

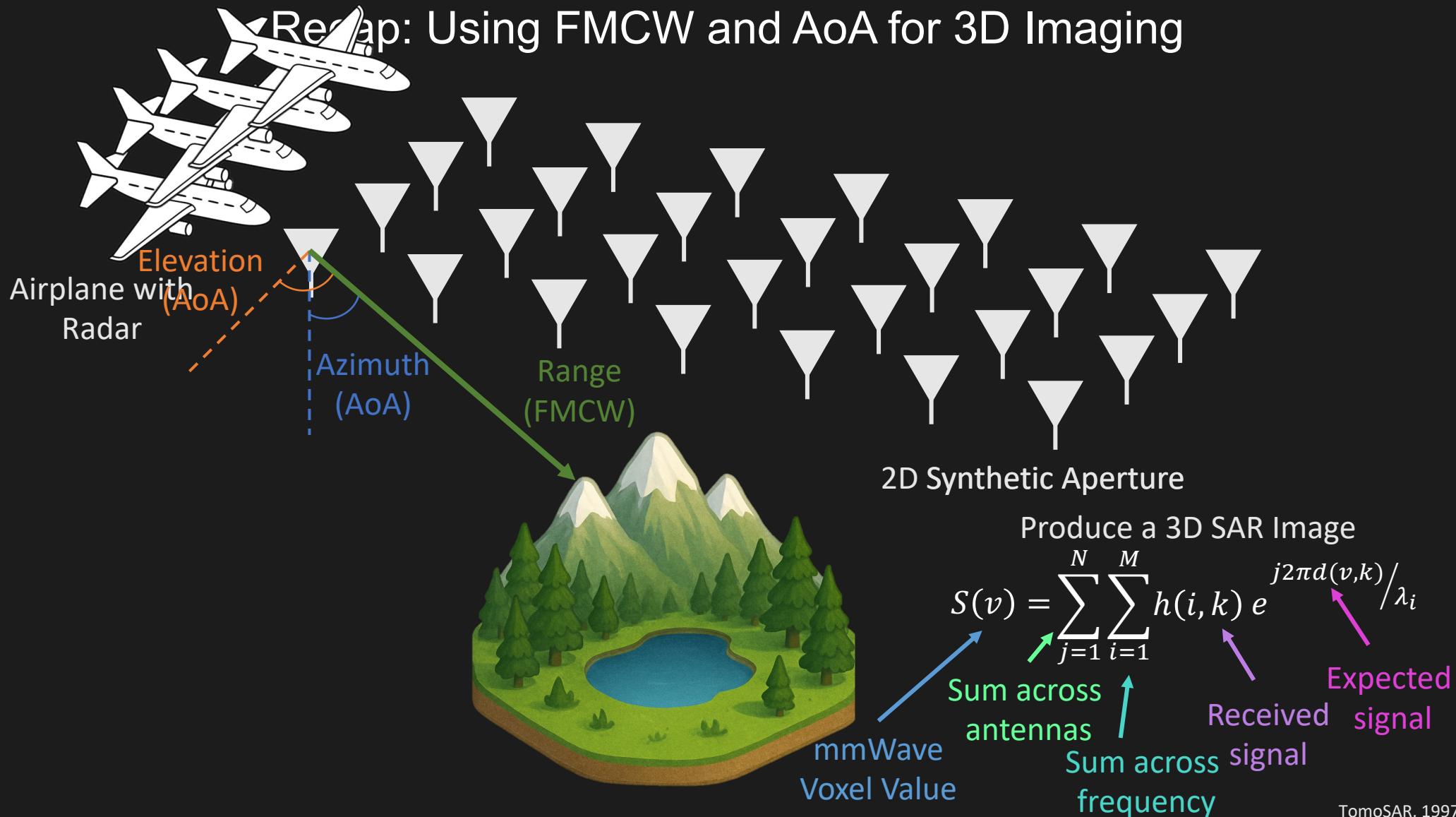
Wireless Imaging & 3D Reconstruction

Lecturer: Laura Dodds

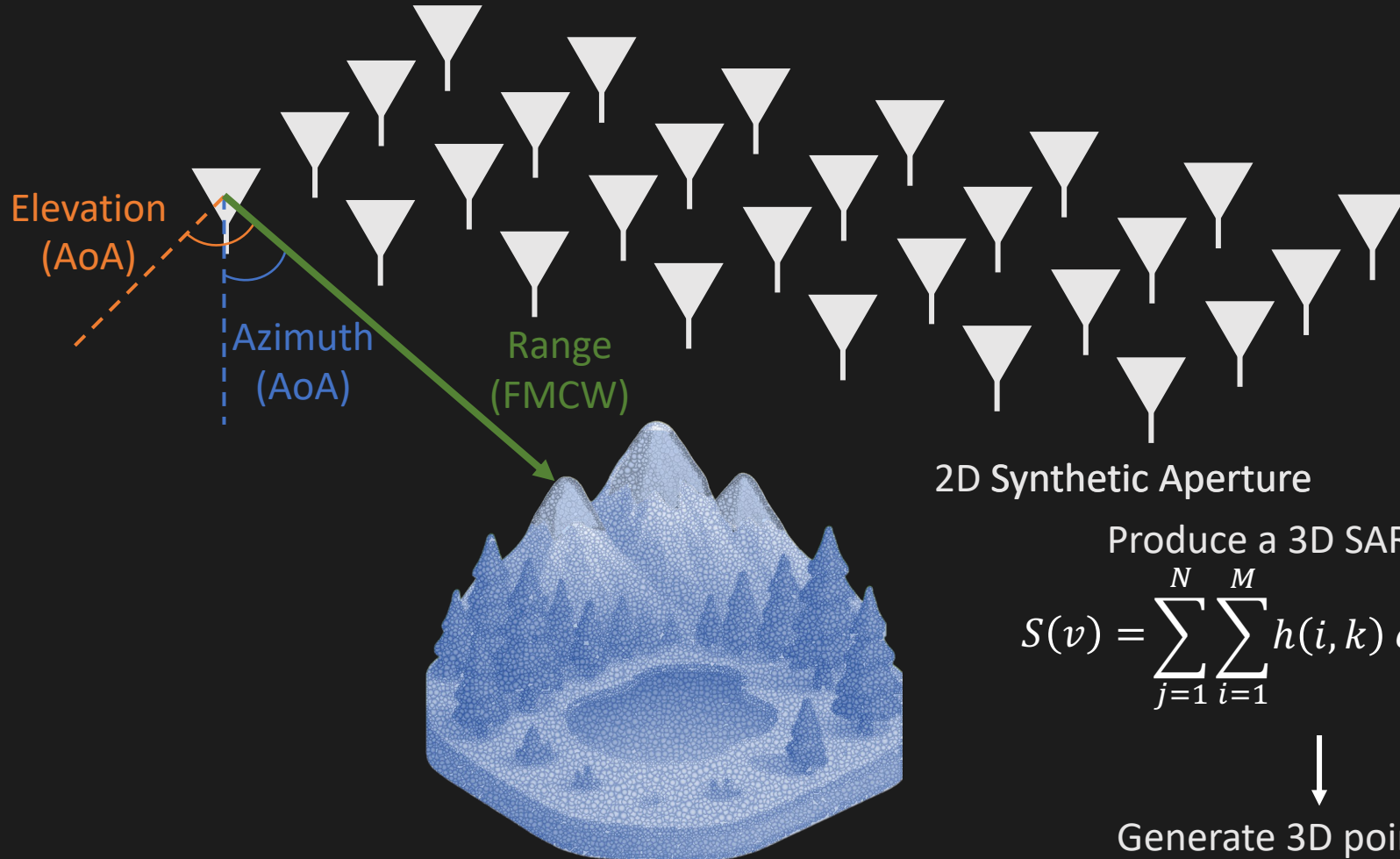
Lecture Objectives

- Recap the fundamental techniques for wireless imaging and 3D reconstruction
- Learn how state-of-the-art systems build on these fundamentals to improve non-line-of-sight (NLOS) reconstruction performance
- Discuss the applications of various NLOS imaging technologies

Recap: Using FMCW and AoA for 3D Imaging



Recap: Using FMCW and AoA for 3D Imaging



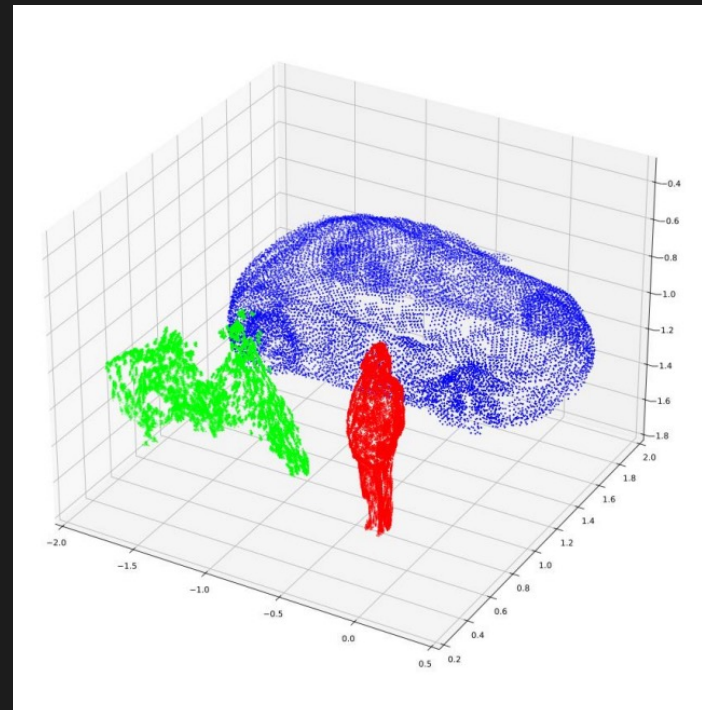
Non-Line-of-Sight Wireless Imaging and 3D Reconstruction



Wireless 3D Reconstruction
Through Boxes

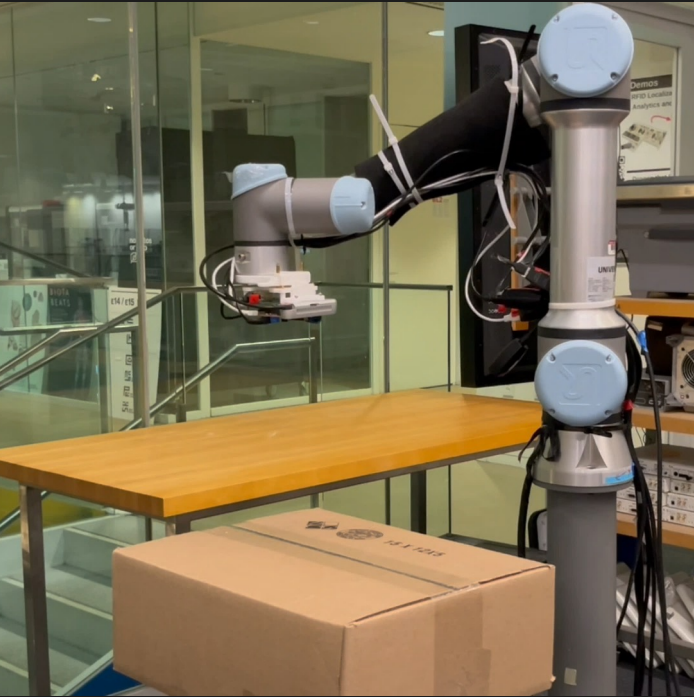


Around-the-Corner
Wireless Imaging



Wireless Reconstruction
In Low Visibility

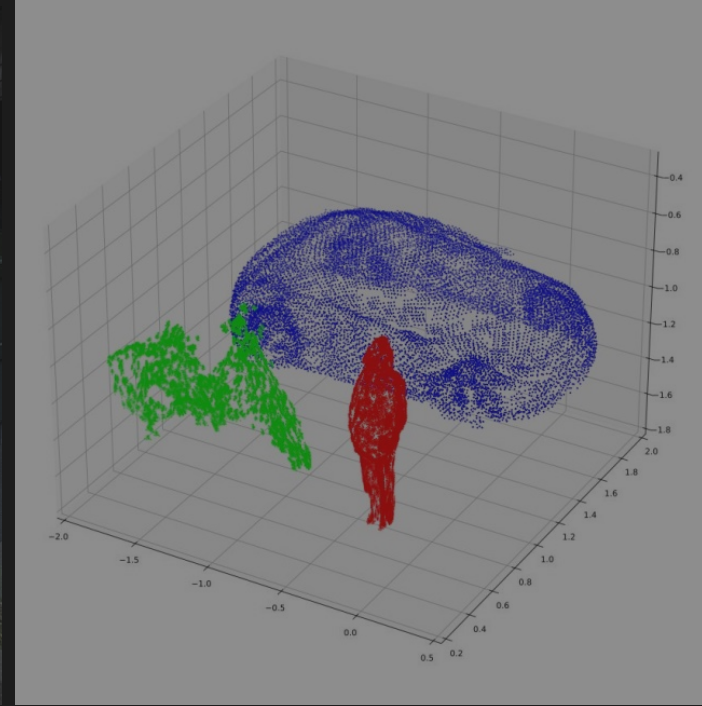
Non-Line-of-Sight Wireless Imaging and 3D Reconstruction



Wireless 3D Reconstruction
Through Boxes



Around-the-Corner
Wireless Imaging



Wireless Reconstruction
In Low Visibility

Non-Line-of-Sight 3D Object Reconstruction via mmWave Surface Normal Estimation

Laura Dodds, Tara Boroushaki, Kaichen Zhou, Fadel Adib



Can we enable high-accuracy non-line-of-sight
3D object reconstruction with millimeter-waves?

