Experimental Evaluation of Radio Tomographic Imaging Algorithms for Indoor Localization with Wi-Fi

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Abstract—Object localization is at the core of several context-aware applications envisioned for the Internet of Things. However, the present localization approaches are often too expensive, or are limited by indoor layouts and noise. In recent years, radio tomographic imaging (RTI) has generated great interest as a device-free localization approach. While several RTI algorithms have been proposed in the literature, their robustness and comparative performance in indoor environments, with real-world impairments, has not yet been experimentally studied. In this paper, we compare the performance of three state-of-the-art RTI algorithms and analyze the impact of different environmental conditions and algorithm parameters on the localization accuracy. Our experimental results show that multipath propagation is the main limiting factor for indoor localization using RTI: our measurements over a diverse set of indoor locations exhibit a 90th percentile localization error of between 0.8 m and 2.85 m. Additionally, our experiments reveal that co-channel interference and external human mobility further degrade the accuracy by 5\%–20\%. Furthermore, we show that while some improvements are achieved through modifications in network configuration and the fundamental RTI algorithm, these changes (such as increased node density and multi-channel RTI) are not feasible for cost-effective deployments.

I. INTRODUCTION

Numerous context-aware applications that rely on accurate user localization, such as [1], [2], have been proposed under the umbrella of the Internet of Things (IoT). While several traditional indoor localization techniques, based on infrared, ultrasonic, camera [3] and active RF signal-triangulation [4], are present in the literature, these solutions are often expensive for non-commercial use, or are limited by background noise and indoor layouts to support such applications.

Over the last decade, radio tomographic imaging (RTI) [5] has emerged as an alternative, passive, device-free localization technique. In RTI, any object entering the area of interest (AoI), encompassed and monitored by a multi-node, point-to-point wireless sensing network, alters the RF signal propagation, and thereby changes the received signal strength (RSS) at the receiving nodes. Based on the fundamental principle that these RSS changes are caused by the shadowing of the line of sight (LOS) links by the object in the AoI, the RTI approach accordingly computes a spatial distribution image of the target object to localize it. Proposed in [5], the fundamental RTI approach is first reported in [6] to accurately localize objects for sensing network deployments in simple, free-space-like outdoor environments.

However, adopting RTI for practical applications, as envisioned in [1], [2], would necessitate the deployment of sensing networks in real-world, cluttered indoor environments. Operating in such multipath-rich indoor environments, we expect the localization accuracy to degrade severely given the reliance of the RTI model on LOS links. Furthermore, it is reasonable to assume a high level of human activity around an indoor sensing network, which affects the propagation conditions, along with the presence of interfering co-channel traffic from other wireless devices operating in the same frequency band. Such external factors can significantly hinder the RTI operation, thereby further worsening the localization accuracy. Therefore, it is pertinent to evaluate the RTI approach thoroughly in real indoor environments, to determine its robustness and suitability for indoor localization applications in IoT. However, in the current RTI literature [6]–[10], all experimental evaluations are conducted under idealized conditions. In this paper, we systematically experimentally evaluate the RTI approach in several realistic indoor scenarios, under diverse impairment conditions such as co-channel interference and human mobility.

Several modifications to the fundamental RTI approach in [6] have been proposed in the literature to improve indoor localization. In [7], the authors propose considering RSS changes on multiple channels to mitigate small scale fading effects indoors. In [8], the fade level change is considered to adaptively determine a LOS link model for better positioning. The authors in [9] consider short-term RSS variance instead of instantaneous RSS change to combat high attenuation indoors. The algorithm in [10] dynamically updates the object-free state RSS to account for the changes in the AoI. While all these works report improved indoor localization, their conclusions are based on limited testing in a few simple indoor or outdoor scenarios only. Importantly, these algorithms are evaluated in near-ideal conditions and hence, a robustness assessment of these algorithms is not possible from the reported results.
Furthermore, we also note that a comparison of these RTI algorithm variants based on the presented results is also not possible given the large differences in the experimental setups and the common algorithm parameters.

