LiquImager: Fine-grained Liquid Identification and Container Imaging System with COTS WiFi Devices

Fei Shang[1], Panlong Yang[1,2,*], Dawei Yan[1], Sijia Zhang[1], and Xiang-Yang Li[1]

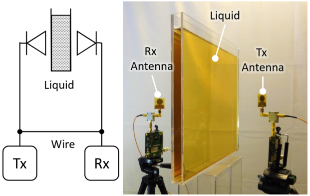
USTC[1],NUIST[2]

Ubiquitous Sensing Makes Production and Life More Colorful

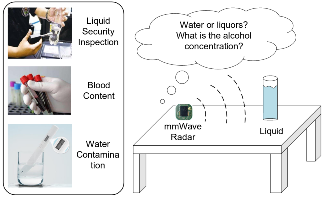
Due to the effectiveness of wireless signals in low-light conditions, wireless-based shape and material identification finds diverse applications in both industrial production and everyday life.

Related Work

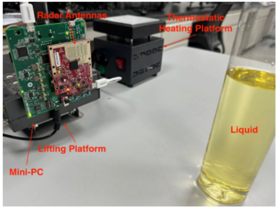
In recent years, many outstanding works have attempted to use wireless signals to identify the material composition of liquids, which offers the potential for ubiquitous liquid sensing.



LiquID[1]



Fg-Liquid[2]



LiqDetector[3]

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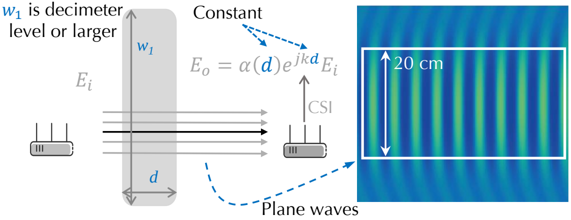
[1] Ashutosh Dhekne et al. “LiquID: A Wireless Liquid IDentifier”. In: Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services. MobiSys ’18: The 16th Annual International Conference on Mobile Systems, Applications, and Services. MobiSys ’18. Munich Germany: ACM, June 10, 2018, pp. 442–454. ISBN: 978-1-4503-5720-3. DOI: `10.1145/3210240.3210345`.

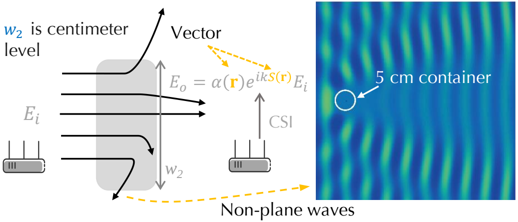
[2] Yumeng Liang et al. “FG-LiquID: A Contact-less Fine-grained Liquid Identifier by Pushing the Limits of Millimeter-wave Sensing”. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 5.3 (Sept. 9, 2021), pp. 1–27. ISSN: 2474-9567. DOI: `10.1145/3478075`.

[3] Zhu Wang et al. “LiqDetector: Enabling Container-Independent Liquid Detection with mmWave Signals Based on a Dual-Reflection Model”. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 7.4 (Dec. 19, 2023), pp. 1–24. ISSN: 2474-9567. DOI: `10.1145/3631443`.

Related Work

However, due to the small size of these containers, diffraction phenomena make the container shape have a great impact on liquid identification. In actual scenarios, containers come in various shapes.





Related Work

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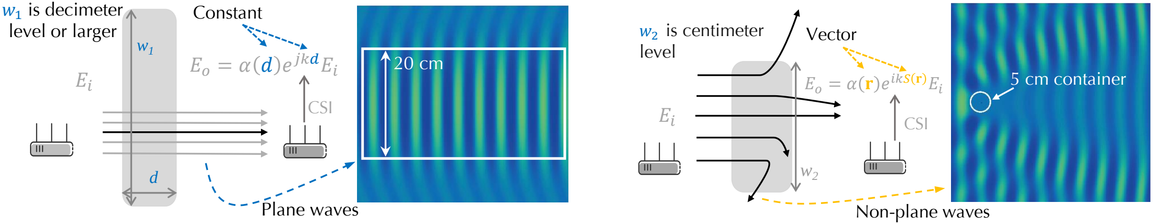
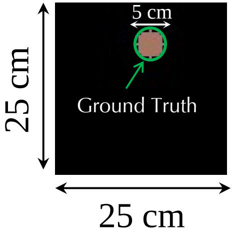


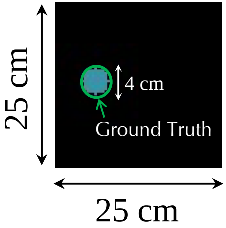
We need to pay attention to the impact of material and shape on the received signal at the same time.

