Demonstrating Device-free Localization based on Radio Tomographic Imaging

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***Abstract*—Radio tomographic imaging (RTI) is one well-known localization algorithm that can estimate the position of an object on the basis of the received signal strength indicator (RSSI) acquired by WiFi or other wireless networks. In this paper, we demonstrate the RTI approach by utilizing full electromagnetic simulations of an indoor environment. In particular, we consider dielectric cylinders with fixed radius size and varying permittivities and deploy 20 WiFi nodes on the perimeter (6 m by 3 m) of the room. The RTI approach based on the line-of-sight (LOS) weighting model with total variation based regularization was then used to demonstrate device-free localization.**

I. Introduction

Advancements in wireless communications have resulted in the emergence of location based services (LBSs) and these have become essential for users to make decisions or plan activities. Device-free localization (DFL) is an emerging technology that overcomes the issue of equipping the target with the wireless transceiver device. DFL techniques can detect and locate a human or an object by measuring received signal strength indicator (RSSI) changes in the environment through the implementation of Wireless Sensor Networks (WSNs).

Radio tomographic imaging (RTI) is a technique that can perform DFL using image reconstruction for localization. It is able to reconstruct or image the attenuation due to objects using the shadowing losses measured at sensors in the WSNs. This algorithm is suitable for indoor applications because the induced reflection created by the objects develop a strong non-linear attenuation field map [1]. The deployment of WSNs in a monitoring area makes it possible to establish wireless links between each sensor that continuously send packets of information to the other sensors to obtain RSSI [2]. As a result, RTI can detect objects such as the human body and furniture. Therefore, when an object enters in a region with WSNs, radio-frequency (RF) signals pass through the object thus resulting in shadowing losses and change in RSSI of the sensor links [3].

II. Radio Tomographic Imaging

Given that there are $K = 20$ WiFi nodes deployed in the indoor room, the total number of two-way wireless links can be denoted as $M = \frac{K^2-K}{2}$ where reciprocity in the links is accounted for [3]. Let N be the total number of square pixels in the image representation of the room. Now when an object is present in the room, some of the node links will be blocked by the object and this will cause the WiFi signal to experience significant attenuation. The RSSI expression can be simplified as:

$$\Delta \mathbf{y} = \mathbf{W} \Delta \mathbf{x} \tag{1}$$

where

$$\begin{aligned} \Delta \mathbf{y} &= [\Delta y_1, \Delta y_2, ..., \Delta y_M]^T \\ \Delta \mathbf{x} &= [\Delta x_1, \Delta x_2, ..., \Delta x_N]^T \\ \mathbf{W} &= [w_{ij}]_{M \times N} \end{aligned} \tag{2}$$

and $\Delta \mathbf{y}$ represents the change in the RSSI measurements of M links. $\Delta \mathbf{x}$ is the attenuation of the object that will be estimated. $\mathbf{W}$ is the weights matrix with $M \times N$ dimension with the column representing the pixels and the row representing the weight of each pixel for which the particular link passes through. Noise can be considered negligible for the simulation results.

The ellipse model was proposed by [3] as a means of weighting pixels. For a particular link, the two nodes will be the foci of an ellipse and if a pixel falls inside the ellipse, the weight of the corresponding pixel will be set to 1, otherwise it will be zero. The weight will be normalized to $\frac{1}{\sqrt{d}}$ since the distance between two nodes of the link are different. The weighting can be defined as

$$\mathbf{w}_{ij} = \frac{1}{\sqrt{d}} \begin{cases} 1 & \text{if } d_1 + d_2 < d + \delta \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where d is the distance between two nodes, d_1 and d_2 are distances from pixel j and the two nodes respectively for link i. δ is the tunable parameter which is the width of the ellipse which in a typical RTI model should be set low such that it is identical to using the LOS weighting model [4].

