Ph.D. Forum: Field Sensing Model, A New Foundation for RF Sensing

Fei Shang
feishang@mail.ustc.edu.cn
University of Science and Technology of China
Hefei, Anhui, China

ABSTRACT

In recent years, radio frequency (RF) signal-based sensing has garnered significant attention due to its ubiquity, with numerous applications emerging in areas such as target localization, material recognition, and health monitoring. However, current sensing models are often based on ray tracing, which, although computationally convenient, can become severely distorted when the target size is not much larger than the wavelength. Additionally, using signals with smaller wavelengths to mitigate this issue is not always feasible. Noting that RF signals are a form of electromagnetic waves, we have explored the development of field sensing models directly based on Maxwell's equations. These models can finely characterize phenomena such as diffraction and multiple scattering, thereby enhancing the upper limits of sensing system capabilities. Based on this approach, we have achieved integrated material recognition and imaging of centimeter-scale targets using WiFi signals. This work has been accepted for presentation at Ubicomp 2024.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**.

KEYWORDS

wireless sensing, radio frequency, field model

ACM Reference Format:
Fei Shang. 2024. Ph.D. Forum: Field Sensing Model, A New Foundation for RF Sensing. In *The 22nd ACM Conference on Embedded Networked Sensor Systems (SENSYS '24), November 4–7, 2024, Hangzhou, China.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3666025.3699668

1 INTRODUCTION

Due to its ubiquitous nature, radio frequency (RF) signal-based sensing has garnered increasing attention over the past decade. Compared to traditional sensing methods, RF-based sensing solutions are cost-effective and easy to deploy, offering a wider range of coverage. Unlike vision-based approaches, RF-based methods can operate in low-light or non-line-of-sight conditions and provide additional information such as material properties, aiding in better decision-making [1, 2]. In summary, as a valuable complement to existing sensing techniques, RF signal-based sensing exhibits unique advantages across various fields, including health monitoring and vehicle-to-infrastructure (V2I) coordination.

The feasibility of using RF signals for sensing is based on a fundamental observation: the propagation of RF signals changes with the state of the target. To analyze the characteristics of RF signals, it is often necessary to model and analyze the signal propagation process. Over the past five years, many classical sensing models, such as the Fresnel zone model, have been built based on **ray tracing models**. Although ray tracing models are simple to implement and easy to solve, they suffer from significant distortion when the target size is not much larger than the wavelength due to factors like diffraction and multiple scattering. While it is possible to use signals with smaller wavelengths for finer-grained sensing tasks—such as using millimeter waves for centimeter-level sensing and high-frequency terahertz signals for millimeter-level sensing—the cost and deployment complexity of these signals can vary greatly. In practice, deploying the most suitable frequency band is not always feasible. Notably, sub-6G signals, such as LTE, Wi-Fi, Bluetooth, and RFID, which are among the most widely deployed and used, have wavelengths exceeding 5 cm. This is comparable to or even larger than the sizes of many common sensing targets, such as water cups, small material boxes, and eggs. Without a high-precision sensing model that accurately characterizes the effects of diffraction and other factors on the signal, the ubiquitous nature of RF sensing will be significantly limited.

Let's return to the fundamentals: As an electromagnetic wave, the propagation behavior of RF signals in space—whether it be transmission, reflection, or diffraction—can be fully characterized by Maxwell's equations. If we can build a new paradigm for wireless sensing based on Maxwell's equations, it would offer several advantages:

(1) Enhance the performance ceiling of sensing systems. On one hand, we have the opportunity to characterize the propagation of RF signals with finer granularity, enabling us to attempt more challenging sensing tasks, such as using WiFi signals for centimeter-level target detection. On the other hand, this approach can push the performance limits of sensing algorithms. For example, the resolution limit of inverse imaging schemes based on ray tracing is λ, where λ is the wavelength, whereas schemes built on Maxwell's equations can achieve a resolution of 0.13λ [6].