Can we enable high-accuracy non-line-of-sight
3D object reconstruction with millimeter-waves?

Can we enable high-accuracy non-line-of-sight
3D object reconstruction with millimeter-waves?

Can we enable high-accuracy non-line-of-sight 3D object reconstruction with millimeter-waves?

Hidden Object



**Existing mmWave
Reconstruction***



mmNorm



High-Accuracy Non-Line-of-Sight 3D Reconstruction has Many Applications



Robotics

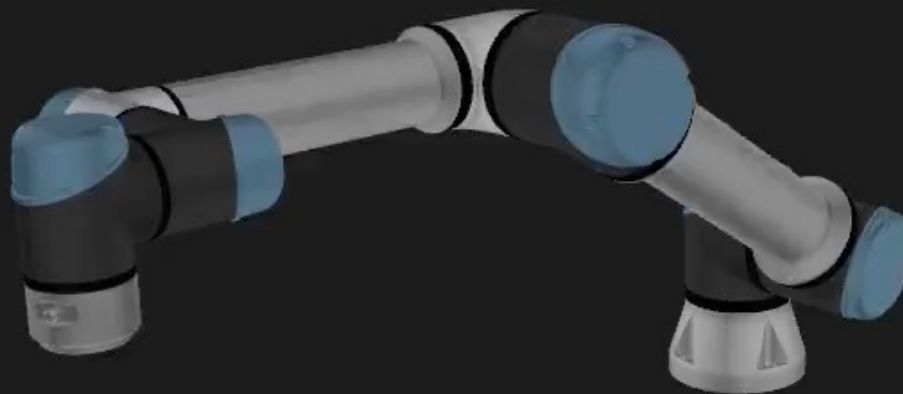


Shipping & Logistics



Augmented Reality

Why are existing 3D reconstruction methods limited?



Object to
Reconstruct

Produce a 3D SAR Image

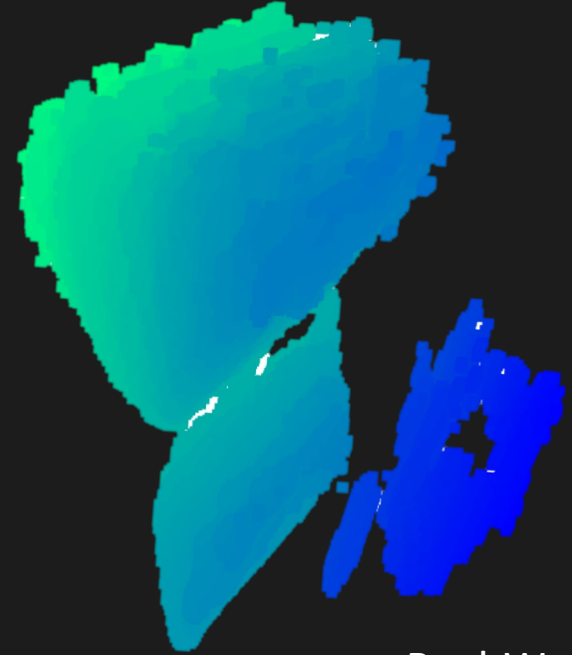


Generate 3D point cloud



Reconstruction quality is limited by
SAR resolution (i.e., bandwidth)

Why are existing 3D reconstruction methods limited?



Real-World
3D Point Cloud

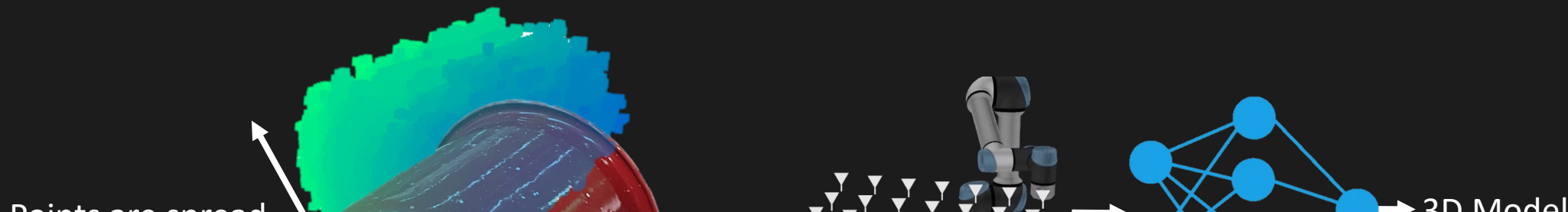


Reconstruction quality is limited by
SAR resolution (i.e., bandwidth)

Why are existing 3D reconstruction methods limited?

First-Principles Methods

Machine-Learning Methods



We need a fundamentally new approach for
mmWave 3D object reconstruction

Our Idea: Directly estimate the curvature of the object

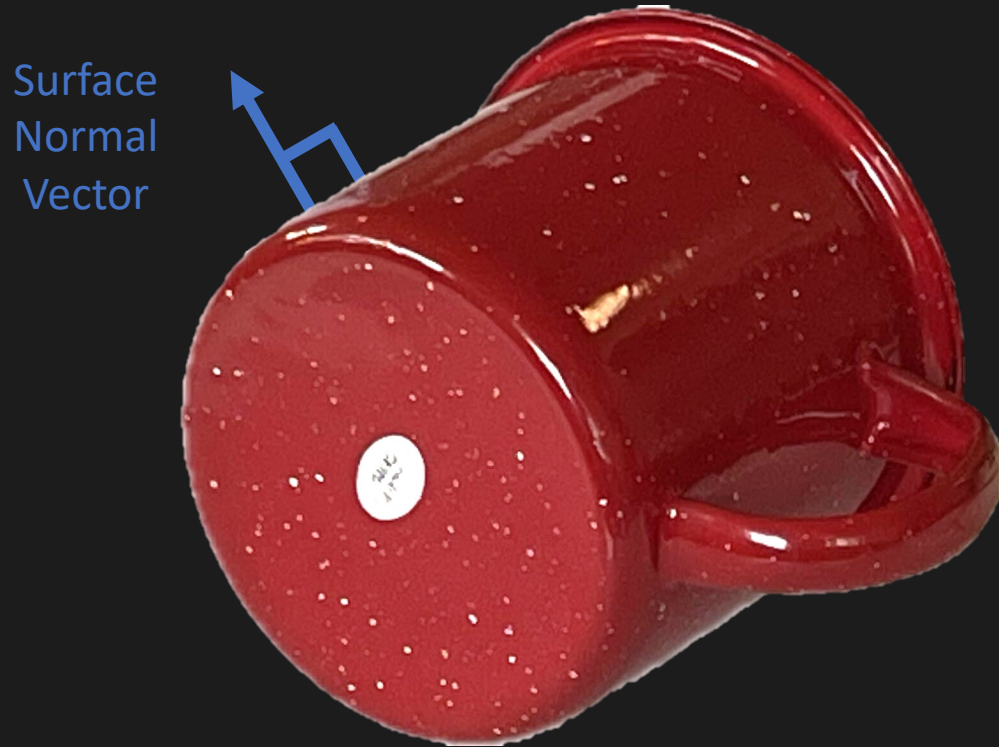


SAR resolution (i.e., bandwidth)

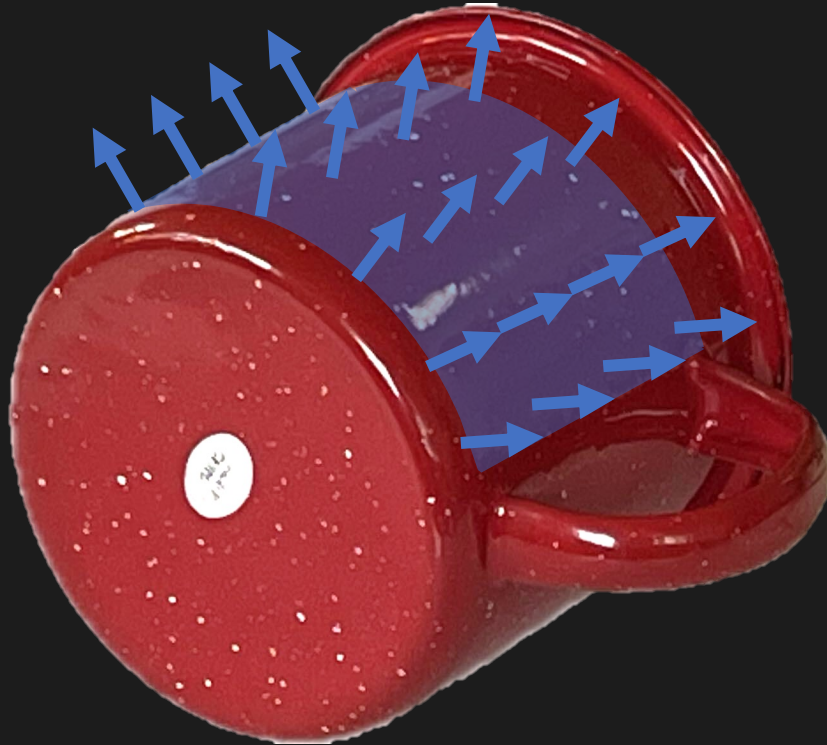


subset of objects

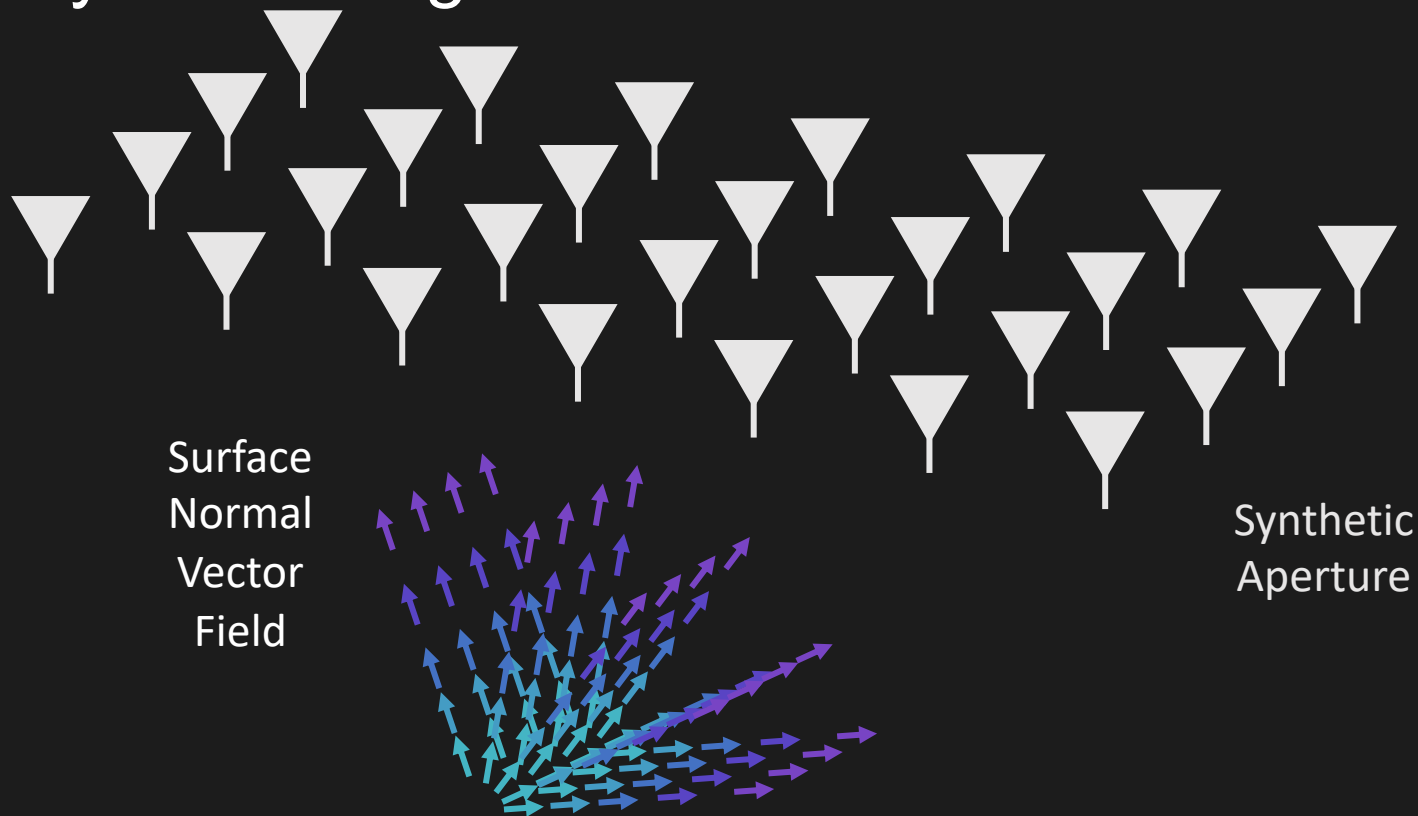
Our Idea: Directly estimate the curvature of the object
by estimating surface normal vectors