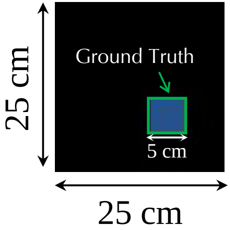
In This Paper

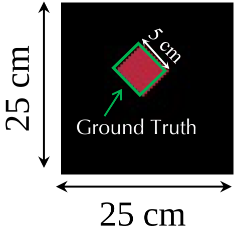
We propose **LiquImager**, a system that can simultaneously identify liquids and image containers using COTS Wi-Fi devices.

- Imaging of centimeter-level containers.
- Container-shape-independent and position-independent liquid identification.



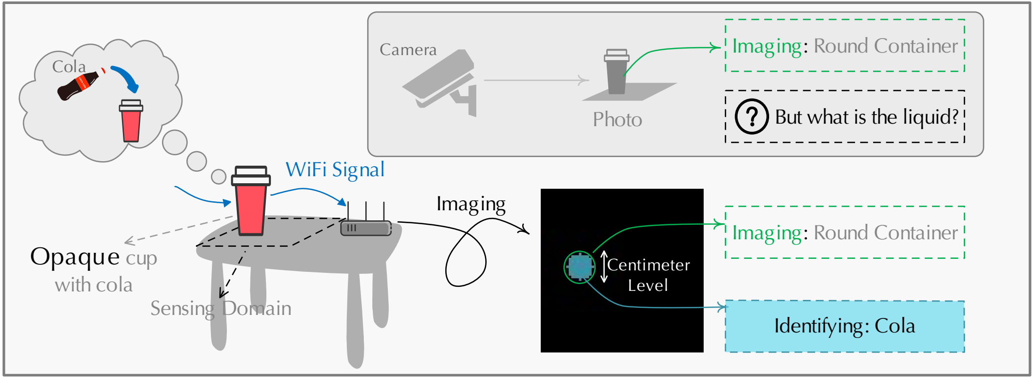






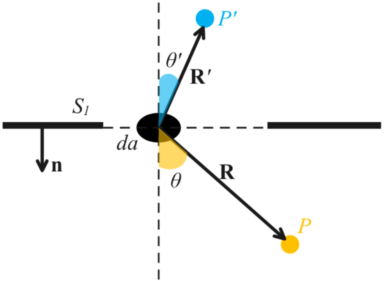
Basic Idea

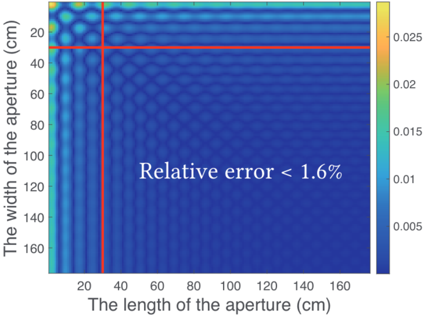
Unlike traditional approaches that treat liquid identification and container imaging as two independent tasks, we try to present both material and shape information in one image.



Challenges

How to describe the complex influence of centimeter-level media on Wi-Fi signals?





When the target material is less than 10cm, the relative error of the ray tracing model exceeds 20%[4].

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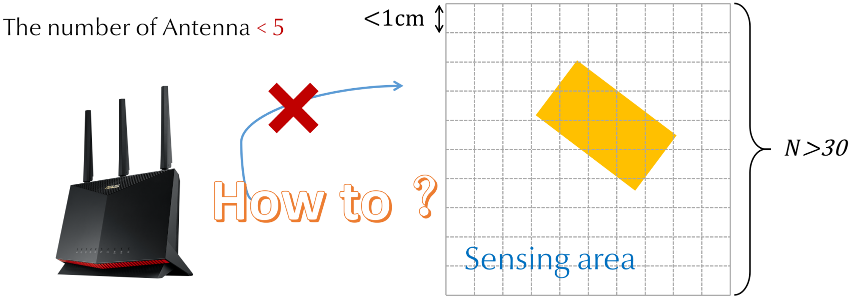
[4] Fei Shang et al. "LiqRay: Non-Invasive and Fine-Grained Liquid Recognition System". In: Proceedings of the 28th Annual International Conference on Mobile Computing And Networking. ACM MobiCom '22: The 28th Annual International Conference on Mobile Computing and Networking. MobiCom '22. Sydney NSW Australia: ACM, Oct. 14, 2022, pp. 296–309. ISBN: 978-1-4503-9181-8. DOI: 10.1145/3495243.3560540.

