Object reconstruction via radar detection behind walls

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Abstract

This paper explores the through-the-wall inverse scattering problem via machine learning. The reconstruction method seeks to discover the shape, location, and type of hidden objects behind simulated walls. We use radar frequency (RF) sources and receivers placed outside the room to generate observation data with objects randomly placed inside the room.

1. Introduction

Inverse problems have always been a highly researched area of mathematics due to their obvious physical and engineering applications. One important example of this type of problem is through-the-wall radar imaging. In this problem, one wishes to use scattered data from receivers positioned outside of a walled room, where a transmitter is also positioned, to locate and analyze an object inside the room. Previous work has used Doppler-type radar to detect and analyze humans where there is no direct line of sight, whether it be studying human motion with standard Doppler radar, noise forms, or micro-Doppler radar, which looks for smaller scale movements such as arm movement and heartbeats. In [1], a Support Vector Machine approach was used to discriminate between child and adult in a through-the-wall setting. More recently, neural networks were exploited to estimate human pose through walls.

In this presentation, we discuss the behind walls setting and a process for numerically reconstructing obstacles from scattered data. The main feature of this reconstruction is that it uses a source within the numerical field, so that the incoming field is not generated by a plane wave, and that the object is located within a set of walls that will interfere with the ability to analyze the object normally. The data used for performing this reconstruction is generated numerically, but it is also only assumed that the scattered field can be known at certain locations outside of the walled area, instead of known as a function. All of these changes violate the assumptions of the theoretical reconstructions, so a different approach is needed. We develop an appropriate adjustment to the theoretical methods presented in the literature to analyze obstacles in this setting, and present some numerical results towards this end. The reconstruction method seeks to discover the shape, size, and conductivity of the obstacles using a behind walls analysis. Specifically, in [2], locations of hidden objects behind walls were estimated by observing the time difference between signals from an empty room and that when an object was present. Based on the physics of electromagnetic wave propagation, ellipses with foci at the source and receiver pairs were constructed to provide the contour of the objects. In [3], a form of linear sampling method was used for the reconstruction. Specifically, a reciprocity gap functional to the electromagnetic field solution and the fundamental solution of the Helmholtz equation was used to derive an integral equation; the properties of whose solution gave indication of the location of the objects. We also explore machine learning using similar RF data as in [2-3], which was generated by numerically modeling the Maxwell's equations. We experiment with two types of neural networks and use an 80-20 train-test split for both reconstruction and classification.

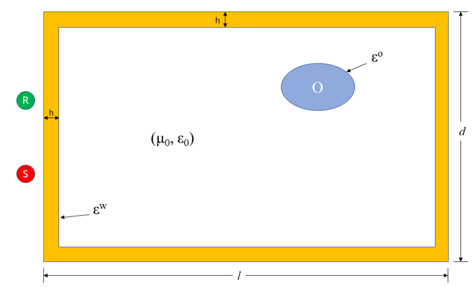

Figure 1: Model setup

2. Problem Setup

To model the actual physical problem, we will record and use data that could be gathered from a set of antenna transmitters and receivers. Thus, for any given simulation, we will assume that the electromagnetic waves are generated from a source antenna (S) positioned outside of the room and the data is recorded from a (finite) set of receivers (R), also positioned outside the room as shown in Figure 1.

We consider a two-dimensional radar imaging problem, assuming that all materials are invariant in the z-direction. The room is rectangular of size l by d. The walls are of a uniform thickness h, with relative electric permittivity

ϵ^w. The object that is to be detected is a convex domain $O \subset [0, l] \times [0, d]$ that has relative electric permittivity ϵ^o and is away from the boundaries of the room. We assume the medium throughout is nonmagnetic, thus $\mu_r = 1$. The source will be a pulse wave and monochromatic, emitting two full cycles of the wave before turning off. We observe that $k = \omega\sqrt{\mu\epsilon}$ and $\lambda = c_0/\sqrt{\epsilon_r}\omega$, where k is the wavenumber, ω frequency, λ wavelength, and c_0 free space speed of light.

3. Experiments

Here we present an example of object reconstruction using a simple pattern recognition algorithm, the k-NN. The main reason for this choice is its ease of adaptation. Since our data is generated by simulation, the density of the data for training can be very large, given enough computing power. Thus the lack of efficiency (in both time and memory), a main disadvantage of k-NN, is not of major concern.

For our experiment, each observation was obtained by setting the type of object to be placed in the room, and randomly assigning a location within the room. Three types of objects were considered: small circle of radius 0.1, small rectangle of size 0.1×0.2, and large rectangle of size 0.3×0.6. An equal number of data for Object 1 and Object 2, and a smaller amount for Object 3 were collected. Symmetries in the data were also used; the locations of the objects were initialized to be in the top half of the room, then the simulations run, and data for an object in the same location on the bottom half of the room were inferred by switching the readings of the receivers appropriately. In all, over $10,000$ observations were generated, taking up about 16GB of storage.

Example 1. For this experiment, we placed 6 receivers from behind left wall, taking data at 100 time steps. This yielded 1164 observations with $6 \times 100 = 600$ predictors. Using $k = 1$ nearest neighbor, the average L2-norm distance between predicted and actual location of a circular object with radius 0.1 was only 0.1049, and the variance was 0.0501. It took 0.044528 seconds for each run. See Figure 2

Example II. Here we use only partial data for the reconstruction and compare the results between those of ML, k-NN in this case, and of the linear sampling method (LSM). The LSM is a well known mathematical method for solving inverse scattering problems, see [**?**]. In this experiment, both the sources and receivers are placed on one side of the room only. This is perhaps more applicable given that it may only be possible to access one external wall of the room.

For circle objects of radius 0.1, k-NN returned prediction error of the same order as the radius when 24 receivers were used, and only double that with a total of just 3 receivers placed on one side of the external wall. See Figure 3.

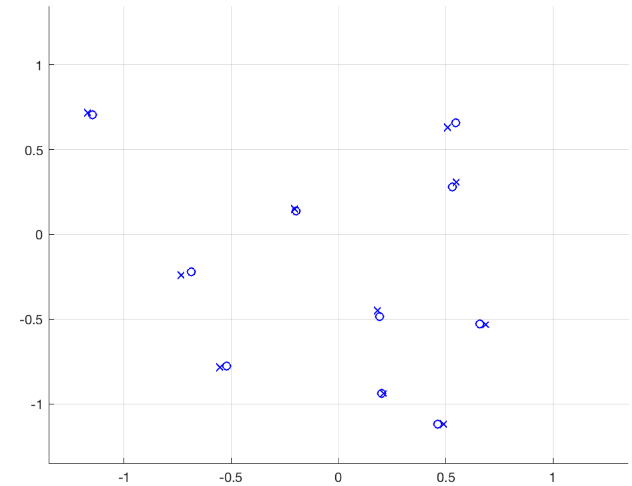

Figure 2: Illustrations k-NN prediction of center of circle.

Number of receivers	24	12	6	3
Average error	0.1523	0.1386	0.2440	0.2764
Variance of error	0.1202	0.1565	0.2518	0.2921

Figure 3: Sources & receivers on one side of room by K-NN

4. Conclusion

Through-the-wall object detection is an important area of research that has a wide range of physical and engineering applications. Using both traditional inverse methods and machine learning, we have reconstructed unknown targets behind walls using simulated data. In addition, our machine learning algorithms are capable of classifying different types of objects and determining material properties of the targets that the other reconstruction methods did not attempt. Moving forward, we would be interested in exploring more complex models including multiple objects, multiple reflections, and moving targets, to name a few.

Acknowledgement

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