Our Idea: Directly estimate the curvature of the object
by estimating surface normal vectors

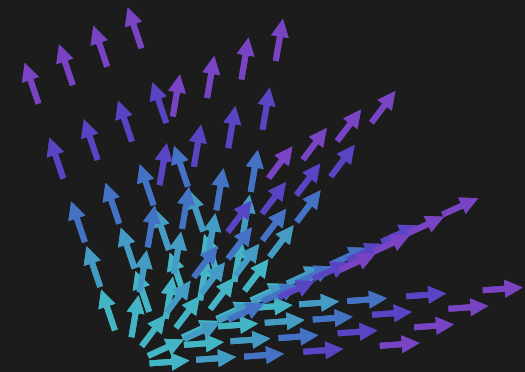


Our Idea: Directly estimate the curvature of the object
by estimating surface normal vectors



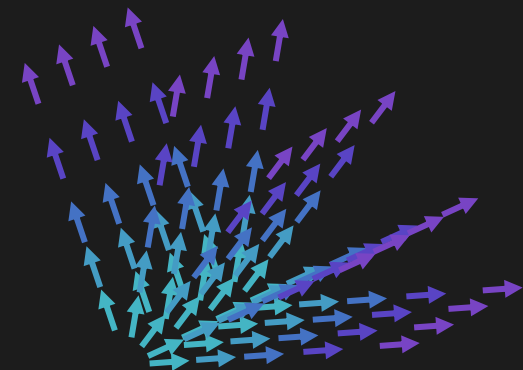
Our Idea: Directly estimate the curvature of the object by estimating surface normal vectors

1. Normal Field Estimation

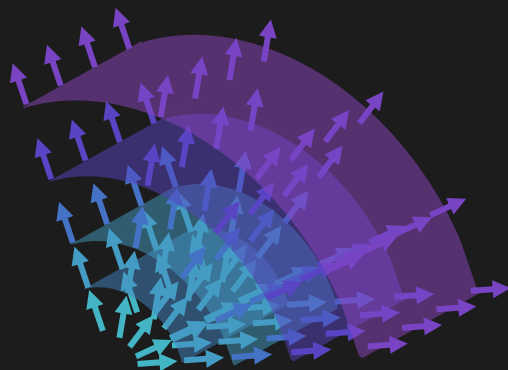


Our Idea: Directly estimate the curvature of the object by estimating surface normal vectors

1. Normal Field Estimation

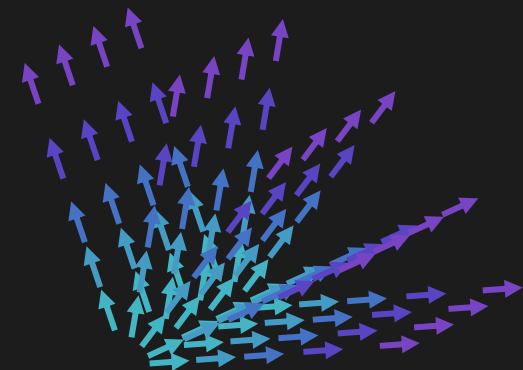


2. Multiple Valid Surfaces

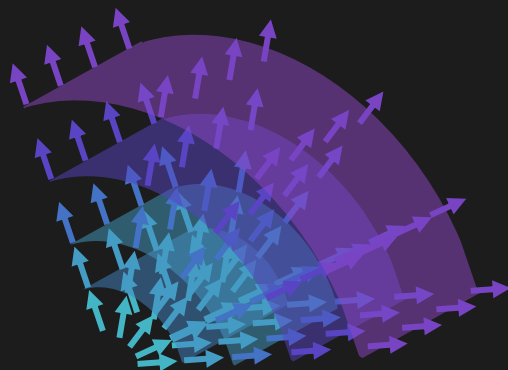


Our Idea: Directly estimate the curvature of the object by estimating surface normal vectors

1. Normal Field Estimation



2. Multiple Valid Surfaces



3. Single Unifying Function

Relative Signed
Distance Function

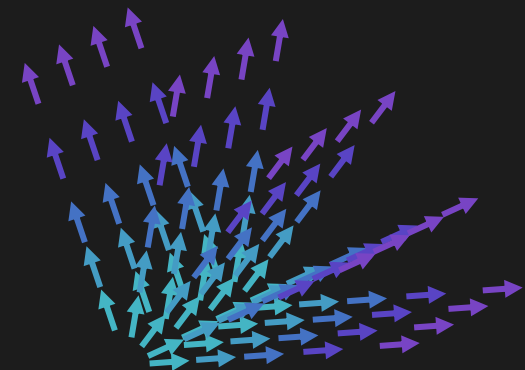


Isosurface: Surface
of constant value

4. Isosurface Optimization

Our Idea: Directly estimate the curvature of the object by estimating surface normal vectors

1. Normal Field Estimation

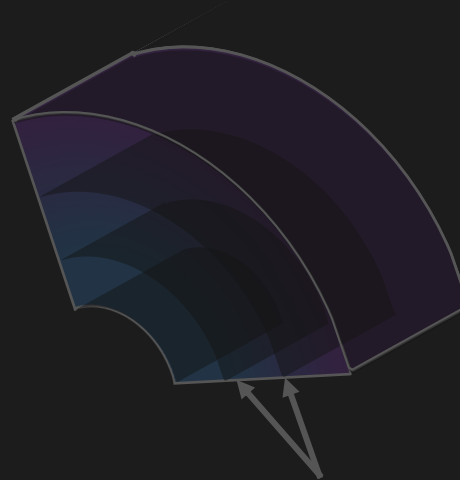


2. Multiple Valid Surfaces



3. Single Unifying Function

Relative Signed
Distance Function



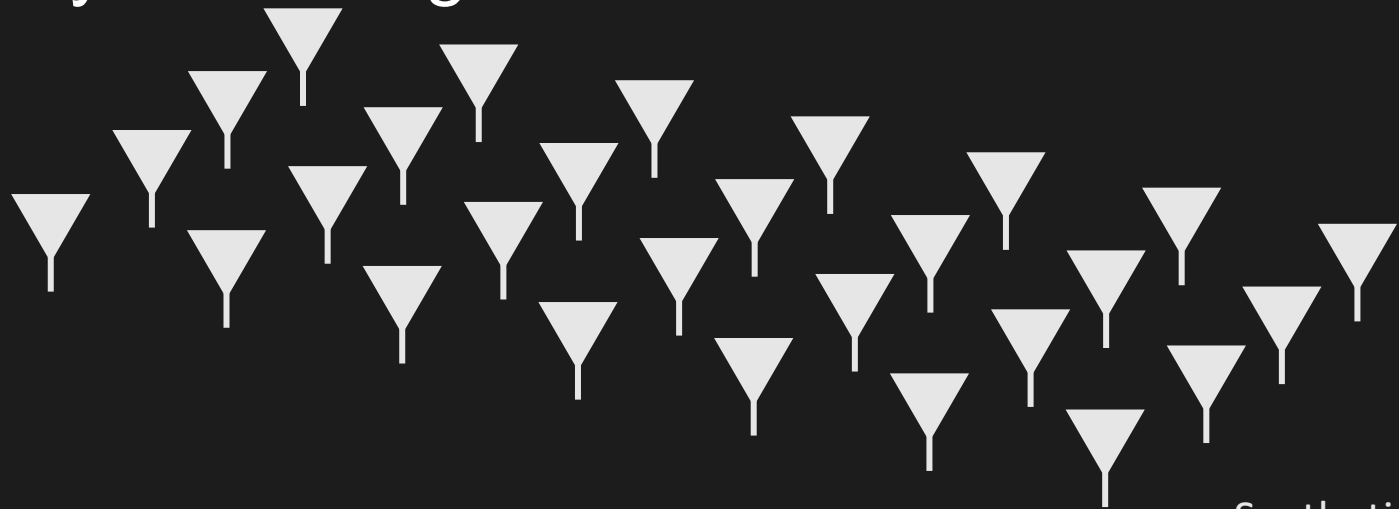
Isosurface: Surface
of constant value

4. Isosurface Optimization



Final Surface
Estimate

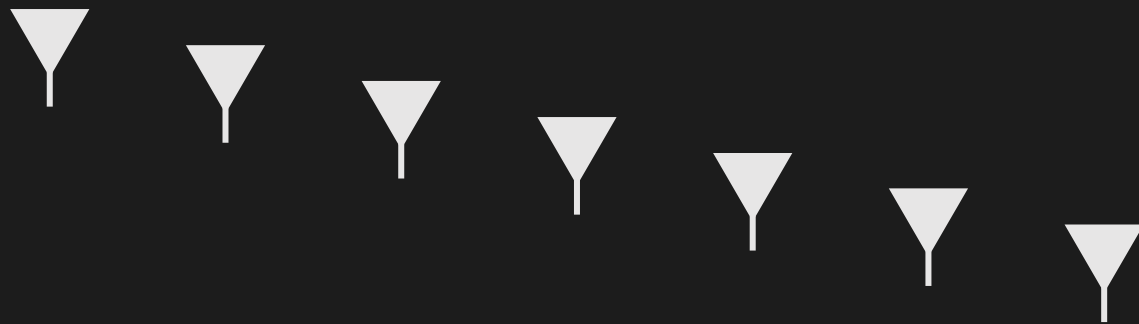
Our Idea: Directly estimate the curvature of the object
by estimating surface normal vectors



Synthetic
Aperture



Our Idea: Directly estimate the curvature of the object
by estimating surface normal vectors



Synthetic
Aperture



Our Idea: Directly estimate the curvature of the object
by estimating surface normal vectors