In our work, we deploy a sensing network of low-cost IEEE 802.11 Wi-Fi devices in four indoor locations (and one outdoor location as a reference case) to thoroughly evaluate the performance of the fundamental shadow RTI algorithm [6] and two other major RTI variants [7], [8] proposed in the literature. We firstly evaluate the performance of the shadow RTI algorithm in different sensing network locations to study the effects of surroundings and network parameters on localization accuracy. Next, we study the effects of co-channel interference and human motion outside the AoI on the shadow RTI algorithm to test its robustness. Finally, we evaluate the localization accuracy. Next, we study the effects of co-channel shadow RTI algorithm in different sensing network locations the literature. We firstly evaluate the performance of the

in the AoI. Since the measurements are corrupted by noise,

Mean RSS obtained during calibration phase

\[
\text{RSS}_j(t) \xrightarrow{\text{Measurement Vector Computation}} y \xrightarrow{\text{Image Estimation}} \hat{x} \approx x
\]

Transmitting node, \(TX_i\)
Receiving node, \(RX_i\)
dist \((TX_i, p_i^l)\)
dist \((RX_i, p_i^l)\)
dist \((TX_i, RX_i)\)
LOS ellipse for link, \(l\)
Pixel, \(p_i^l\)
Selected set of pixels, \(N_i\)

Fig. 1: Operation of an RTI algorithm.

Fig. 2: Example of the elliptical LOS model for non-zero weighted pixels selected for a link, \(l\).
it is desirable to find an approximate solution, \( \hat{x} \), in a least squares sense such that

\[
\hat{x} = \arg \min_x ||Wx - y||_2^2. \tag{6}
\]

RTI estimation is an ill-posed inverse problem as the number of links \( L \) in the sensing network is typically smaller than the number of AoI pixels \(|M|\) and consequently, small measurement noise can make the image unstable and meaningless. Therefore, regularization techniques that incorporate additional data to stabilize the image must be applied in RTI algorithms. Using Tikhonov Regularization \([11]\), \( \hat{x} \) is determined by adding a weighted smoothing norm to \( (6) \), resulting in the damped least squares formulation

\[
\hat{x} = \arg \min_x ||Wx - y||_2^2 + \alpha ||Dx||_2^2, \tag{7}
\]

where \( D \) is the regularization matrix, chosen to impose desired properties to the image, and \( \alpha \) is the regularization parameter that controls balance between the residual and the smoothing norm. Finally, the solution to the Tikhonov regularized least square problem is given by

\[
\hat{x} = (W^TW + \alpha D^TD)^{-1} W^T y = P y, \tag{8}
\]

where \( P \in \mathbb{R}^{[M] \times L} \) is the projection matrix that is dependent on the regularization matrix \( D \), the regularization parameter \( \alpha \) and the weight matrix \( W \) (which depends on the sensing network coordinates, the pixel edge length \( d \) and elliptical LOS parameter \( \lambda \)). Once computed, \( P \) remains constant, whereas \( y \) varies with changes in the object position.

Alternatively, image estimation is also possible by choosing a regularized weighted least square formulation of the inverse problem \([12]\), such that \( \hat{x} \) is represented as

\[
\hat{x} = \arg \min_x ||Wx - y||_2^2 + \alpha ||C_n x||_2^2, \tag{9}
\]

where \( C_n \in \mathbb{R}^{L \times L} \) and \( C_z \in \mathbb{R}^{[M] \times [M]} \) are covariance matrices of noise and the attenuation image, respectively. Assuming the noise on each link is i.i.d. Gaussian noise, the regularized weighted least square problem is solved as

\[
\hat{x} = (W^TW + \sigma_n^2 C_x^{-1})^{-1} W^Ty, \tag{10}
\]

where \( \sigma_n^2 \) is the measurement noise variance. Similar to the Tikhonov regularization based approach, the image estimation using regularized least square formulation is done by multiplying a constant matrix (dependent on covariance matrix \( C_x^{-1} \), the noise variance \( \sigma_n^2 \) and the weight matrix \( W \)) with \( y \).

III. RTI ALGORITHM VARIANTS

In this section, we present the three RTI algorithms that we consider for evaluation in our work, focusing on the main differences of the algorithms compared to the fundamental shadow RTI algorithm, and highlighting the parameters considered in the original literature.

- Shadow RTI (SRTI) – SRTI \([6]\) follows the fundamental radio tomography procedure in Section II and provides the basis for the development of several other RTI algorithms. Periodically receiving instantaneous RSS measurements from the sensing network, SRTI computes an attenuation image to estimate the position of the object in the AoI. In \([6]\), the authors propose regularization using the Tikhonov approach and the algorithm is verified experimentally for a sensing network deployed in a simple outdoor scenario, considering \( d = 0.15 \) m, and for different values of \( \alpha \) (0 to 100) and \( \lambda \) \((10^{-4} \text{ to } 1)\). The algorithm was not tested in \([6]\) for multipath-rich environments.

