2D Through-Wall Imaging with WiFi Power Measurements and Belief Propagation

Neeli Tummala June 14, 2019

Abstract—In this project, I combine concepts from two papers related to through-wall imaging with WiFi signals. In [1], WiFi power measurements are used to create 2D images of unknown areas behind walls. The paper focuses on comparing reconstructions of the areas based on two wave models, the line-of-sight (LOS) model and the Rytov model. In [2], 3D images of unknown areas are reconstructed using WiFi power measurements and improved using a belief propagation algorithm. The goal of this project is to investigate the utilization of the mentioned belief propagation algorithm in the 2D case. I reproduce results from [1] and show that the Rytov model provides a more accurate reconstruction of the unknown area than does the LOS model. Finally, I show that the results of the belief propagation algorithm provide a cleaner version of the 2D images and suggest future improvements for the project.

I. Introduction

Through-wall imaging with WiFi signals is exciting for many reasons. It does not require a device to be placed inside the unknown area, involves relatively little equipment, and preserves privacy. In addition, it has many possible applications including disaster relief, search and rescue, and surveillance. This project attempts to combine two ideas in this area to improve 2D images constructed from WiFi power measurements. I use experimental data collected in [1] and implement code in MATLAB to reproduce the results from the papers. The data collection process is briefly described next.

Two robots, one the transmitter and the other the receiver, travel in coordinated paths around the unknown area. They are equipped with directional antennas that have a beamwidth of 21 degrees and operate at 2.4 GHz. This setup is shown in Fig. 1 below, where the unknown area is highlighted in a red prism. The robots travel in parallel paths at several different angles around the unknown area. An example of these paths are shown in Fig. 2. The receiver records power measurements every 0.02m travelled. The measurements for the 0 degree path from the occluded cylinder area can be seen in Fig. 3.

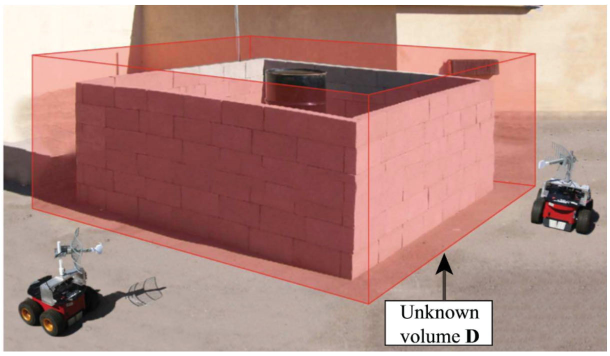

Figure 1: Experimental setup. *Source*: [1]

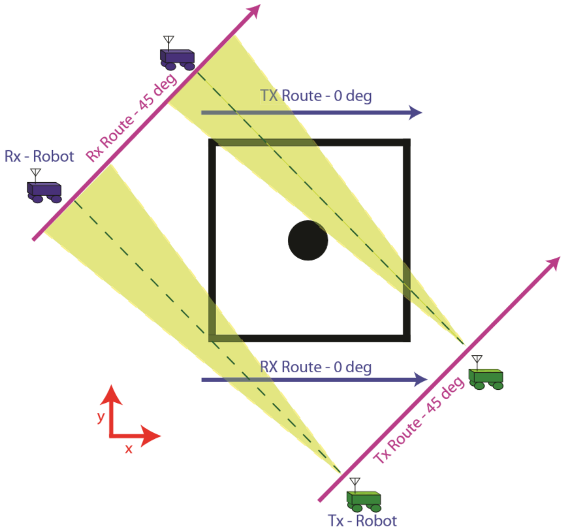

Figure 2: Robot paths for 2D imaging. *Source*: [1]

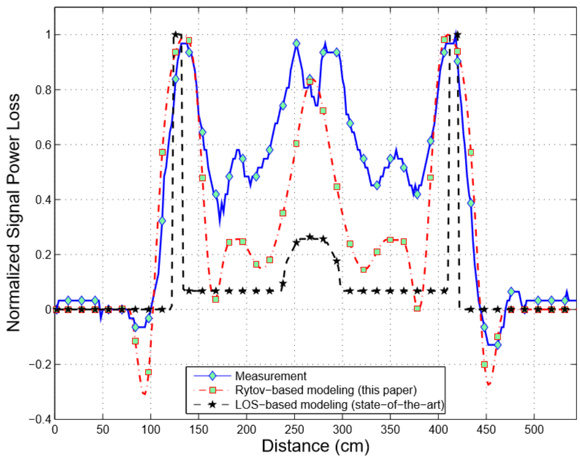

Figure 3: Signal power loss for 0° path in occluded cylinder experiment. *Source*: [1]