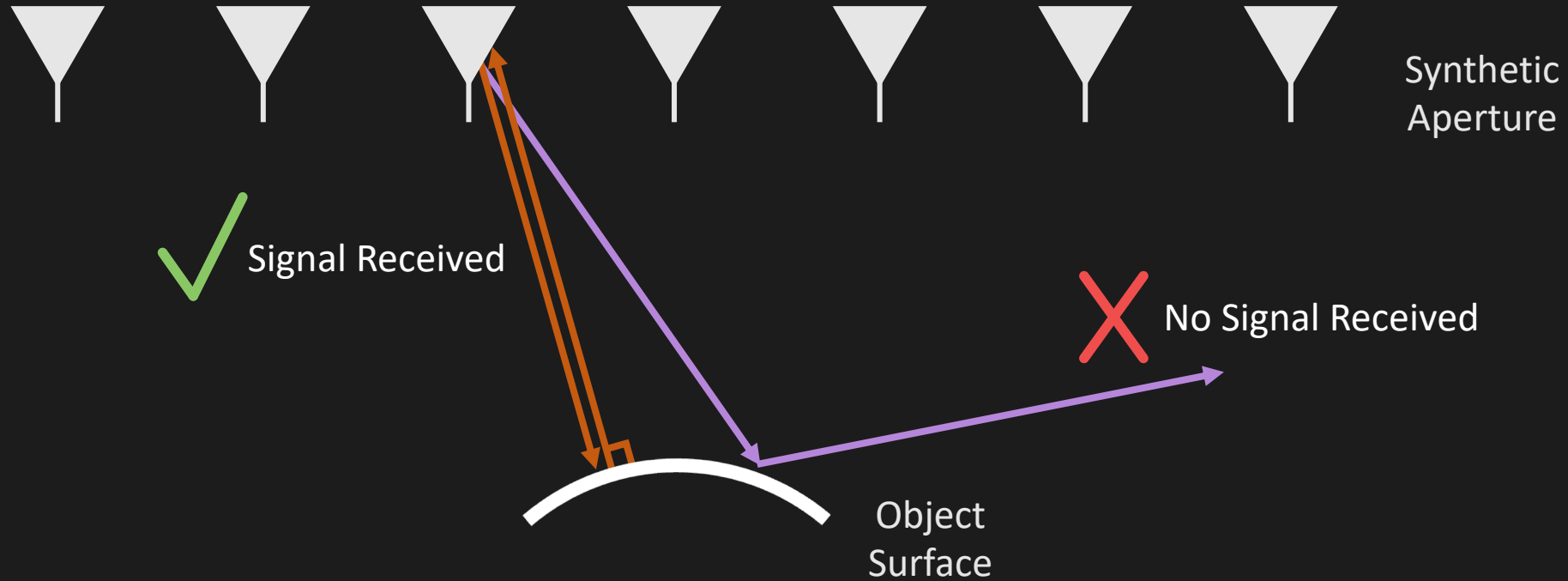


Synthetic
Aperture



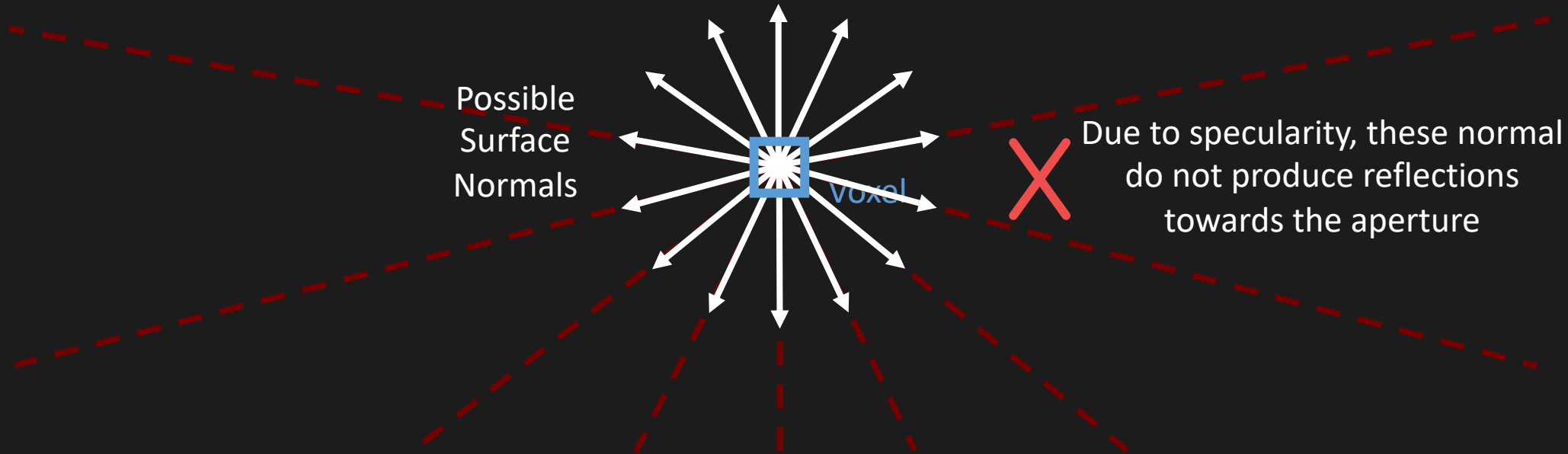
Object
Surface

mmWave signals experience primarily specular reflections

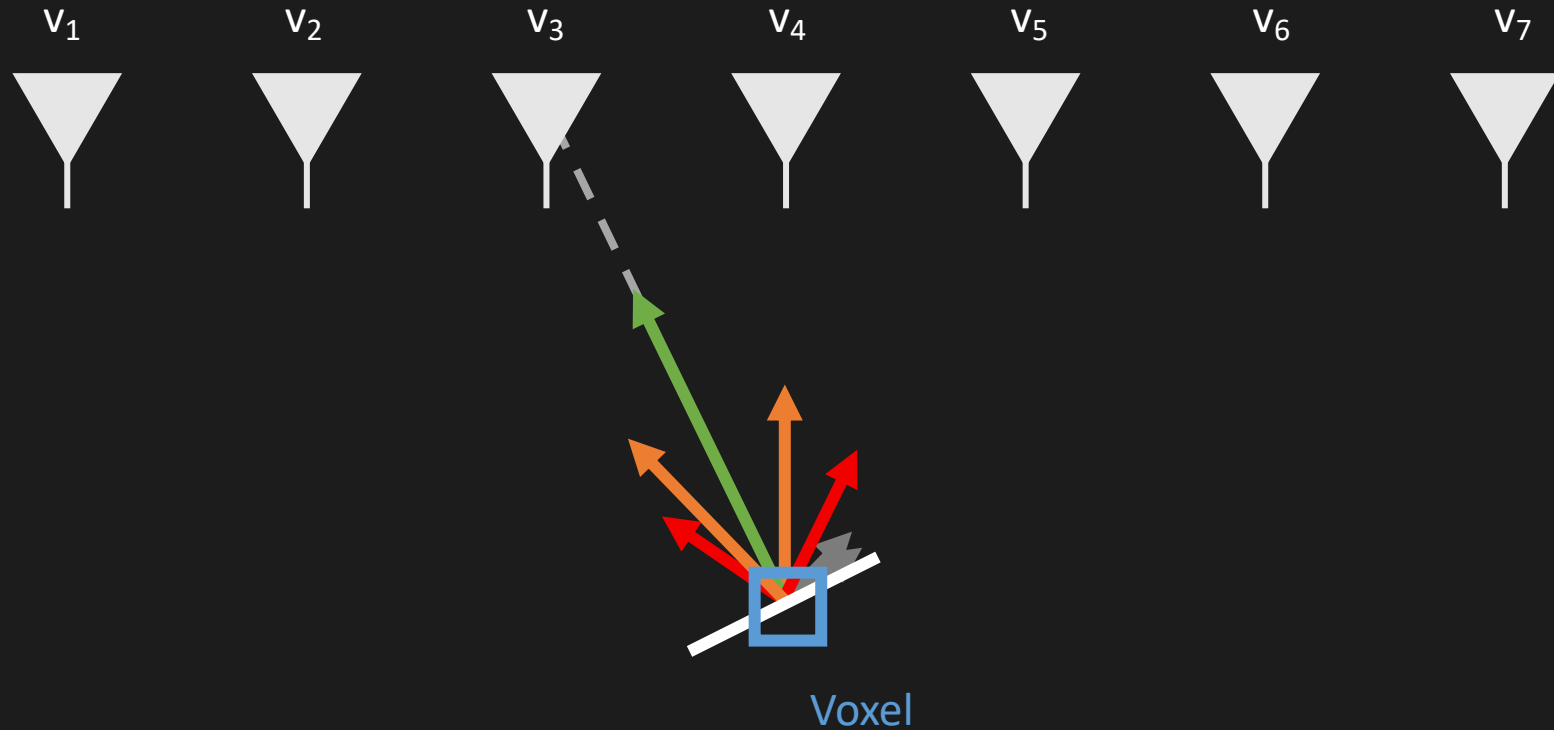


At a given voxel, what direction is the surface normal?

Lets say one of these antennas receive a reflection from this voxel

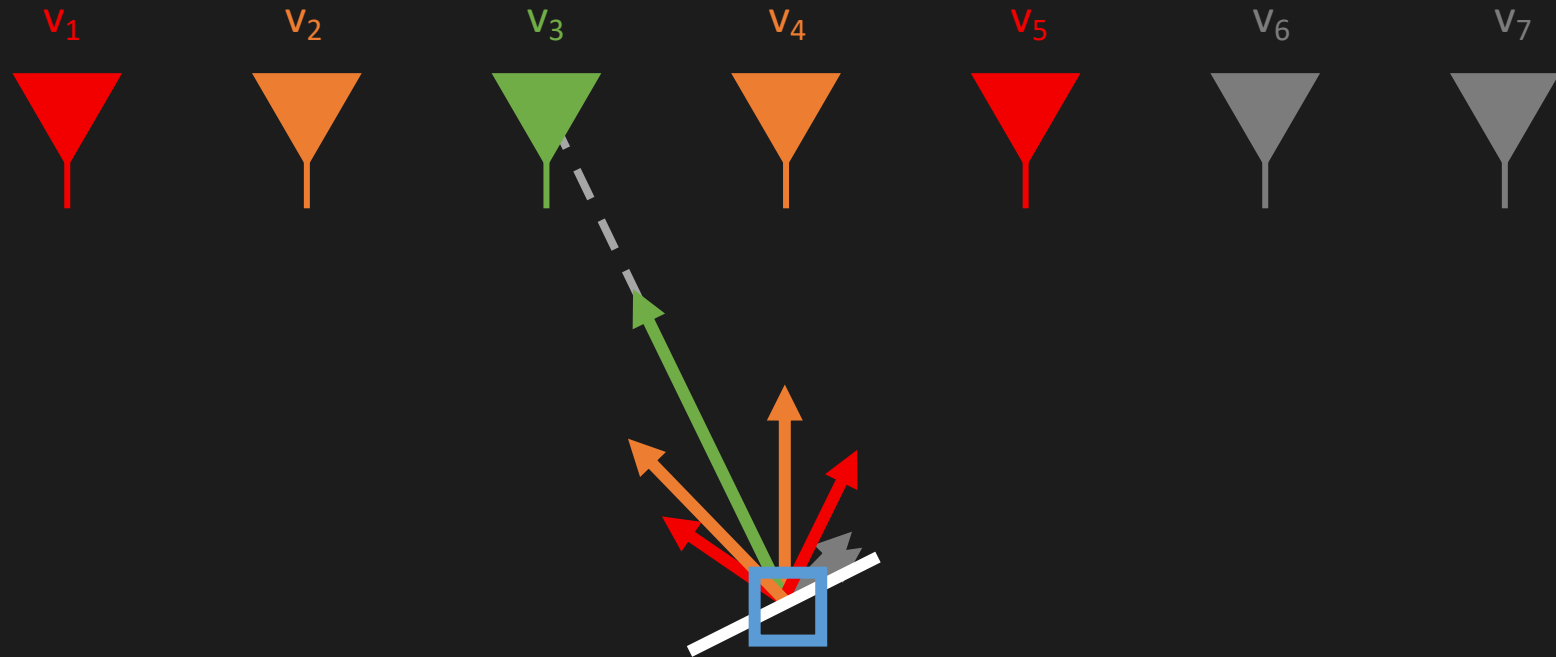


At a given voxel, what direction is the surface normal?



Reflection amplitude acts as a vote

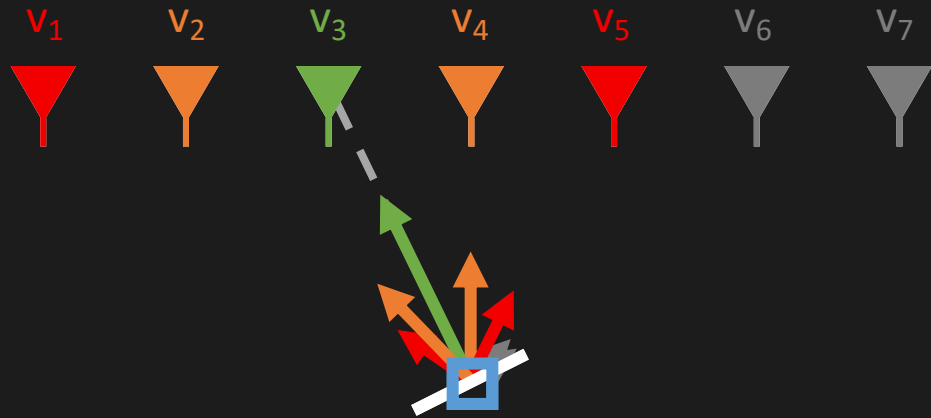
At a given voxel, what direction is the surface normal?