Challenges

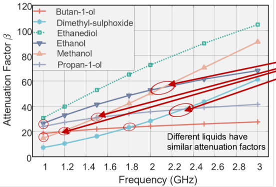
How to describe the complex influence of centimeter-level media on Wi-Fi signals?
How to solve the complex model using few measurements?



Challenges

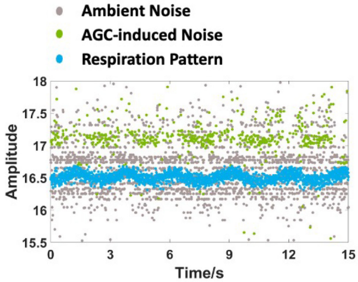
How to describe the complex influence of centimeter-level media on Wi-Fi signals? How to solve the complex model using few measurements?

How to fine-grained identify centimeter-level liquids using noisy data?



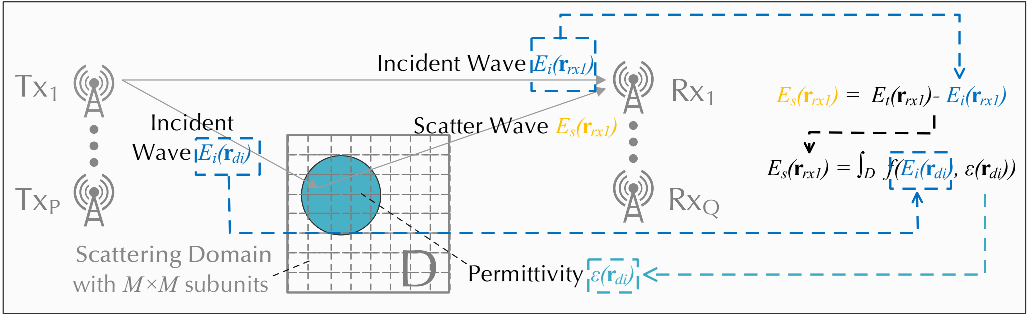
The attenuation factors are so similar

Indistinguishable



Basic Model: Forward Process

Unlike the ray-tracing model, we construct the signal scattering model directly from the Maxwell equations, and then solve the dielectric distribution in the sensing domain.



$$E_s(\mathbf{r}_{rx1}) = E_t(\mathbf{r}_{rx1}) - E_i(\mathbf{r}_{rx1})$$

$$E_s(\mathbf{r}_{rx1}) = \int_D f(E_i(\mathbf{r}_{di}), \varepsilon(\mathbf{r}_{di}))$$

Basic Model: Forward Process

Unlike the ray-tracing model, we construct the signal scattering model directly from the Maxwell equations, and then solve the dielectric distribution in the sensing domain.

$$\begin{cases} E_t(\mathbf{r}) = E_i(\mathbf{r}) + k_0^2 \int_D G(\mathbf{r}, \mathbf{r}')I(\mathbf{r}')d\mathbf{r}' & \text{for } \mathbf{r} \in D \\ E_s(\mathbf{r}) = k_0^2 \int_D G(\mathbf{r}, \mathbf{r}')I(\mathbf{r}')d\mathbf{r}' & \text{otherwise,} \end{cases}$$

where k_0 is the wavenumber of the air. $G(\mathbf{r}, \mathbf{r}') = -\frac{j}{4}H_0^2(k_0|\mathbf{r} - \mathbf{r}'|)$ is the 2-D free space Green's function, where $H_0^2(.)$ is the 0-th order Hankel function of the second kind and $j^2 = -1$. The equivalent current density $I(\mathbf{r})$ is $I(\mathbf{r}) = [\epsilon(\mathbf{r}) - 1]E_t(\mathbf{r})$.

Basic Model: Inverse Process

We use the backpropagation scheme to calculate the dielectric distribution[5].

$$\epsilon(\mathbf{r}_{di}) - 1 = \mathbf{\Lambda}(i) = \frac{\sum_{p=1}^{P} \tilde{\mathbf{I}}^p(i)\left[\tilde{\mathbf{E}}_t^p(i)\right]^*}{\sum_{p=1}^{P} \|\tilde{\mathbf{E}}_t^p(i)\|^2}$$

where

$$\begin{cases} \tilde{\mathbf{E}}_t = \mathbf{E}_i + \mathbf{G}_D \tilde{\mathbf{I}} = \mathbf{E}_i + \xi \mathbf{G}_D \mathbf{G}_S^H \mathbf{E}_s \\ \xi = \arg\min_{\xi} \|\mathbf{E}_s - \mathbf{G}_S \tilde{\mathbf{I}}\| = \dfrac{(\mathbf{E}_s)^T (\mathbf{G}_S(\mathbf{G}_S^H \mathbf{E}_s))^*}{\|\mathbf{G}_S(\mathbf{G}_S^H \mathbf{E}_s)\|^2} \end{cases}$$

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[5] Xu Dong Chen. Computational Methods for Electromagnetic Inverse Scattering. John Wiley & Sons, 2018.