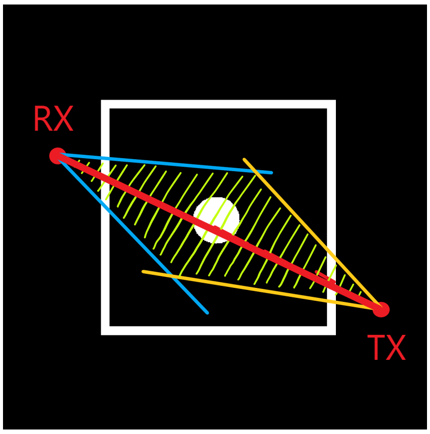

Figure 4: LOS and Rytov models

II. 2D Image Reconstructions

The WiFi power receptions can be modelled in many ways, some more complex than others. In this project, I explore the line-of-sight (LOS) and Rytov models, as described in [1]. A visual summary of these two models is shown in Fig. 4.

In order to simplify the problem, the unknown area is discretized into cubes of equal size with side lengths of 0.02m. Using this, the unknown area can be represented as a vector with each entry corresponding to one of the cells in the area. In addition, the received power measurements are changed to take into account the line of sight or incident power as shown in the following equation,

$$P = \frac{P_r(dBm) - P_{inc}(dBm)}{10\log_{10}(e^{-2})},$$

where P_r is the original received power and P_{inc} is the received power when there are no objects between the receiver and transmitter.

A. LOS Model

The LOS model is widely used because of its linear properties and simplicity. In this model, only objects along the direct line between the transmitter and receiver are considered, which is shown as the red line in Fig. 4. As a result, this model does not take into account any multipath phenomena such as scattering and reflections. The power loss along the LOS path is linearly related to the objects along the path. This can be viewed through the lens of the distance dependent path loss equation shown in class, since in the dB domain, the power loss can be expressed as subtractions of each object contribution along the LOS path. The linearized model can then be represented as a system of linear equations $P = A\Gamma$, where P is the vector built from the received power measurements as described above, A is a matrix with ones along the direct path between the transmitter and receiver and zeros elsewhere, and Γ is the object map we wish to estimate.

B. Rytov Model

In contrast to the LOS model, the Rytov model does take into account multipath phenomena by considering contributions from all cells within the beamwidths of the receiver and transmitter. These cells are shown in the shaded green area between the yellow and blue beams in Fig. 4.

Again, the linearized Rytov Model can be represented as a system of linear equations $P = A\Theta$, where P is the vector described above. The A matrix is populated with Green's function terms that take into account distance dependent contributions at each cell inside the beamwidths. The matrix is zero elsewhere. The Θ vector is again the object map we wish to estimate, but it is important to note that it contains different information about the unknown area than the Γ vector in the LOS model. Since this model takes more information about our unknown area into account, it is expected that it will result in a more accurate reconstructions, which will be shown in the Results section. In addition, we can see from Fig. 3 that the Rytov-based modeling results in received power approximations that match the original measurements better than the approximations from the LOS-based modeling.

It should be noted that there are errors in my code for this model. The entries of the A matrix in this model contain terms that are reliant upon the volume of each cube in the unknown area, which is $0.02^3 m^3$. However, because I misinterpreted the paper, the volume in my code is an area, $0.02^2 m^2$. As a result, the scaling of my matrices in the arguments of the TVAL3 algorithm are different from those used in the original paper. In addition, the original paper implements cosine beam fading, where the cells at middle of the beam contribute more than those towards the edge of the beam. In this project, I assume that each cell contributes with an equal weight, regardless of its position within the beams. Additionally, the construction of the A matrix in the occluded cylinder case takes 18.57s in my project, whereas in the original paper, this process takes 9 minutes. This discrepancy may be related to the cosine beam fading. Though my results closely match those of the original paper even with these differences, I plan to fix them in the future.

C. Sparse Signal Processing

These models result in underdetermined systems of linear equations with many more unknowns than equations. Without an objective function, there is no way to solve for a unique solution. The assumption that the spatial variations of the unknown areas are sparse allows us to use a sparse signal processing algorithm to solve this system. The algorithm, called TVAL3 (TV Minimization by Augmented Lagrangian and Alternating Direction Algorithms), solves the optimization problem by minimizing the total variation of the area.