Reflection amplitude acts as a vote

At a given voxel, what direction is the surface normal?

Example 1

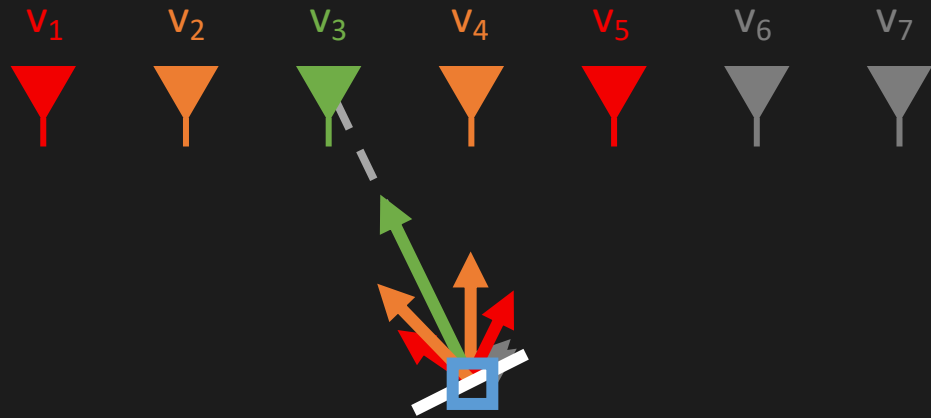


Example 2

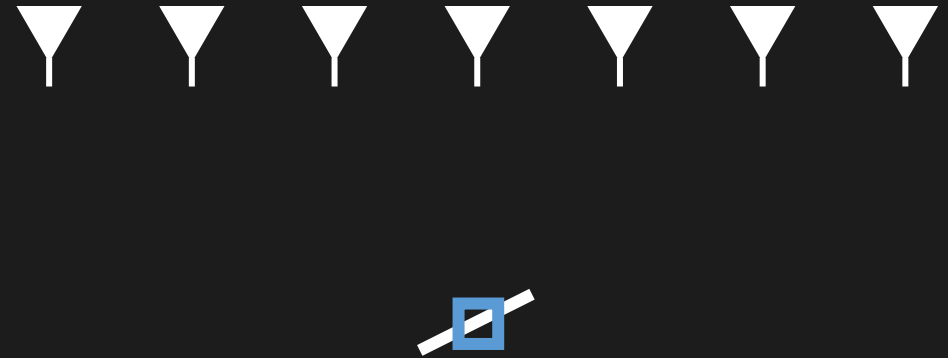
Reflection amplitude acts as a vote

At a given voxel, what direction is the surface normal?

Example 1



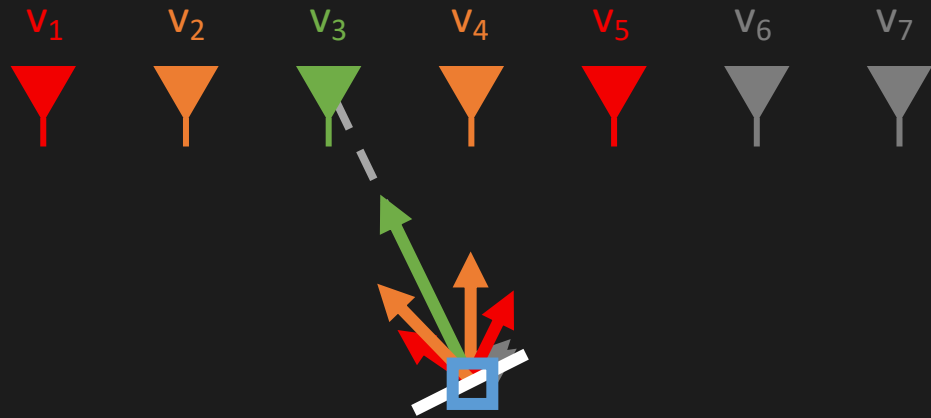
Example 2



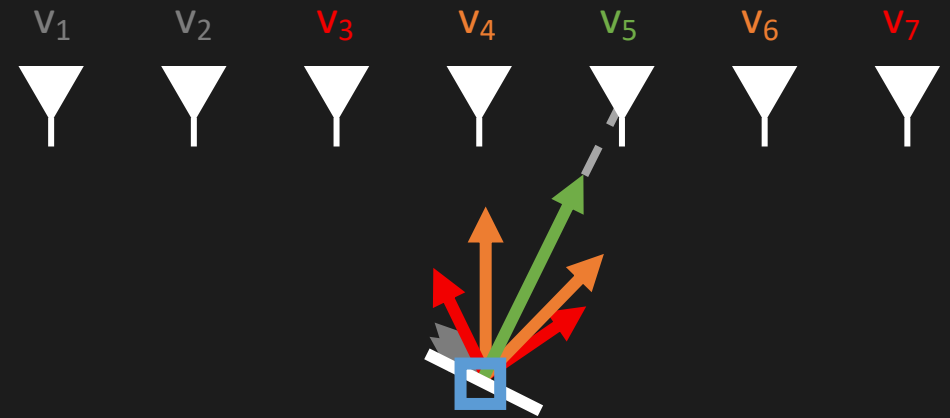
Reflection amplitude acts as a vote

At a given voxel, what direction is the surface normal?

Example 1



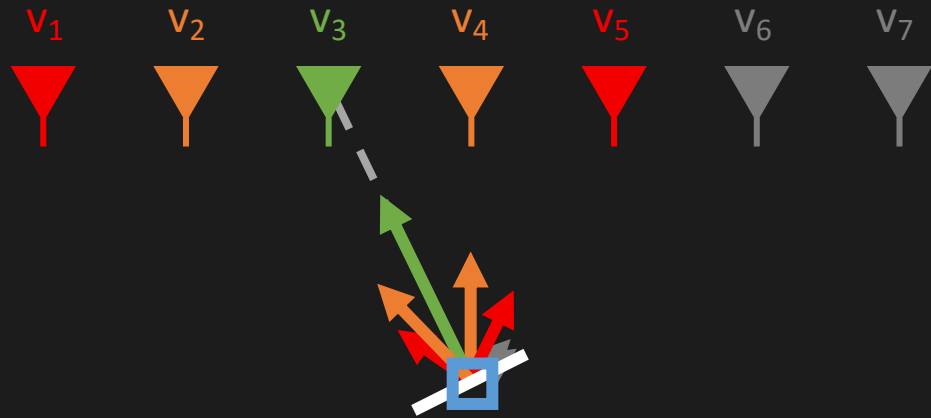
Example 2



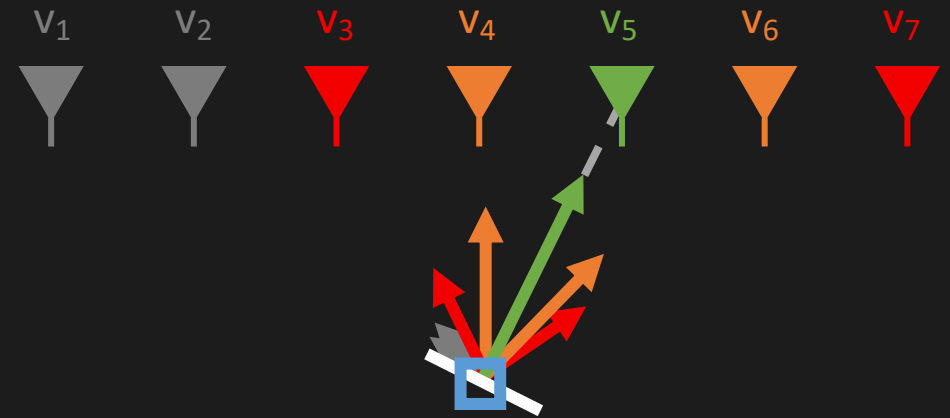
Reflection amplitude acts as a vote

At a given voxel, what direction is the surface normal?

Example 1



Example 2

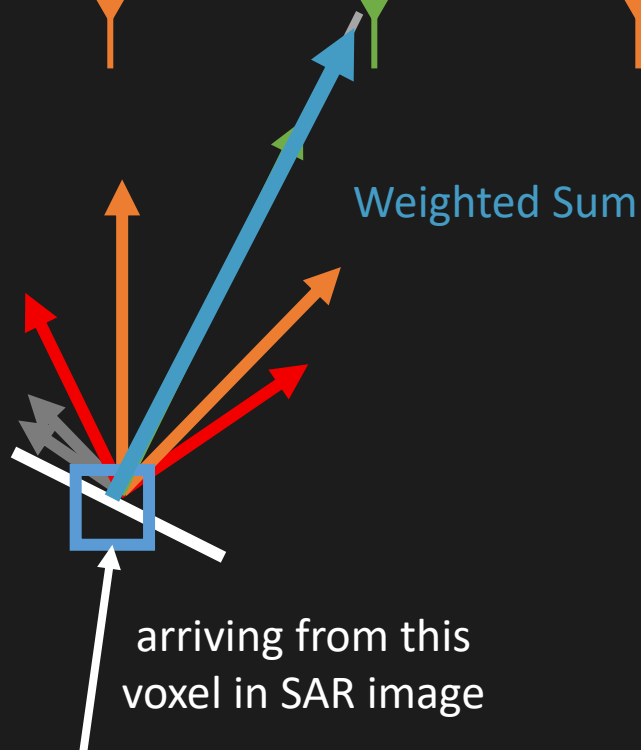


Reflection amplitude acts as a vote

At a given voxel, what direction is the surface normal?



$$\vec{n}(u) = \sum_{k=0}^N v_k \frac{p_k - u}{||p_k - u||}$$

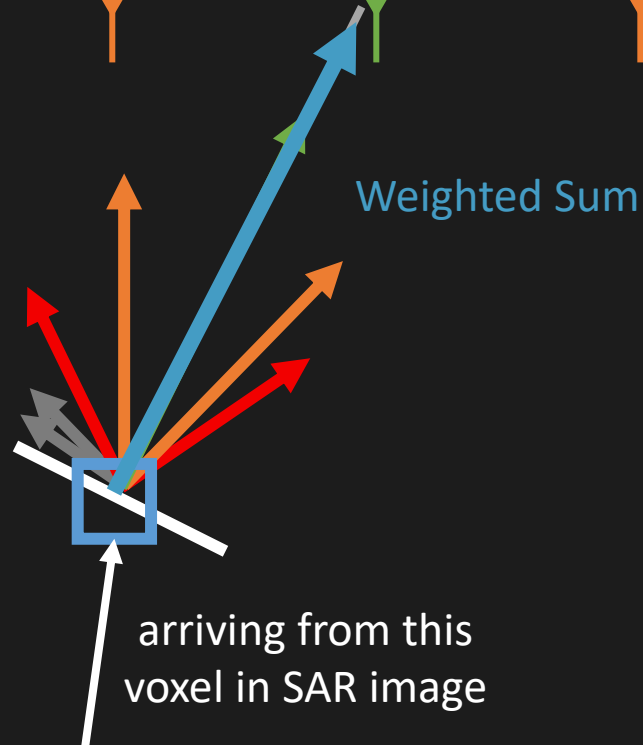


Reflection amplitude acts as a vote

How do we compute the voting function?



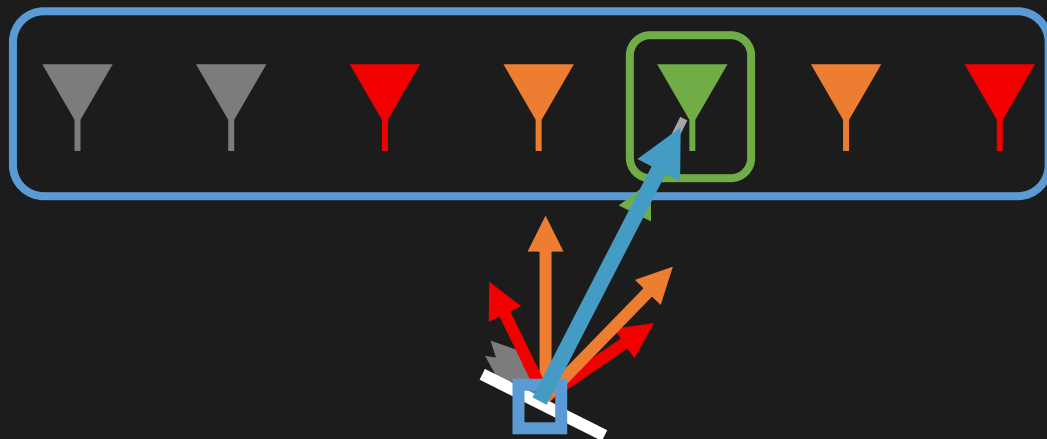
$$\vec{n}(u) = \sum_{k=0}^N v_k \frac{p_k - u}{||p_k - u||}$$



Reflection amplitude acts as a vote

How do we compute the voting function?