(2) Enhance explainability. The strong representational power of the model allows us to quantify the interference of different targets in the environment on RF signals, which can improve the robustness and transferability of the system. Additionally, since the amount of data available for building sensing systems is often

SENSYS '24, November 4–7, 2024, Hangzhou, China

ACM ISBN 979-8-4007-0697-4/24/11…$15.00
https://doi.org/10.1145/3666025.3699668

limited, the introduction of physical prior knowledge can enhance the model's convergence and reduce the data requirements.

We have explored this area and proposed LiquImager, which can perform integrated imaging and material sensing for centimeter-scale targets using WiFi signals. This system overcomes the impact of diffraction on RF sensing. Our evaluation shows that, compared to black-box sensing approaches, the introduction of a field model can reduce the required training data by 80%. The related work, "LiquImager: Fine-grained Liquid Identification and Container Imaging System with COTS WiFi Devices," has been accepted by Ubicomp 2024 [5].

2 THE DIFFERENCES BETWEEN RAY TRACING AND FIELD MODELS

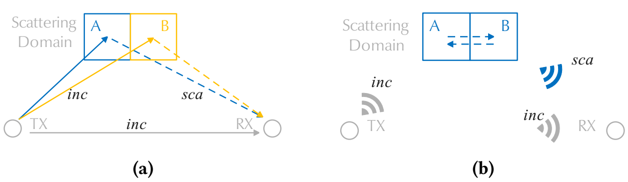

Figure 1: Comparison of ray tracing and field model. (a) Ray tracing model. We equivalently represent the RF signal as rays, treating each scattering subunits as an independent target. The RF signal travels to the receiving antenna via scattering within the scattering domain. We consider the total scattering signal as the linear sum of scattering signals from different subunits. (b) Scattering model. We use Maxwell's equations to calculate the equivalent scattering field of the scattering domain, which can accurately describe the interaction between the various subdomains. After collecting the scattering signals, we infer the distribution of the complex permittivity in the scattering area.

For ray tracing-based imaging schemes, we reverse the "light path" to infer the location of the scattering points. Because the ray tracing model cannot account for the interactions between scattering points within the scatterer, it leads to information loss. *Building a scattering model directly from Maxwell's equations accurately captures the multi-level scattering occurring inside the scatterer, thereby providing additional information for radio frequency imaging to enhance resolution.*

In particular, as shown in Figure 1a, the ray tracing model is equivalent to the RF signal as rays, treating each scattering subunit as an independent target. The received signals are treated as their linear superposition [4]. After acquiring the scatter signal, we reverse the "light path" to deduce the location of the scatter point. In this case, *we ignore the interaction within the scatterer.* On the contrary, the field model we established can more accurately reflect the impact of scatterers on the RF signal.

We perform simulation calculations for the two models. The result is shown in Figure 2. We set the sensing area as a square with a side length of 2.5λ, which is shown in Figure 2a. Set up a "rabbit" (yellow part in the figure) as a scatterer, surrounded by air (blue

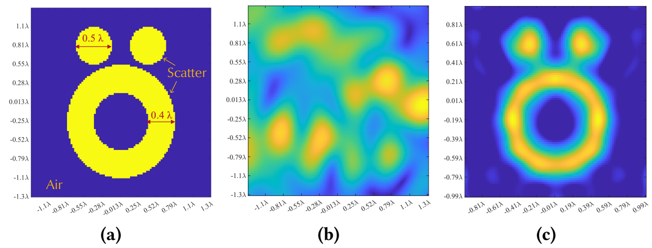

Figure 2: Simulation of radio frequency imaging. (a) The sensing domain is 2.5 times the wavelength in both length and width, with scatterers marked in yellow and blue representing air. (b) Since the ray tracing scheme does not consider the interaction within the scatterer, when the size of the scatterer is small, it is only possible to vaguely identify the presence of scatterers in this area. (c) After several rounds of nonlinear iterations using the field model, we obtain the shape of the scatterer.