Practical Issue

For traditional solutions, we need to acquire the scattering field $\mathbf{E}_s$ at the receiving antenna and the total field $\mathbf{E}_t$ at the scattering domain D.

However, they are difficult to measure directly.

Unlike ideal electric field data, CSI data contains a lot of noise.

How To Estimate the Scattering Field $\mathbf{E}_s$?

Thanks to the superposition nature of electric fields. We use the difference method to estimate the scattered field, which is given by

$$\mathbf{E}_s = \mathbf{E}^r_{t,w} - \mathbf{E}^r_{t,w/o}.$$

- When the target is present

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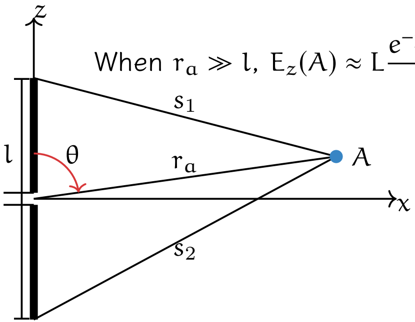
- When the target is present
- When the target is not present

How To Estimate the Incident Field $\mathbf{E}_i$?



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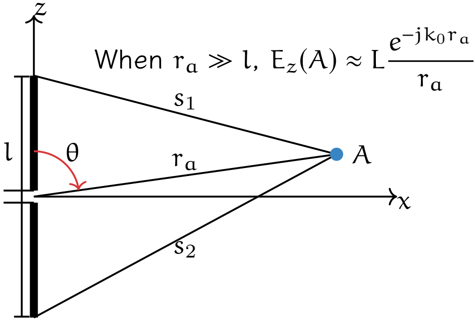

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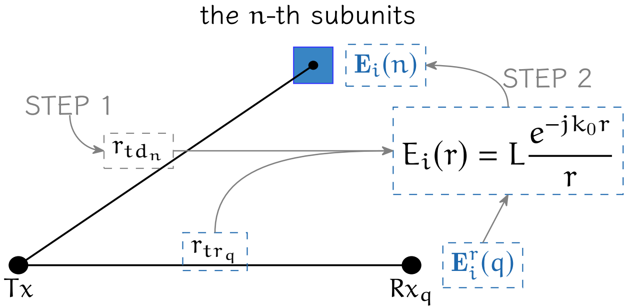
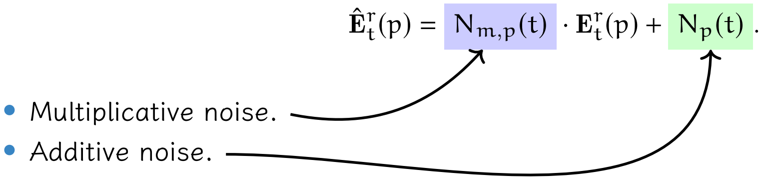


$$E_i(r) = L\frac{e^{-jk_0 r}}{r}$$

How To Do Pre-Imaging in the Presence of Noise?

The data collected by commercial Wi-Fi equipment contains a lot of noise. As a result, with one transmitting antenna, the CSI received by the p-th antenna $\hat{\mathbf{E}}_t^r(p)$ can be expressed as:



$$\hat{\mathbf{E}}_t^r(p) = N_{m,p}(t) \cdot \mathbf{E}_t^r(p) + N_p(t) .$$

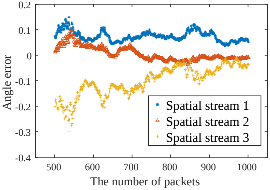
- Multiplicative noise.
- Additive noise.

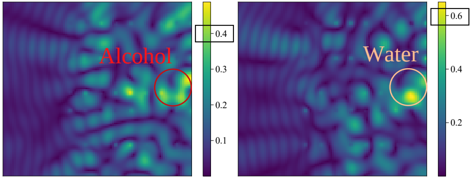
How To Do Pre-Imaging in the Presence of Noise?

We use statistical methods to insulate imaging from noise.

$$\mathbb{E}[\hat{\mathbf{E}}_t^r(p)] = \mathfrak{N}_m \cdot \mathbf{E}_t^r(p) + \mathbb{E}[N_p(t)] = \mathfrak{N}_m \cdot \mathbf{E}_t^r(p).$$

The impact of $\mathfrak{N}_m$ is offset during the BP process.