- Channel Diversity RTI (CRTI) – Given the dependence of multipath propagation on the RF signal frequency, CRTI \([7]\) mitigates small-scale fading effects by selectively choosing the channels that contribute to the RSS change vector \( y \). Apart from the computation of \( y \) and using a regularized least squares approach \((\sigma_n^2 = 1)\) to the inverse problem, the algorithm remains true to the SRTI approach. CRTI was experimentally verified in \([7]\) in two indoor environments (one free-space and one through-wall) for \( \lambda = 0.02 \) m and \( d = 0.15 \) m, and the results were compared to the performance of SRTI to show the improvements of CRTI.

- Fade Level Adaptive RTI (FRTI) – To mitigate the effects of multipath propagation, the FRTI algorithm proposed in \([8]\) considers the changes in fade level \([13]\) at the receiver to adaptively determine the elliptical link parameter, \( \lambda \). Furthermore, the algorithm adopts a stochastic model that describes the probability of an object being located within the ellipse, given the fade level and the measured RSS change, to determine \( y \). Adopting a regularized least squares approach \((\sigma_n^2 = 20)\) to the inverse problem, FRTI is tested in \([8]\) for three indoor (two free-space-like and one through-wall) environments with \( d = 0.15 \) m, and is reported to outperform CRTI in open environments.

IV. EXPERIMENT METHODOLOGY AND SCENARIOS

In this paper, we experimentally evaluate the three RTI algorithms (SRTI, CRTI and FRTI) in Section III to determine their performance and robustness under different realistic network and environmental conditions. To understand the effects of different sensing network locations, we evaluate SRTI in one outdoor and four indoor scenarios, while considering different deployment geometries, pixel sizes and node separation distances. We also study the effects of external influences such as co-channel interference and human movements outside the AoI on the performance of SRTI for one indoor scenario. Finally, we evaluate and compare the localization performance of the RTI algorithms in Section III for one indoor scenario.

For our experiments, we deployed a sensing network of sixteen IEEE 802.11 Wi-Fi nodes, such that each node is able to determine the RSS from the other network nodes. Following the initial calibration, during which the mean RSS for each link is obtained for an empty AoI, the RSS is measured for each link for different object positions inside the AoI. The RSS changes for all the links are then fed to the RTI algorithm, which then processes the data to estimate the object position. We then determine the accuracy of the algorithm by comparing the actual and the estimated object positions. In the following subsections, we present the measurement hardware...
and procedure, the chosen RTI processing parameters, the estimation procedure, and the measurement scenarios.

A. Measurement Hardware and Procedure

The sensing network for our study consists of sixteen Raspberry Pi 3 single-board computers equipped with a TP-Link TL-WN722N IEEE 802.11 wireless network adapter. The adapter features an omnidirectional antenna of 4 dBi gain and supports IEEE 802.11 b/g/n PHYs in the 2.4 GHz band. To enable point-to-point communication between nodes, the Raspberry Pis are configured to form an independent basic service set with each node assigned an IP address in the same subnet. The sensing network nodes are placed in a regular square formation at a height of 0.95 m on tripods and each node is separated by a distance of 1 m. The nodes transmit with a power of 20 dBm on IEEE 802.11 channel 1. The baseline sensing network parameters are listed in Table I. The sensing network parameters such as the node separation, the node deployment geometry and the transmission channel are further altered according to the measurement scenarios to study the effects of their variation on the localization accuracy.

To collect RSS measurement information for each link, we executed a Python script on the nodes, such that each node broadcasts UDP datagrams periodically to the IP addresses in the sensing network subnet. Our IEEE 802.11 sensing network is based on the CSMA/CA MAC scheme. Therefore, a sufficiently large broadcast interval of 30 ms is chosen in order to prevent congestion.

B. Study Parameters

The RSS data, collected periodically from the sensing network, is forwarded to a central computer where the RSS changes over the links are processed to generate an attenuation image via the processing mechanism explained in Section II. To analyze the measurement data, we implement the RTI algorithms in MATLAB. We apply regularization using the Tikhonov approach with the regularization parameter $\alpha = 2$. The relevant RTI parameters and their baseline values are presented in Table I.