Reflection amplitude arriving from this voxel in SAR image acts as a vote



Individual
Antenna
Value

$$I(k) = \sum_{i=1}^M h(i, k) e^{j2\pi d(v, k) / \lambda_i}$$

Sum across frequency (points to $\sum_{i=1}^M$)

Received signal (points to $h(i, k)$)

Expected signal (points to $e^{j2\pi d(v, k) / \lambda_i}$)

$$S = \sum_{k=1}^N I(k)$$

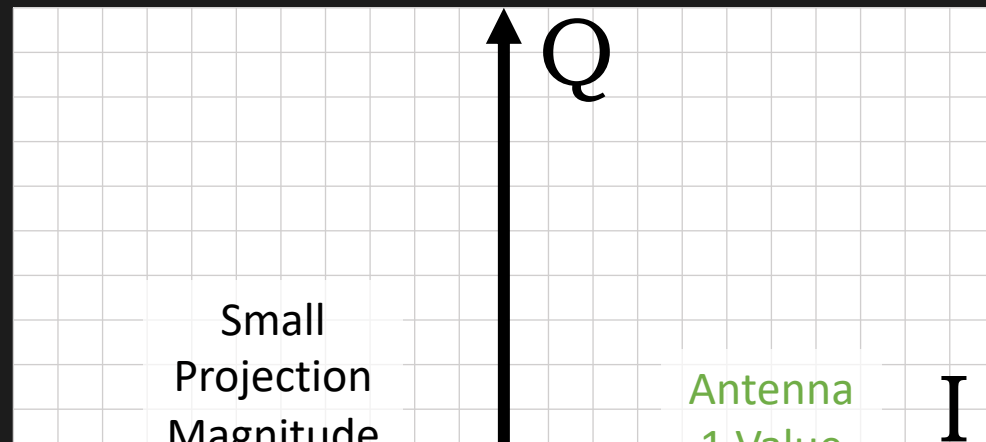
mmWave Voxel Value (points to S)

Sum across antennas (points to $\sum_{k=1}^N$)

Individual Antenna Values (points to $I(k)$)

How do we compute the voting function?

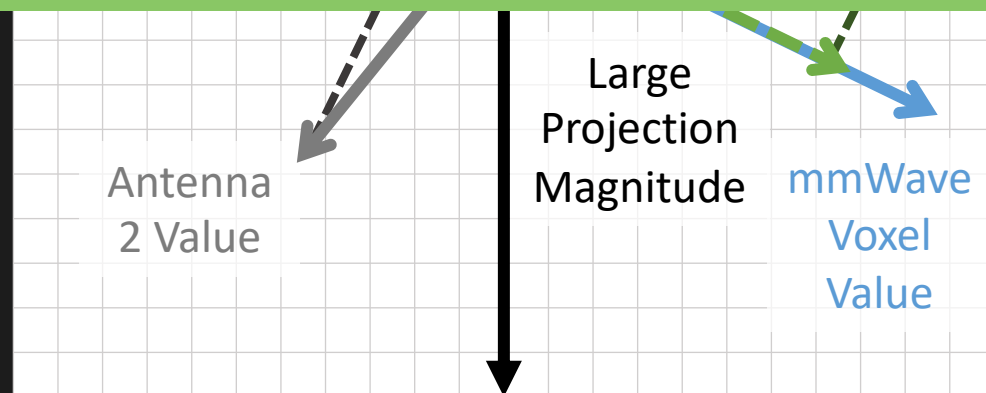
Reflection amplitude arriving from this voxel in SAR image acts as a vote



We repeat this at every voxel in space to produce a normal vector field

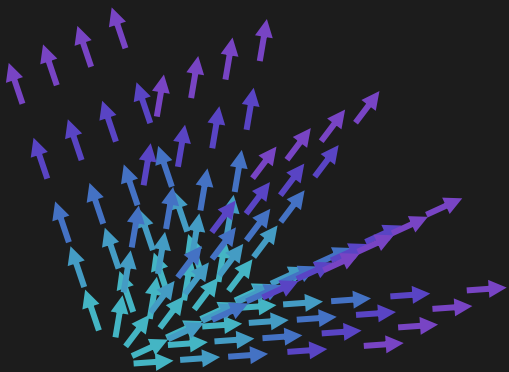
$$I(k) = \sum_{i=1}^M h(i, k) e^{j2\pi d(v, k) / \lambda_i} \quad S = \sum_{k=1}^N I(k)$$

$$\text{Voting Function: } v_k = \frac{\Re\{I(k)\}\Re\{S\} + \Im\{I(k)\}\Im\{S\}}{\|S\|}$$

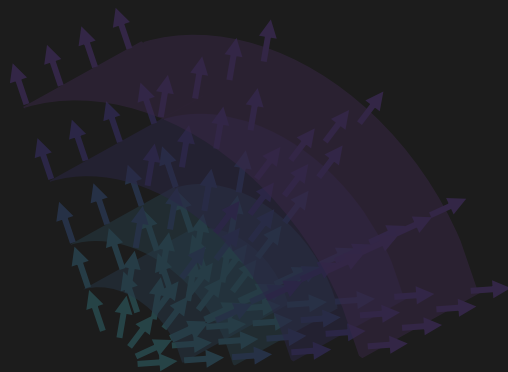


Our Idea: Directly estimate the curvature of the object by estimating surface normal vectors

1. Normal Field Estimation

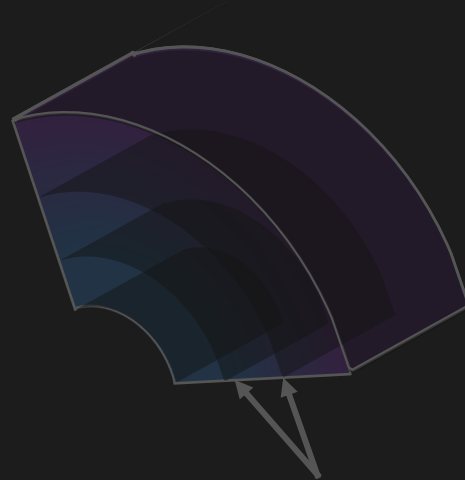


2. Multiple Valid Surfaces



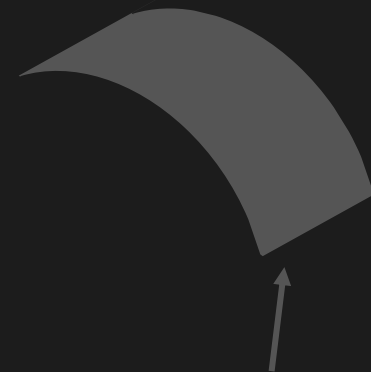
3. Single Unifying Function

Relative Signed
Distance Function



Isosurface: Surface
of constant value

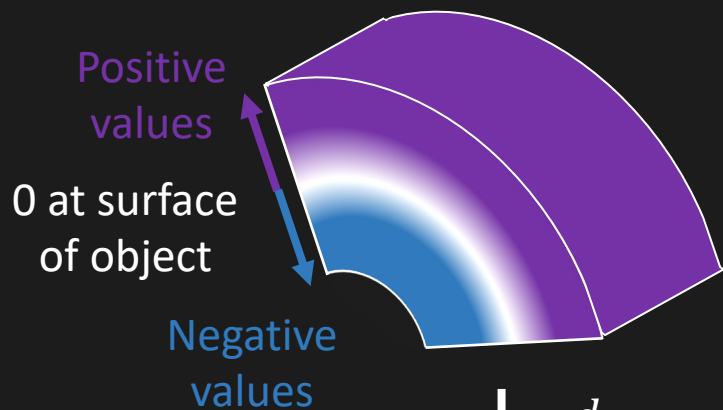
4. Isosurface Optimization



Final Surface
Estimate

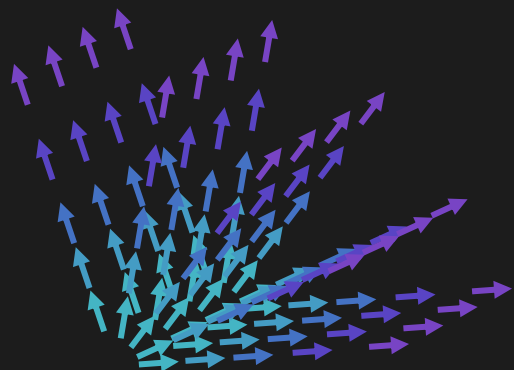
How can we capture all ambiguous surfaces in one function?

Computer Graphics Community



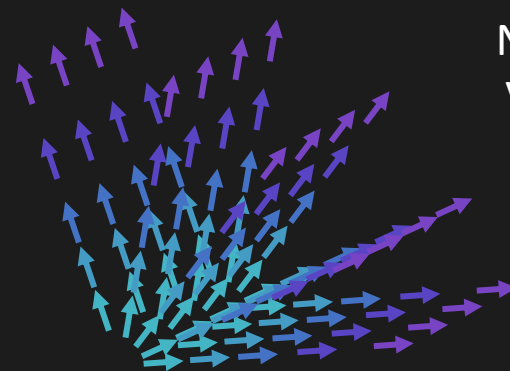
Signed
Distance
Function

$$\downarrow \frac{d}{dx}$$



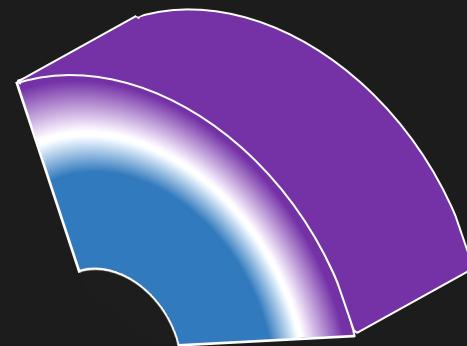
Normal
Vector
Field

mmNorm



Normal
Vector
Field

$$\downarrow \int dx$$

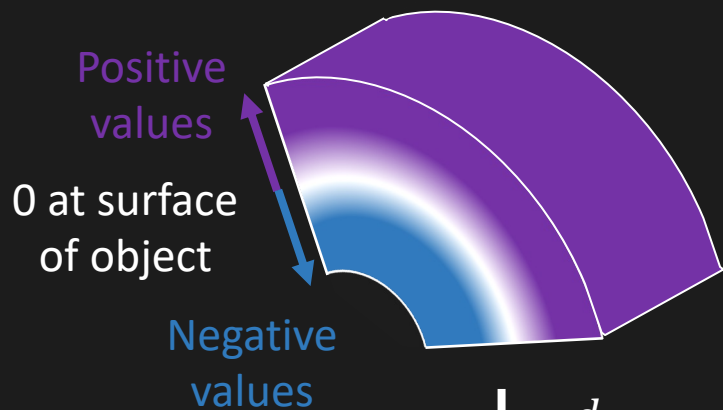


Relative
Signed
Distance
Function

Unknown constant offset

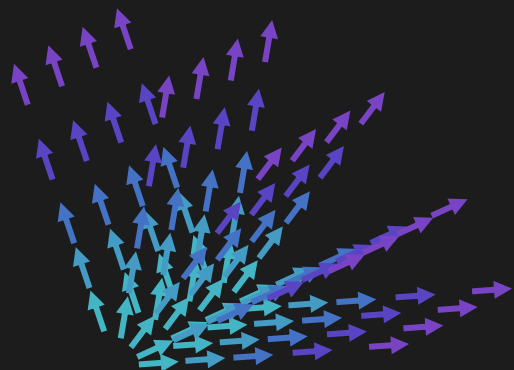
How can we capture all ambiguous surfaces in one function?