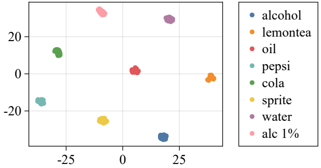


Image Enhancement Using LIQU-NET

If material identifying is not considered, the goal of our image augmentation module is similar to binary semantic segmentation. Based on U-Net, we introduce a network called LiqU-Net for image enhancement.

Issues

- ✈ Input. The input of the U-Net network is 3-channel RGB data, but the result of our pre-imaging is the single-channel complex permittivity.
- ✈ Output. The output of the U-Net network is a binary geometry (for example, only two values of 0 and 1), but this cannot complete the material identification task.

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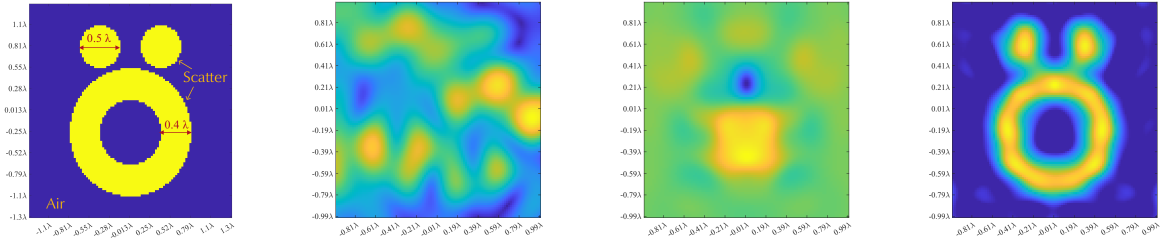
Structure

- **Input**. The input of the network is a three-dimensional tensor whose shape is $[N_{tone} \times 2, M, M]$.
- **Output**. Different values are used to represent different materials.

$$\mathcal{L}_{bce}\left(\frac{\max\hat{y}-\hat{y}}{\max\hat{y}-\min\hat{y}}, \frac{\max y-\hat{y}}{\max y-\min y}\right)+\mathcal{L}_{mse}(\hat{y},y)$$

Imaging Resolution



a b c d

The resolution of using nonlinear methods to reversely infer the complex permittivity distribution in the sensing area can reach 0.13λ or even lower[6].

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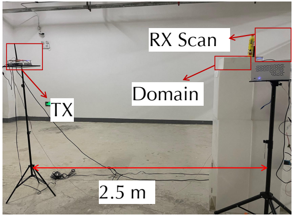
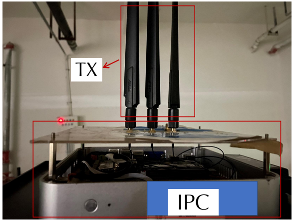
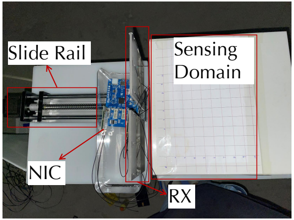
[6] Fan Yin et al. “Superresolution Quantitative Imaging Based on Superoscillatory Field”. In: Optics Express 28.5 (Mar. 2, 2020), p. 7707. ISSN: 1094-4087. DOI: 10.1364/OE.384866.

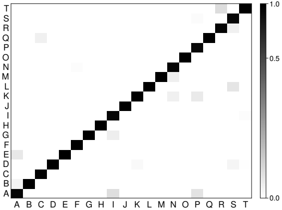
Evaluation

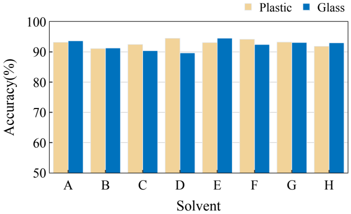


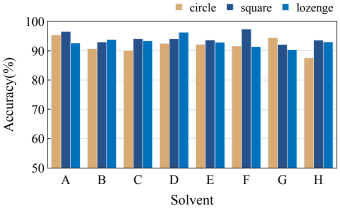




Accuracy > 91%







Contributions

- ✈ We design LiquImager, which can use COTS Wi-Fi devices to image centimeter-level containers and identify liquids regardless of liquid position and container shape.
- ✈ We build an electric field scattering sensing model directly based on Maxwell's equations, which can more accurately describe the influence of the dielectric properties, position, and size of the medium on the signal.
- ✈ We use 4 different types of containers to hold liquids, and LiquImager still has a precision of more than 91% in identifying liquids.