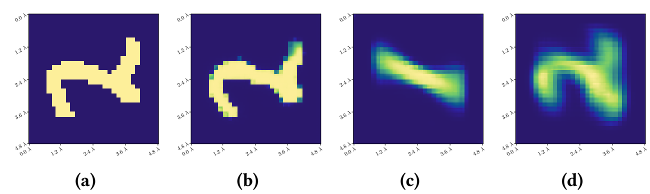

Figure 3: It is easier to achieve good training results by first using the backpropagation algorithm for data preprocessing. (a) Schematic diagram of a scatterer. (b) Imaging results when first using the backpropagation algorithm for data preprocessing, and then using 20% of the training samples for training. (c) Imaging results when directly using 20% of the training samples for training. (d) Imaging results when directly using all training samples for training.

part). The relative complex permittivity of the scatterer is set to 2. And 32 transmitting antennas and receiving antennas are placed at equal intervals on a circle 4λ away from the center of the scattering area. Figure. 2b and 2c are image results reconstructed using ray tracing model and field model, respectively. It can be found that in the imaging results of the ray tracing model, only the presence of scatterers in this area can be vaguely distinguished. But *in the imaging results of the field model, we can distinguish the basic shape and position of the scatterers.*

3 THE MAIN RESULTS

Using *physical models* for data preprocessing can help *reduce the amount of training required for network training* [3]. Our evaluation results show that this method can achieve better imaging results by using only 20% of the data for training than directly training deeplearning with the entire data. The results are shown in Figure 3.

We test *LiquImager* in a area of 25 cm × 25 cm, and the accuracy rate of liquid identification is more than 93.11%. We use 4 different types of containers to hold liquids, and *LiquImager* still has a precision of more than 91% in identifying liquids. In addition, *LiquImager* can accurately image containers arbitrarily placed in the field, and distinguish the shape of the container with an accuracy of 100%.

REFERENCES

[1] Fadel Adib, Chen-Yu Hsu, Hongzi Mao, Dina Katabi, and Frédo Durand. 2015. Capturing the Human Figure through a Wall. *ACM Transactions on Graphics* 34, 6 (Nov. 2015), 1–13. https://doi.org/10.1145/2816795.2818072

[2] Yande Chen, Chongzhi Xu, Kexin Li, Jia Zhang, Xiuzhen Guo, Meng Jin, Xiaolong Zheng, and Yuan He. 2024. Wireless Sensing for Material Identification: A Survey. *IEEE Communications Surveys & Tutorials* (2024), 1–1. https://doi.org/10.1109/COMST.2024.3456076

[3] Kyong Hwan Jin, Michael T. McCann, Emmanuel Froustey, and Michael Unser. 2017. Deep Convolutional Neural Network for Inverse Problems in Imaging. *IEEE Transactions on Image Processing* 26, 9 (Sept. 2017), 4509–4522. https://doi.org/10.1109/TIP.2017.2713099

[4] Anurag Pallaprolu, Belal Korany, and Yasamin Mostofi. 2022. Wiffract: A New Foundation for RF Imaging via Edge Tracing. In *Proceedings of the 28th Annual International Conference on Mobile Computing And Networking*. ACM, Sydney NSW Australia, 255–267. https://doi.org/10.1145/3495243.3514261

[5] Fei Shang, Panlong Yang, Dawei Yan, Sijia Zhang, and Xiang-Yang Li. 2024. LiquImager: Fine-grained Liquid Identification and Container Imaging System with COTS WiFi Devices. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 1 (March 2024), 1–29. https://doi.org/10.1145/3643509

[6] Fan Yin, Chang Chen, Weidong Chen, Wen Qiao, and Jian Guan. 2020. Superresolution Quantitative Imaging Based on Superoscillatory Field. *Optics Express* 28, 5 (March 2020), 7707. https://doi.org/10.1364/OE.384866