There are several parameters in this algorithm that can be tuned to improve the image quality. The main parameters are μ and β, which are penalty parameters. I experimented with these for each unknown area to get the the best image.

III. Belief Propagation

The unknown area can be modelled as a Markov Random Field (MRF) where each discretized cell is a node in the graph. Each node has a label marking it as either occupied or unoccupied and we wish to pick the best label based on the original grayscale image. In an MRF, each node is independent of all other nodes in the graph when conditioned on its neighbors. This allows us to find the joint probability of the labels across the graph. However, solving directly for the labels that maximize the posterior probability is computationally prohibitive. Instead, we utilize belief propagation as an efficient way to get an approximate solution.

Each node in the 2D setting has four neighbors and one associated observation node, as shown in Fig. 5. The blue circles are the neighbors of the hidden node in the center and the blue square

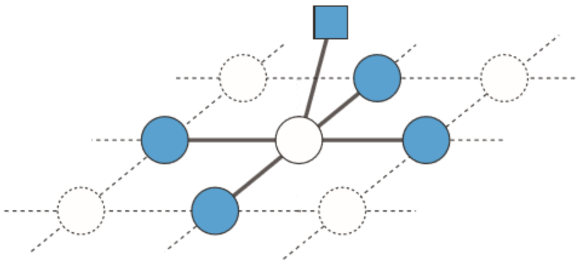

Figure 5: MRF structure. *Source*: [2]

is the associated observation node. Each observation node comes from the original grayscale output of the TVAL3 algorithm.

Belief propagation is an iterative message passing algorithm that allows us to maximize the marginal distribution at each node. At each step, nodes pass a message to each of their neighbors indicating what label the node believes its neighbor is and with what probability. Using this, a marginal distribution is computed at each node and the label that maximizes it is chosen, resulting in a binary object map.

While belief propagation is an efficient way to estimate the labels of each node, it does have its downsides. First, we model each node as having 4 neighbors. This does not take into account the other nodes around it, such as those on the diagonals, which certainly contribute to the label of the node. An interesting extension to this idea would be to include more neighbors in the construction of the graph. Additionally, belief propagation results in a binary map, which throws away all information related to the properties and materials of the objects in the unknown area, which can be seen in the original grayscale images.

IV. Results

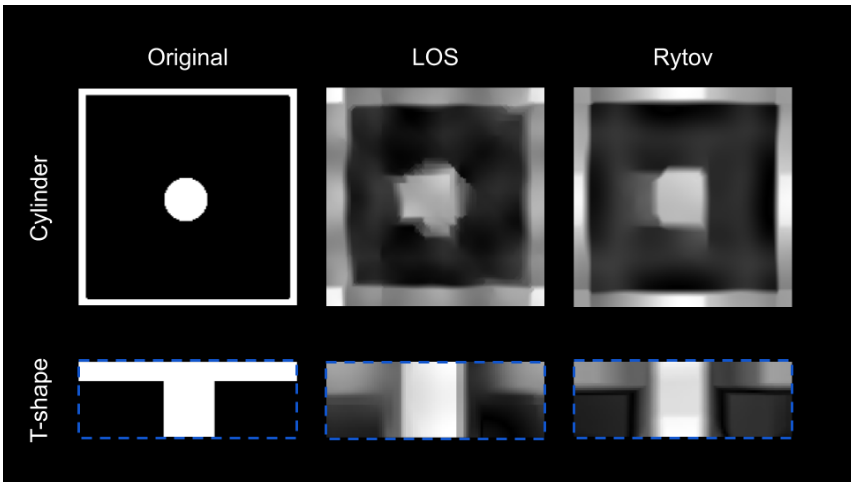

Figure 6: LOS and Rytov model reconstructions of occluded cylinder and T-shape areas