Computer Graphics Community



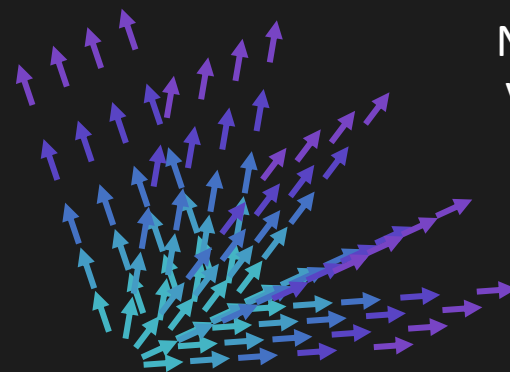
Signed
Distance
Function

$$\downarrow \frac{d}{dx}$$



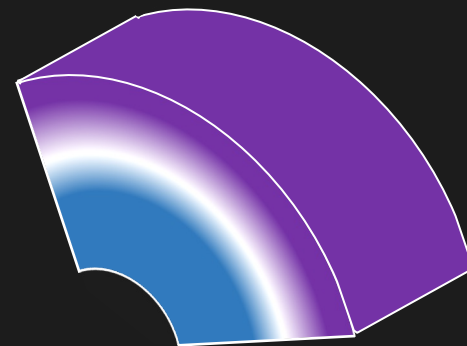
Normal
Vector
Field

mmNorm



Normal
Vector
Field

$$\downarrow \int dx$$

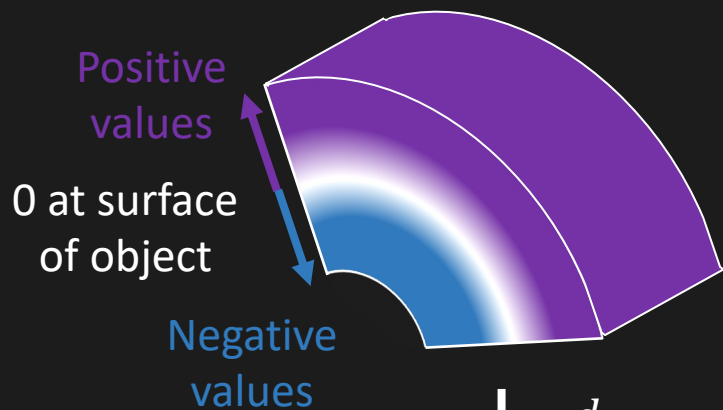


Relative
Signed
Distance
Function

Unknown constant offset

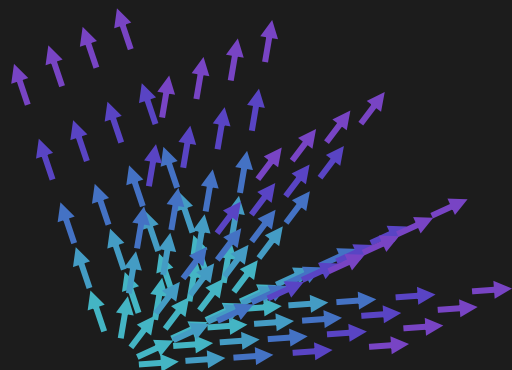
How can we capture all ambiguous surfaces in one function?

Computer Graphics Community



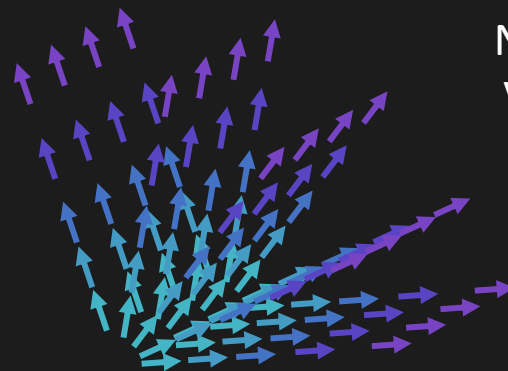
Signed
Distance
Function

$$\downarrow \frac{d}{dx}$$



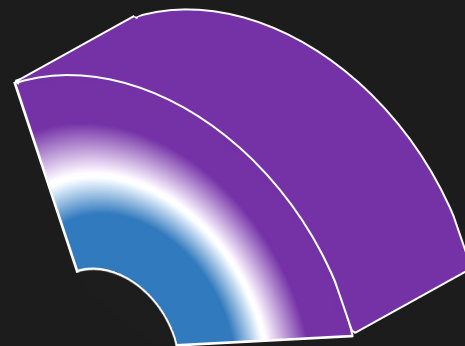
Normal
Vector
Field

mmNorm



Normal
Vector
Field

$$\downarrow \int dx$$

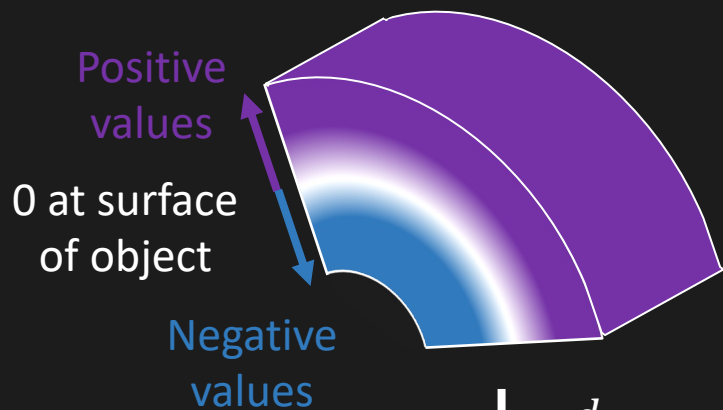


Relative
Signed
Distance
Function

Unknown constant offset

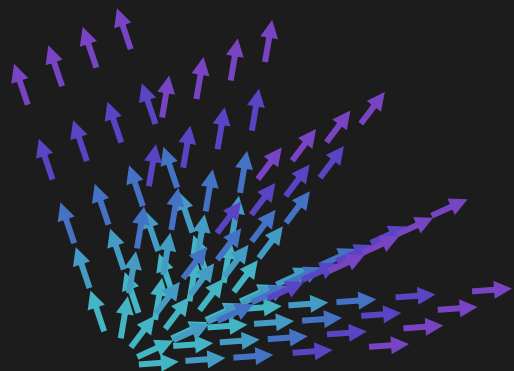
How can we capture all ambiguous surfaces in one function?

Computer Graphics Community



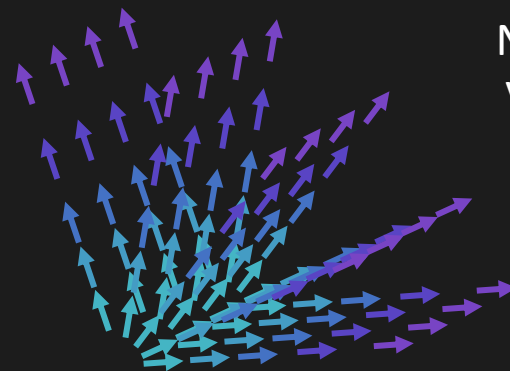
Signed
Distance
Function

$$\downarrow \frac{d}{dx}$$



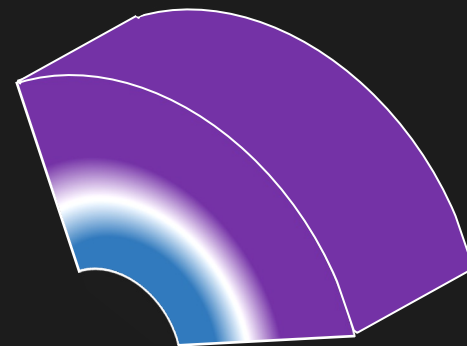
Normal
Vector
Field

mmNorm



Normal
Vector
Field

$$\downarrow \int dx$$

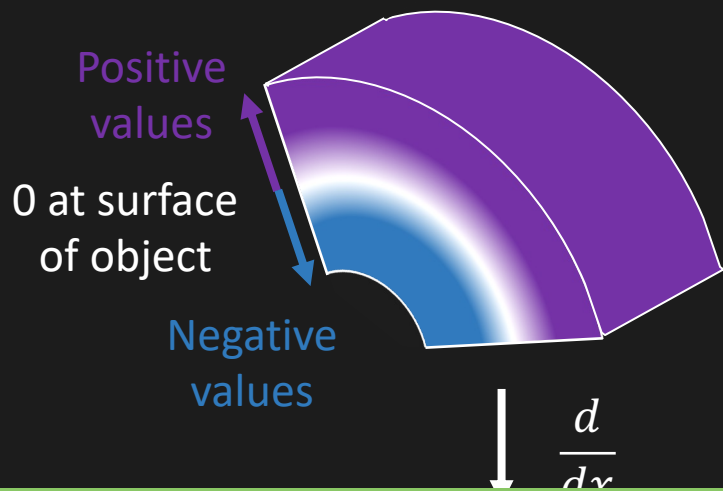


Relative
Signed
Distance
Function

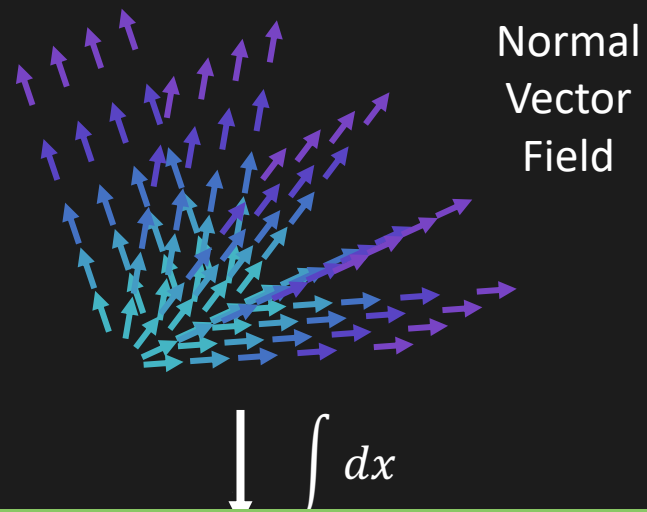
Unknown constant offset

How can we capture all ambiguous surfaces in one function?

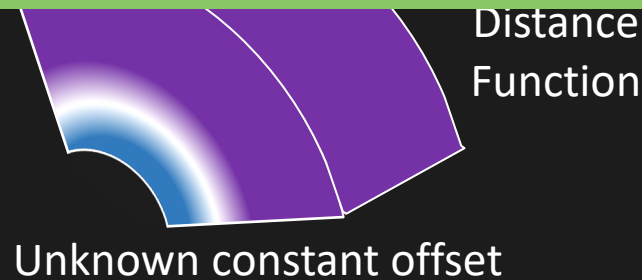
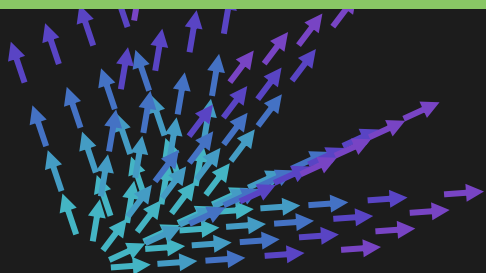
Computer Graphics Community



mmNorm

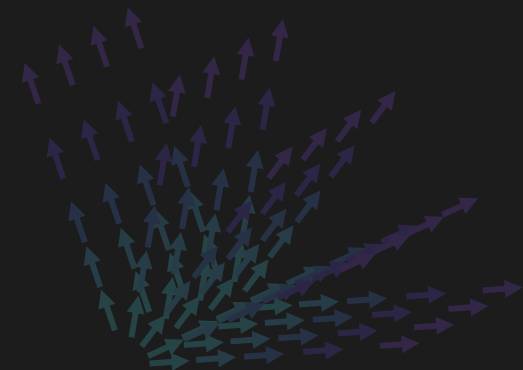


We can determine the surface by finding this unknown constant offset

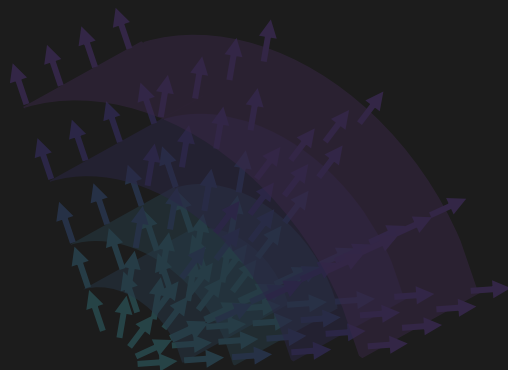


Our Idea: Directly estimate the curvature of the object by estimating surface normal vectors

