRACKING ERROR FOR BEST ANTENNA TYPE AT EACH SITE COMPARED TO RANDOM ESTIMATOR AND NUMBER OF NODES.

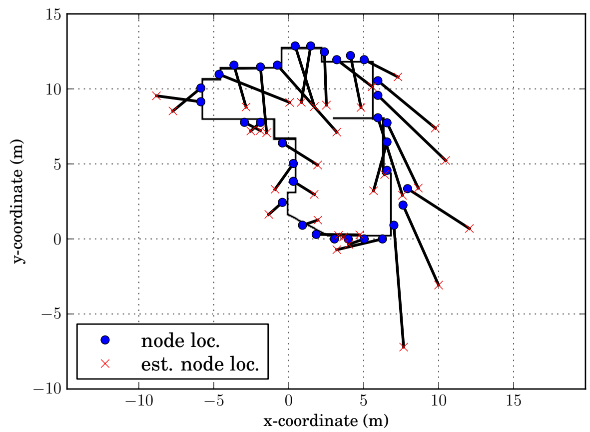


(a)

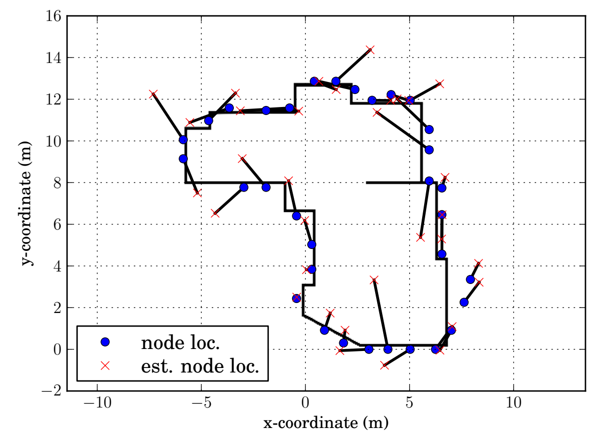


(b)

Fig. 4. A subset of tracking results from: (a) Site A using directional antennas and multi-channel KRTI resulting in an average error of 1.1 m; (b) Site B using directional antennas and multi-channel KRTI resulting in an average error of 0.46 m.



(a)



(b)

Fig. 5. Multi-channel dwMDS (a) without *a priori* information or augmented cost function and (b) with *a priori* information and augmented cost function.

somewhat mitigating the errors caused by the imperfect large scale path loss model. Using the augmented cost function leads to an average error of 1.5 m.

We note that our work investigates the accuracy of target tracking vs. the accuracy of node locations regardless of the methods used to localize the nodes. As expected, the accuracy of tracking decreases as the error of node location increases. However, keeping the mean squared error (MSE) of the node location estimates below 4 m^2 allows for average tracking errors of less than 1.5 m. The results are presented in Fig. 6.

C. Directional vs. Omni-Directional Antennas

Fig. 6 shows the tracking performance at each experiment site vs. error variance in the network self-localization for both antenna types. Directional antennas offer better performance at Site A, but the two types of antennas result in similar performance at Sites B and C.

The difference in the performance may be due in part to network connectivity: Site A shows improved connectivity, in terms of packet reception rates, when using directional antennas instead of omni-directional antennas, while Sites B and C exhibit similar network connectivity regardless of antenna type.

D. Number of Nodes

Fig. 7 shows the tracking results from each site, for network sizes ranging from 10 to 30 nodes, and both antenna types. Tracking results for the maximum number of nodes at each site can be seen in Fig. 6. Surprisingly, we find that with as few as ten nodes, we are able to achieve less than 1.3 m average tracking error in most cases. If we guess randomly and uniformly at the location of the target across the area of the deployments at Sites A, B, and C, we find average errors of 6.0 m, 3.6 m, and 3.8 meters respectively.

The tracking accuracy appears to improve with the number of nodes. Although our experiments used a maximum of 36 nodes, we would expect that further increasing the number of nodes will further decrease the tracking error.

E. End User Feedback

After demonstration of our through-building tracking system, we interviewed SWAT commander Lt. Jake Petersen to receive his feedback and advice regarding the system. The following are quotes from the interview with their respective times in the video. The interview in its entirety can be found at http://www.youtube.com/watch?v=QnQKfz-AEi4. Note that a portion of the tracking demo is contained in the video at time 1:00.

- "This is something that I would use on really any barricaded subject or any hostage situation. Pinpointing exactly where the individual is, or even the hostages, allows us to make a save for these victims much easier. Really it is going to save lives, that's the mission of SWAT." (1:45)
- "Making sure that the technology works is really important and you've given me a lot of confidence in that here today." (4:20)
- "I would not be here if I didn't think that this product could save lives, that's the honest truth." (16:16)
- "I want to save their lives, and I believe this kind of thing could help us do that." (17:00)

V. Conclusion

We have examined the feasibility of a rapidly deployable through-building RTI system for SWAT and other SOF. We have shown that our system can rapidly self-localize and self-calibrate after deployment. The self-localization process requires minimal input from the user, and the system produces useful tracking results even when the node self-localization contains errors. We have also seen that directional antennas help increase through-building tracking accuracies as more power is radiated through the area of interest. Future development may use higher-power transmitters that provide full connectivity for larger building sizes.

Finally, through our interviews with SOF end users, we have further validated the need for this technology in tactical operations. We have shown that a simple, rapidly deployable, and user-friendly through-building tracking system is technically feasible. Future work will include the development of a user interface for SOF that will allow them to input deployment information, e.g., the building shape and coarse node locations, into the system, and then coordinate operations on top of the tracking data it generates.

