Object reconstruction via radar detection behind walls

Aihua Wood ⁽¹⁾, Ryan Wood ⁽²⁾, and Matthew Charnley ⁽³⁾
(1) Department of Mathematics and Statistics, Air Force Institute of Technology, WPAFB, OH, USA; email: Aihua.Wood@afit.edu
(2) Department of Statistics, Harvard University, Cambridge, MA, USA; email: rwood@college.harvard.edu
(3) Department of Mathematics, Rutgers University, Piscataway, NJ, USA; email: charnley@math.rutgers.edu

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 RF sources and receivers placed outside the room to generate observation data with objects randomly placed inside the room.

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.

References

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