Fig. 3 presents an example attenuation image generated using SRTI. To determine the position accuracy, we compute the object position by comparing the generated attenuation image to the attenuation image for an empty AoI. The pixels with differences higher than a threshold value are selected. We refer to a contiguous set of selected pixels, as shown in Fig. 3, as the object blob. The exact position of the object is estimated by calculating the centroid of the blob. In case more than one blob is identified, then the blob with the highest cumulative difference is selected to estimate the position.

C. Measurement Scenarios

We consider 16 different measurement scenarios in which we vary the sensing network locations, the network parameters, the environmental conditions and the RTI algorithms for our comparative analysis. Fig. 4 shows the different locations considered, along with the sensing network deployments and the object positions (i.e., a single person standing as shown in Fig. 4a) inside the AoI. Table II lists the different measurement scenarios along with the locations and the variations in parameter values (compared to the baseline parameters in Table I). These different measurement scenarios are considered to study the effects of the following:

1) Sensing Network Location and Configuration: We study the effects of varying the sensing network location through measurements conducted in one outdoor and four different indoor locations (lobby, conference hall, office, and two adjacent rooms). For these scenarios (i.e., Out-1, Lob-1, Con-1, Off-1, and 2Rm-1), we consider the baseline sensing network and RTI processing parameters. We conduct measurements for scenarios Out-2, Lob-2, Con-2, Off-2, and 2Rm-2 considering a pixel size of $d = 0.2$ m to investigate the effects of changes in pixel size for RTI processing. We also conduct measurements in the Lobby considering a node separation of

<table>
<thead>
<tr>
<th>Name</th>
<th>Location</th>
<th>Algorithm</th>
<th>Parameter Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Out-1</td>
<td>Outdoor</td>
<td>SRTI</td>
<td>–</td>
</tr>
<tr>
<td>Lob-1</td>
<td>Lobby</td>
<td>SRTI</td>
<td>–</td>
</tr>
<tr>
<td>Con-1</td>
<td>Conference Hall</td>
<td>SRTI</td>
<td>–</td>
</tr>
<tr>
<td>Off-1</td>
<td>Office</td>
<td>SRTI</td>
<td>–</td>
</tr>
<tr>
<td>2Rm-1</td>
<td>Two rooms</td>
<td>SRTI</td>
<td>–</td>
</tr>
<tr>
<td>Out-2</td>
<td>Outdoor</td>
<td>SRTI</td>
<td>$d = 0.2$ m</td>
</tr>
<tr>
<td>Lob-2</td>
<td>Lobby</td>
<td>SRTI</td>
<td>$d = 0.2$ m</td>
</tr>
<tr>
<td>Con-2</td>
<td>Conference Hall</td>
<td>SRTI</td>
<td>$d = 0.2$ m</td>
</tr>
<tr>
<td>Off-2</td>
<td>Office</td>
<td>SRTI</td>
<td>$d = 0.2$ m</td>
</tr>
<tr>
<td>2Rm-2</td>
<td>Two rooms</td>
<td>SRTI</td>
<td>$d = 0.2$ m</td>
</tr>
<tr>
<td>Lob-3</td>
<td>Lobby</td>
<td>SRTI</td>
<td>$s = 0.6$ m</td>
</tr>
<tr>
<td>Lob-4</td>
<td>Lobby</td>
<td>SRTI</td>
<td>Irregular deployment</td>
</tr>
<tr>
<td>Con-3</td>
<td>Conference Hall</td>
<td>SRTI</td>
<td>Human movement</td>
</tr>
<tr>
<td>Con-4</td>
<td>Conference Hall</td>
<td>SRTI</td>
<td>Co-channel traffic</td>
</tr>
<tr>
<td>Lob-5</td>
<td>Lobby</td>
<td>CRTI</td>
<td>$c = 1, 6$ and $11$</td>
</tr>
<tr>
<td>Lob-6</td>
<td>Lobby</td>
<td>FRTI</td>
<td>–</td>
</tr>
</tbody>
</table>

![Fig. 3: Example attenuation image of an object in the AoI, along with the selected blob and the estimated object position.](image)
V. RESULTS & PERFORMANCE ANALYSIS

In this section, we present our localization results for the objects in the AoI, estimated using the RTI approach, for the measurement scenarios described in Section IV-C.

A. Effects of Sensing Network Location and Configuration

In Fig. 5, we present the performance results of SRTI for the considered indoor and outdoor measurement scenarios and for two pixel sizes (i.e., $d = 0.1$ m and $d = 0.2$ m).