Acknowledgment

We would like to thank Matt Kankainen for helping with the many experiments necessary for this work.

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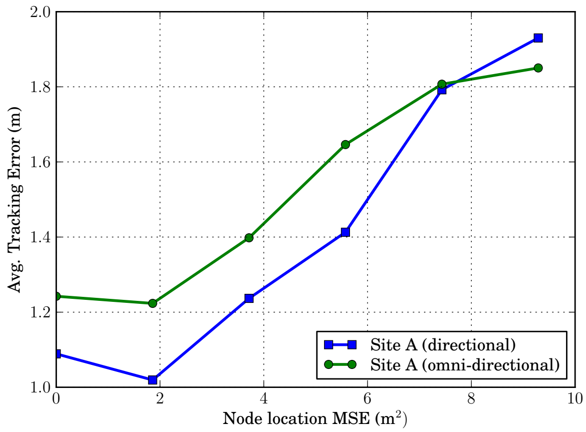
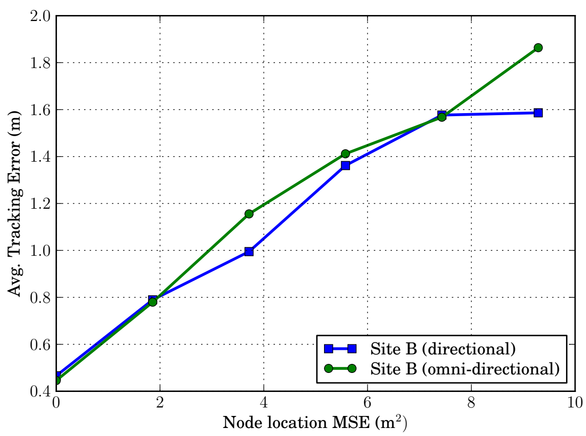


(a)



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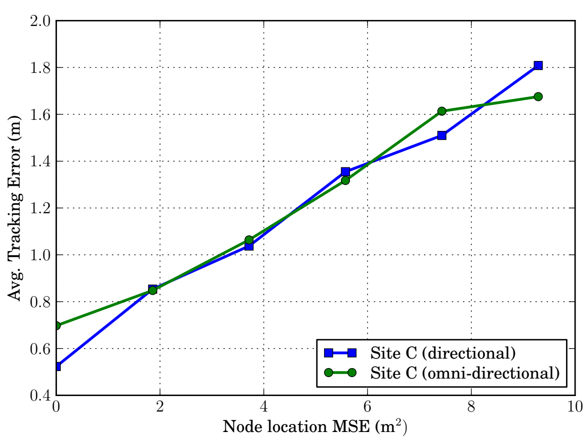

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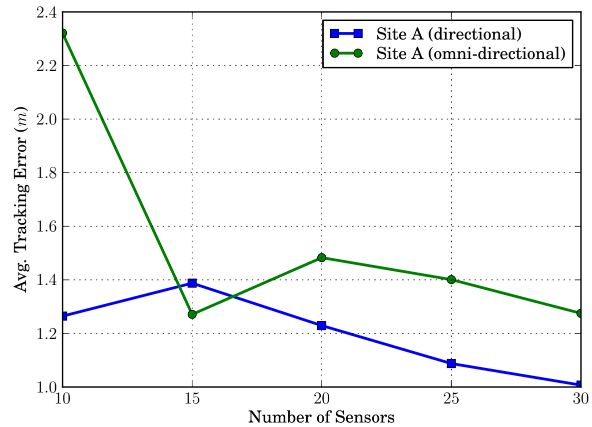
Fig. 6. Average tracking error vs. mean squared error of node locations for directional and omni-directional antennas at (a) Site A, (b) Site B, and (c) Site C.



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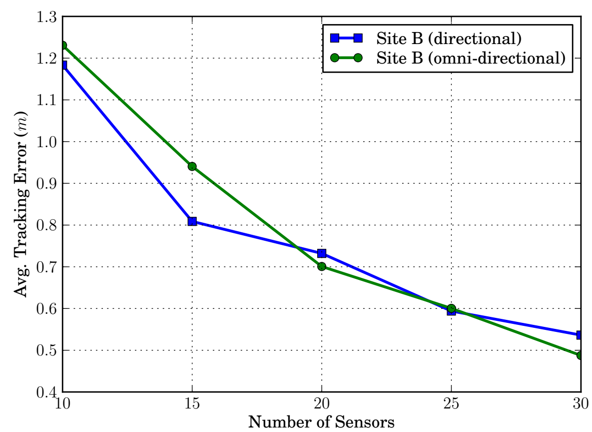

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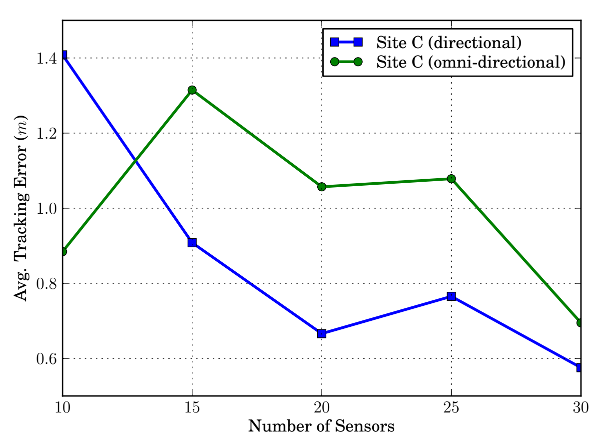

(c)

Fig. 7. Average tracking error vs. number of nodes deployed for directional and omni-directional antennas at (a) Site A, (b) Site B, and (c) Site C.