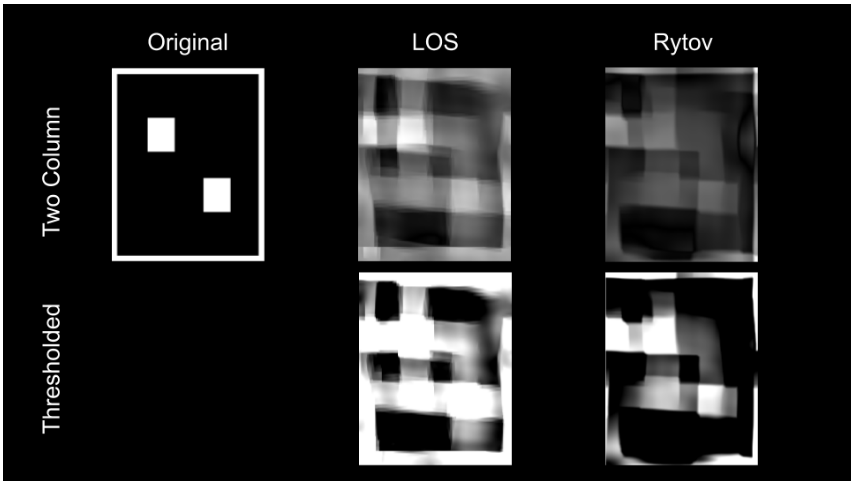

Figure 7: LOS and Rytov model reconstructions of two column area

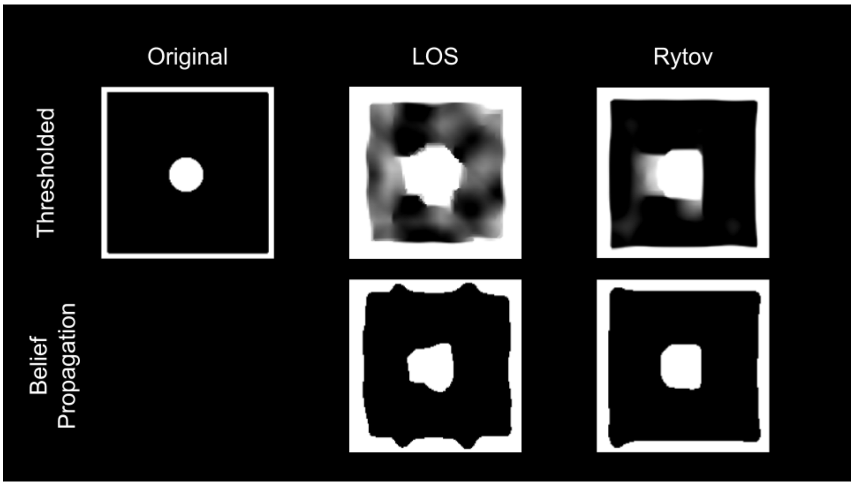

Figure 8: Results of belief propagation algorithm for occluded cylinder area

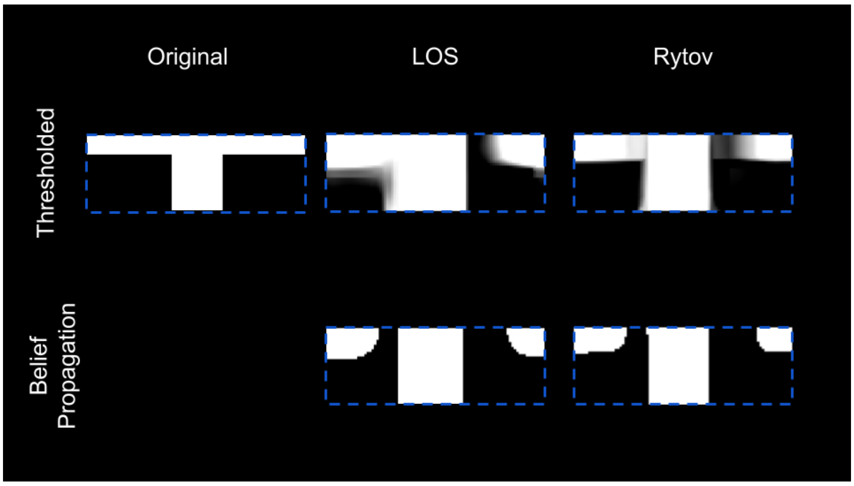

Figure 9: Results of belief propagation algorithm for T-shape area

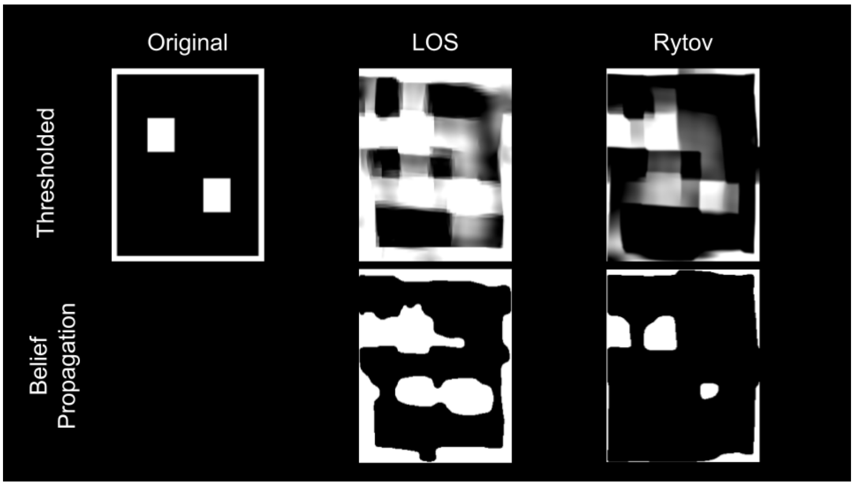

Figure 10: Results of belief propagation algorithm for two column area

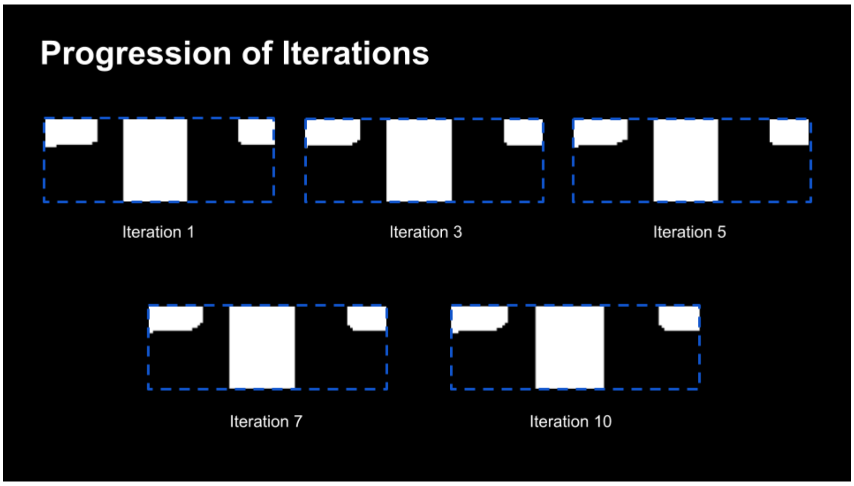

Figure 11: Progress of belief propagation iterations for T-shape area

The results from the LOS and Rytov model reconstructions are shown in Figs 6, 7. As predicted, the Rytov model approximation results in a more accurate image of the unknown areas. This is clearly shown in the case of the two column area, where the LOS model performs much worse than the Rytov model.

All results from the belief propagation algorithm were run with 50 iterations, a value that was chosen through trial and error. In future work on this project, I will investigate using a different number of iterations for areas with different numbers of unknowns. The results are shown in Figs. 8, 9, 10. The results are compared with thresholded versions of the original grayscale images, where any value above 40% and below 20% of the maximum value are thresholded to 40% and 20% respectively.

While the belief propagation algorithm resulted in much cleaner images, it presents some interesting artifacts, particularly in the occluded cylinder case where the wall is warped in a uniform way. This may be a result of minute gradients present in the original grayscale image around those areas. Additionally, it aggressively crops the objects in the T-shape and two-column case. I originally