First considering the scenario with the baseline pixel size of $d = 0.1$ m, we observe that whereas outdoors, the localization error is at most 0.12 m for 90% of the cases, in the indoor lobby, the 90th percentile error increases to 0.8 m. The performance worsens for smaller, more cluttered indoor scenarios, with 90th percentile localization errors in the conference hall, the office, and the two rooms being 2.48 m, 2.85 m, and 2.65 m, respectively. We observe the best performance in the outdoor scenario as it provides the closest approximation to a free-space LOS environment assumed for the underlying RTI principle. In indoor scenarios, multipath propagation causes the measurement data to deviate from the RTI principle hypothesis, that link shadowing is primarily caused by obstructing the LOS component of the RF signal. Within more confined spaces, the multipath effects increase and therefore, the performance is worse in the office compared to the lobby. Interestingly, we observe that even though the lobby and the conference hall are similarly sized and have the same network configuration, the performance is considerably worse in the conference hall. This is primarily a result of the differences in the material properties of the layouts. In the conference hall, the higher number of reflective glass doors results in an increased number of NLOS links, which affects the conference hall measurement data more than the data collected in the lobby. Considering the other scenarios, the reduced accuracy in the office is due to the presence of furniture that enhances multipath propagation, whereas for the two-room scenario, it can be attributed to the wall in the AoI that reduces the RSS between several links, such that the RSS changes are not accurately determined.

Let us now consider the scenario with the pixel size of $d = 0.2$ m. From Fig. 5, we observe that while the results do not vary much for the outdoor scenario (90th percentile error of 0.13 m), the accuracy improves considerably indoors. Whereas in the lobby, the 90th percentile error is only 0.15 m (an improvement of 81% compared to $d = 0.1$ m), we observe that the localization accuracy increases by 45% and 52% for the conference hall and the office, respectively, with a 90th percentile error of 1.37 m in both scenarios. Given a fixed AoI size, increasing the pixel size reduces the number of pixels in the attenuation images. Thus, each link of the propagation model affects fewer pixels resulting in larger attenuation per pixel when the link experiences an RSS change. In scenarios that experience weak RSS changes, this increases the contrast in the attenuation images, which is beneficial for a more robust detection of object blobs. Therefore, we observe that for our measurements, a larger pixel size (closer to the target object
dimension) increases the robustness of SRTI against performance degradation in multipath-rich environments, making it favorable for use indoors. However, a large pixel size may not always be relevant, especially for localization of small objects. In general, the pixel size should be comparable to the target object size, in order to obtain meaningful results.

Fig. 6 shows the error distributions for measurements in scenarios Lob-1, Lob-3, and Lob-4 to study the effect of node deployment and separation distance $s$ on the SRTI performance. While for a regular square deployment with $s = 1$ m, the 90th percentile error is 0.8 m, for $s = 0.6$ m the 90th percentile error reduces to 0.13 m. For Lob-1, the links between the nodes are longer than the Lob-3 links. Given that the attenuation experienced by a link decreases with the increase in the distance between the nodes (see Section II-A), the RSS changes in Lob-1 are less for the same object position compared to the Lob-3 RSS changes. Consequently, given a better attenuation contrast, the attenuation images generated for Lob-3 result in improved localization. For indoor applications, irregular deployments are expected to be more feasible in practice than regular deployments. For our irregular deployment in Lob-4, we observe that the 90th percentile error increases to 2.33 m. Due to the random deployment, some object positions are traversed by fewer links compared to the regular network. Additionally, Fig. 4b shows that the nodes in Lob-4 are more widely spread compared to the Lob-1 nodes. Therefore, the irregular network error is much higher than the regular one.

B. Effects of External Influences

Fig. 7 presents the localization accuracy of SRTI under the influence of co-channel traffic and human motion outside the AoI, along with the baseline result. For measurements conducted in the conference hall, SRTI under no external influences localizes with an error of less than 1 m for 76% of the cases. By comparison, an error of less than 1 m is obtained for only 64% of the cases with human movements outside the AoI. Such movements close to the nodes create a non-stationary propagation environment that changes the measured RSS, thereby acting as an additional noise source to the RTI estimation. Localizing objects using a sensing network under co-channel interference, we observe that an error of less than 1 m is achieved for only 27% of the cases. Transmitting over the same channel, the sensing and the interfering nodes contend for access to the shared channel following the CSMA/CA MAC protocol. Consequently, we observe that without interference, the average reporting rate is 357 frames/s, whereas in the presence of co-channel traffic, the rate reduces to only 227 frames/s. Furthermore, co-channel traffic increases the measurement noise greatly, thereby increasing the variance of the measured RSS. Therefore, the attenuation images are generated from outdated packets that are corrupted by the channel noise and thus result in higher localization errors.