The linear model of RTI is denoted in expression (1) and it is an ill-posed inverse problem. In our simulated configuration, we have only deployed $K = 20$ WiFi nodes thus giving us only $M = 190$ unique measurements and therefore low resolution. With such a small measurement set of $M = 190$, the maximum resolution we can achieve is around 0.31m by 0.31m ($N \approx 190$). However, given that our aim is to detect change in the environment at a high resolution, we decided to choose pixel size of 0.1 m by 0.1 m ($N = 1800$)

which is the typical wavelength of WiFi signals at frequency 2.4 GHz. This therefore becomes an example of a highly underdetermined problem ($N = 1800, M = 190, N \gg M$) whereby the number of unknowns is larger than the number of measurements. As a result, imaging is performed with only 10.5% of the unknowns. Given that the imaging change is performed in successive frames, we can make the assumption that spatial verification in the region of interest will be sparse. Hence, we can implement the total variation based regularization as proposed in. Therefore, the final optimization problem becomes as expressed in equation (4).

$$\Delta \mathbf{x}_{LS} = \arg\min_{\Delta \mathbf{x}} ||\Delta \mathbf{y} - \mathbf{W}\Delta \mathbf{x}||_2^2 + \lambda ||\mathbf{D}\Delta \mathbf{x}||_1 \qquad (4)$$

where λ is the regularization parameter and operator $\mathbf{D}$ is the difference between successive elements of vector $\Delta \mathbf{x}$.

III. Simulation Setup

To perform full electromagnetic simulation of our target room (6 m × 3 m × 4 m (room height)) corresponds to an approximate electrical volume of 37000 cubic wavelengths (approximately 24 by 48 by 32 wavelength). In general this would require significant computing resources if full 3D electromagnetic simulation was to be performed computing RF signals. We simplify the object of interest in the room by using a dielectric cylinder at any location with a particular radius and varying permittivites. This assumption is justified on the bases of detecting change with a focus on detecting a movement of humans or furniture in the room. Although a human body does not have an exact circular shape we approximate as such with permittivity ranging from 20 to 60. Objects like furniture in room are taken to have permittivity ranging from 2 to 3 at the frequency of 2.4 GHz. We simulate a cylinder with a radius 0.3 m with the center at (4,2) as shown in Figure 1.

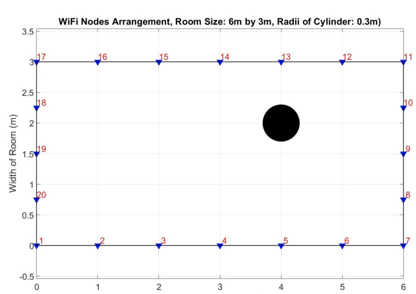

Fig. 1: Cylinder with a radius of 0.3 m with the center positioned at (4,2). The permittivities of the cylinder are arbitrary.

The three permittivites that we simulate are 1.5, 3 and 30. The radius of 0.3 m with permittivies of 1.5 and 3 is a representation of objects such as furniture i.e. wooden table, chair etc. Meanwhile, the radius of 0.3 m with permittivity of 30 is a representation of a human walking in a room.

IV. Simulation Results of RTI Localization

Figures 2, 3 and 4 provide the RTI reconstruction of the cylinder with radius of 0.3 m and permittivites of 1.5, 3 and 30 respectively.

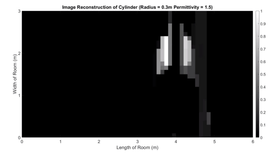

Fig. 2: RTI reconstruction of cylinder with radius of 0.3 m and permittivity of 1.5.

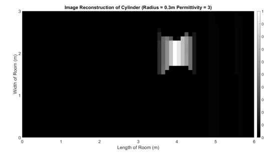

Fig. 3: RTI reconstruction of cylinder with radius of 0.3 m and permittivity of 3.

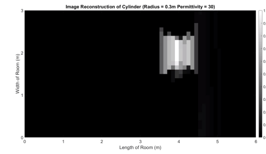

Fig. 4: RTI reconstruction of cylinder with radius of 0.3 m and permittivity of 30.

Based on Figures 3 and 4, it can be seen that the RTI methodology with the implementation of total variation based regularization is able to reconstruct the cylinders with the permittvities of 3 and 30 respectively reasonably well. Furthermore, these cylinders also have a proper localization as it is visible that the center of the reconstructed cylinders is at (4,2). However, upon looking at Figure 2, the RTI methodology is unable to reconstruct the cylinder with a low permittivity of 1.5 and hence, it is difficult to localize the cylinder.

V. Conclusions

This paper demonstrates the simulation of a cylinder with a radius of 0.3 m and three different permittivities in a room with 20 WiFi nodes. Using the LOS weighting model and total variation based regularization, we are able to reconstruct the location of the cylinders with RTI methodology using pixel dimensions of 0.1 m by 0.1 m when the cylinders have permittivity of three and greater. However, the RTI methodology tends to fail when reconstructing cylinders with permittivity of below 1.5 based on the results obtained.

References

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