hypothesizes that this may be a result of too many iterations being run. However, a time lapse of the iterations in the belief propagation algorithm in Fig. 11 show that even at the first iteration, most of the information about the area has been lost. It is possible that taking more neighbors into account would help with this aggressive cropping. Another interesting idea would be to train a machine learning model on common object shapes and investigate if this could combat the loss of information shown in the T-shape and two-column case.

V. Conclusion

In this project, I reproduce and combine ideas from two papers in Professor Mostofi's group [1],[2] related to through-wall imaging with WiFi power measurements. First, I reconstruct 2D images of three unknown areas using the LOS and Rytov models described in [1]. These reconstructions show that the images using the Rytov model approximations match the original areas better. In order to further improve these images, I incorporated the belief propagation algorithm described in [2] to create a binary object map of the area. While this resulted in cleaner images, it was accompanied by unusual artifacts and aggressive cropping off the objects. In the future, improvements such as incorporating cosine beam fading in the Rytov model and machine learning in the belief propagation algorithm would be interesting to explore.

References

[1] S. Depatla, L. Buckland and Y. Mostofi, "X-Ray Vision with Only WiFi Power Measurements Using Rytov Wave Models," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 4, 2015.

[2] C. Karanam and Y. Mostofi, "3D Through-Wall Imaging with Unmanned Aerial Vehicles Using WiFi," *IPSN 2017*, 2017.

My code can be found at https://github.com/neelitummala/xray_vision.