C. Comparison of Different RTI Algorithms

In Fig. 8, we compare the performance of the SRTI, CRTI and FRTI algorithms, obtained for measurements in the lobby, to study the effects of the changes proposed in CRTI and FRTI. For CRTI, the 90th percentile error is only 0.1 m and it achieves an improvement of 0.7 m in the localization accuracy over SRTI. Given that CRTI does not differ from SRTI except for measurement over multiple channels, the results vary...
considerably, as in CRTI the likelihood increases that at least one channel is not affected by the small scale fading present in multipath-rich environments. Additionally, the averaging operation in CRTI reduces the impact of random measurement noise, thereby increasing the localization accuracy. In FRTI, the simple elliptical LOS model is replaced with an adaptive link model with the aim of tackling multipath propagation indoors. However, from Fig. 8, we observe that our results are in complete contrast to the results reported in [8], with the 90th percentile FRTI error increasing to 1.7 m, which is more than double the 90th percentile SRTI error. A possible explanation for this behavior is the difference in the sensing network devices in [8] and in our setup. To determine the fade levels of each link, we compute RSS under ideal, non-multipath conditions assuming identical transmit power for the individual nodes. Since we cannot account for possible variations in the transmit power, caused by manufacturing tolerances in the wireless adapters or antenna mismatch, it possibly results in high error. Additionally, in order to fairly compare the different algorithms, we regularize FRTI using the Tikhonov approach instead of the covariance matrix approach used in [8]. This possibly causes further deviations in the results. Consequently, our results suggest that the FRTI approach is not readily applicable without extensive calibration of the sensing network and verification of the empirical model parameters.

D. Discussion

From the results in Section V-A, we observe that multipath propagation severely degrades the performance of SRTI, with the accuracy decreasing drastically for small rooms with reflective partition materials. Although the performance improves for reduced node spacing, the number of nodes required to monitor a given AoI increases as well. As a dense network deployment is typically not cost-effective for non-commercial applications, increasing node density is not a feasible approach to improve accuracy in practice. Furthermore, a denser network also increases the measurement latency, resulting in inaccurate localization of a moving object. We also observe that the selection of a pixel size comparable to the target object size produces better estimates. Nevertheless, it is still not sufficient for accurate positioning indoors as, with the exception of the lobby, the 90th percentile error remains greater than 1 m. Furthermore, the results in Section V-B show that external influences such as co-channel traffic and human motion further degrade RTI accuracy, such that for a single moving person and a single interfering transmitter, the 90th percentile error increases by 5% and 20%, respectively. We expect the performance to degrade even more with an increase in human activity and interference indoors. Finally, by comparing the algorithms in Section V-C, we see that whereas CRTI mitigates somewhat the multipath propagation effects indoors at the expense of increased sensing node complexity (of synchronizing measurements over multiple operating channels), the FRTI performance is worse in our implementation. For FRTI, precise knowledge of the nodes is necessary to compute the fade level and even small miscalculations of the fade level result in high error.

VI. CONCLUSIONS

In this paper, we experimentally investigated the feasibility of RTI for passive localization in real indoor environments. For our evaluation, we deployed a sensing network of sixteen low-cost, Wi-Fi devices in four indoor (and one outdoor baseline) locations. We determined the effects of sensing network location and configuration on the localization accuracy of the basic SRTI algorithm. The results showed that indoors, multipath propagation significantly degrades the localization accuracy and accordingly, we obtain a 90th percentile error ranging between 0.8 m to 2.85 m for different indoor locations. While we observed improved localization for an increase in node density, we argue that it is not a cost-effective solution. Experiments under co-channel interference and human mobility reveal that the localization accuracy is further reduced by 5%–20%. Comparing the performance of the SRTI, CRTI, and FRTI algorithms, we observed that while CRTI mitigates the small-scale fading effects through increased node complexity, FRTI performs worse than SRTI, given the requirement of precise fade-level computations which are not feasible for low-cost devices. Therefore, our study suggests that, while the RTI approach is promising for localization in free-space-like outdoor environments, the influence of multipath propagation, human movement and co-channel traffic makes RTI unsuitable for precise localization in realistic indoor environments.

REFERENCES