1. Normal Field Estimation

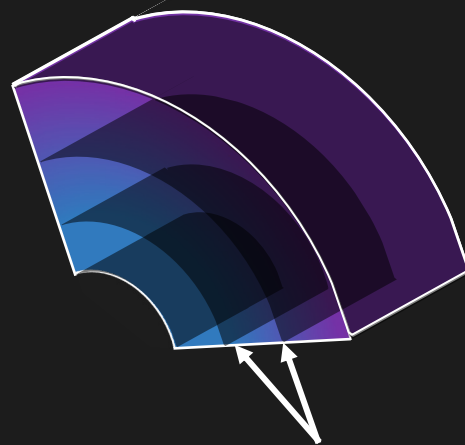


2. Multiple Valid Surfaces



3. Single Unifying Function

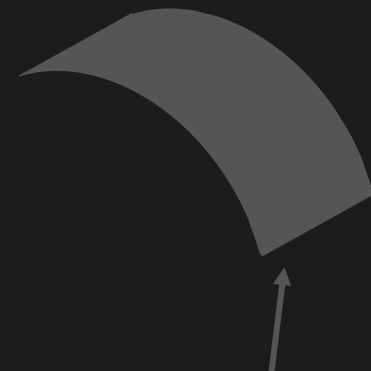
Relative Signed Distance Function



Isosurface: Surface of constant value

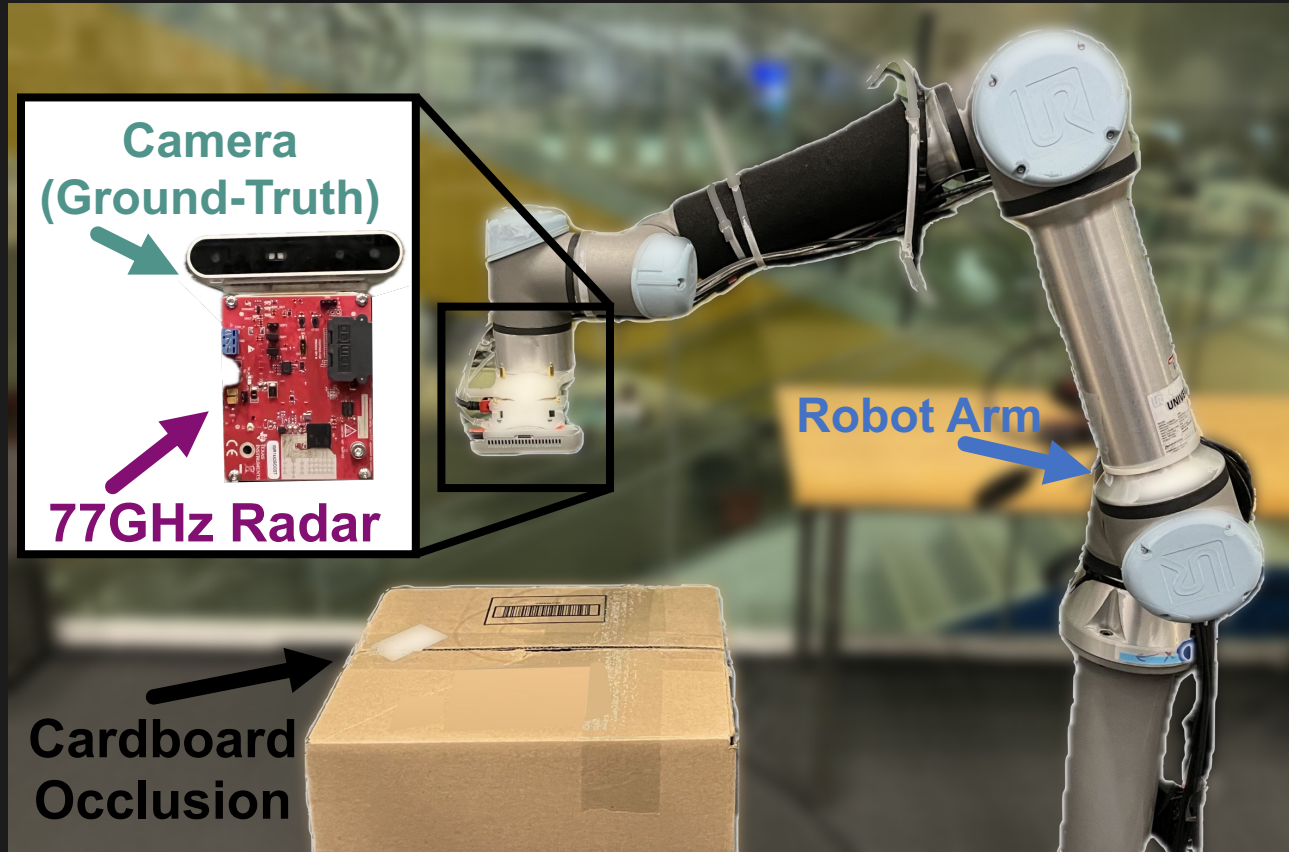
4. Isosurface Optimization

$$L(C) = \sum_{k=1}^N \left\| \frac{|FFT(\widehat{h(i,k)})|}{|FFT(h(i,k))|} - 1 \right\|$$



Final Surface Estimate

Implementation



- UR5e Robot Arm
- TI IWR1443Boost 77GHz Radar
- Intel Realsense RGB-D camera for ground truth
- Measured experiments in line-of-sight and non-line-of-sight (cardboard occlusion)
- Collected experiments across 61 different everyday objects

Qualitative Results

Select every voxel in SAR
image above power
threshold

Qualitative Results

Full Object



RGB Surface



Baseline



mmNorm



Qualitative Results

Full Object



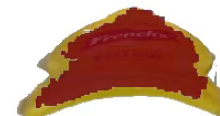
RGB Surface



Baseline



mmNorm



Quantitative Results: 3D F-Score

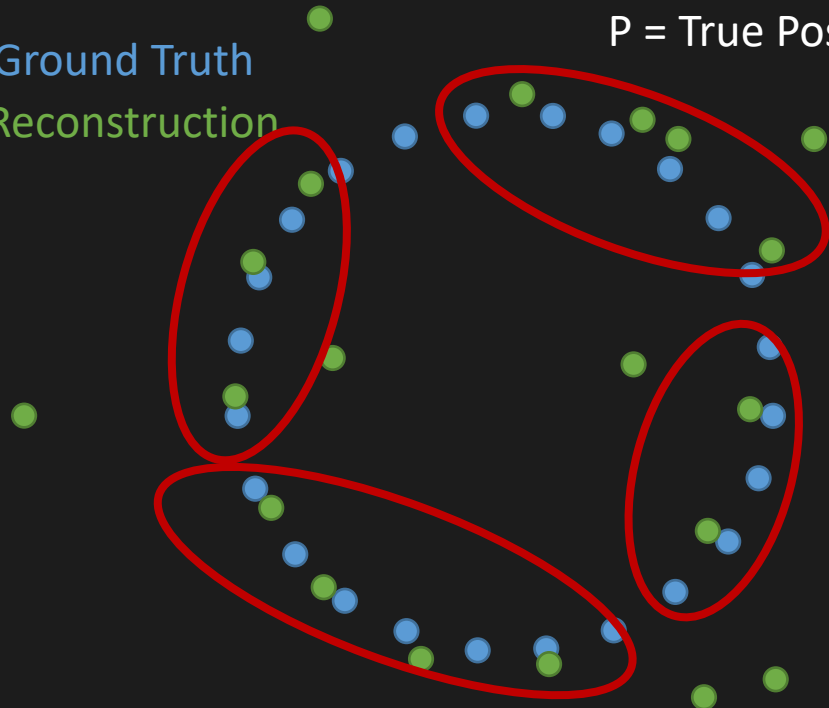
Measured 3D F-Score of each reconstruction relative to ground-truth

Precision

How many points in prediction are accurate?

$$P = \text{True Positives} / \text{Total Recon} \\ = 13 / 20$$

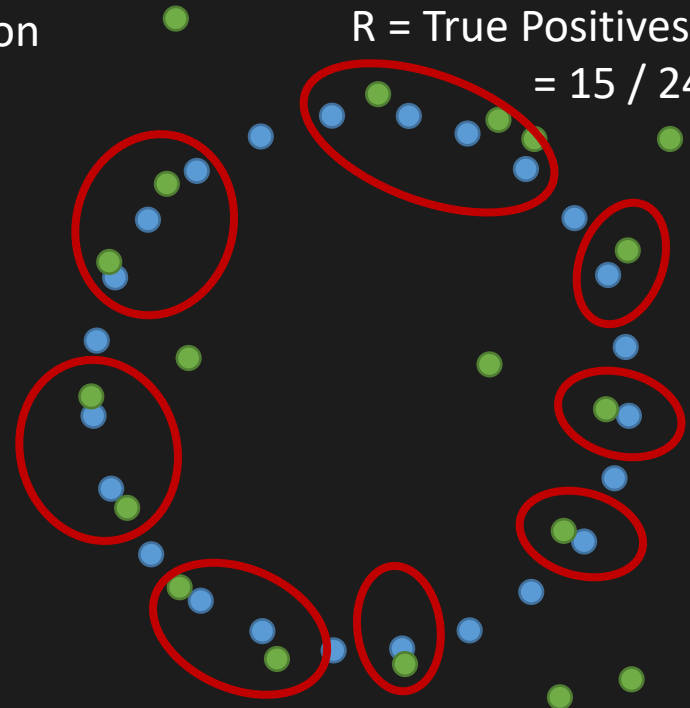
Ground Truth
Reconstruction



Recall

How many points in ground-truth are covered?

$$R = \text{True Positives} / \text{Total GT} \\ = 15 / 24$$

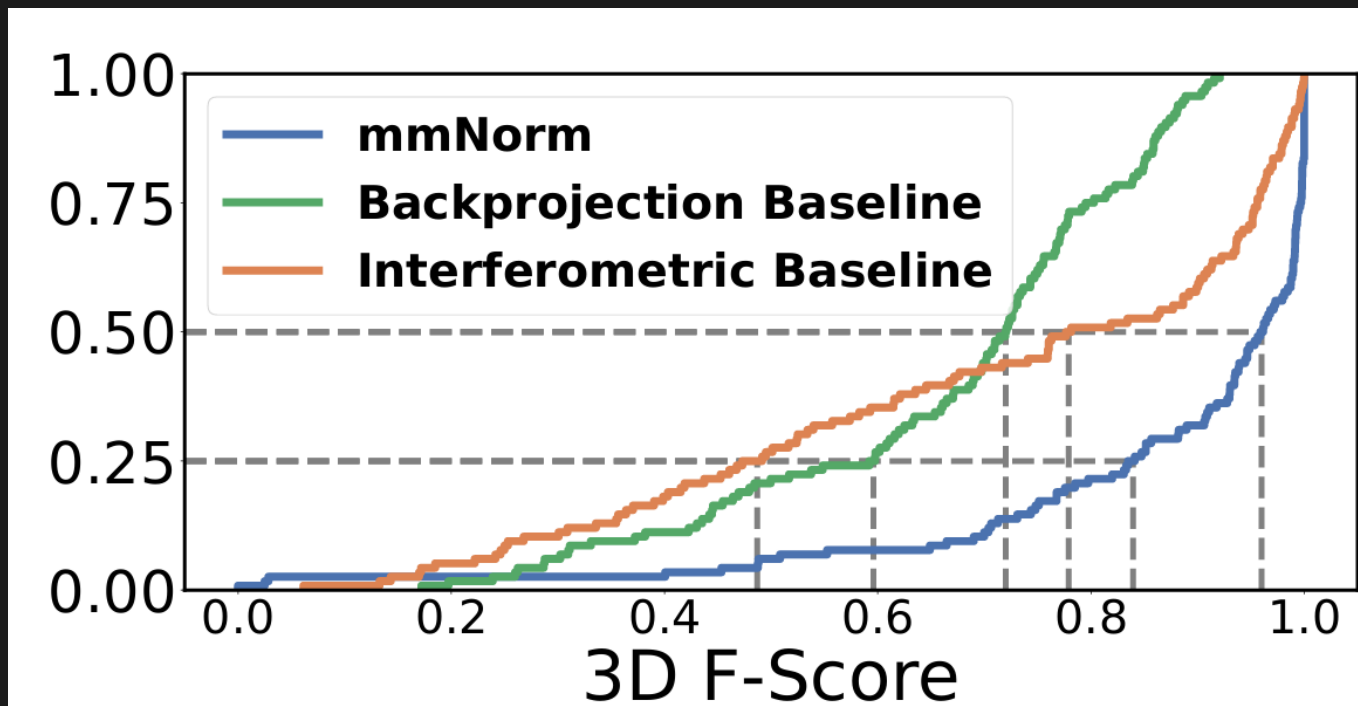


$$F = \frac{2}{\frac{1}{P} + \frac{1}{R}}$$

Quantitative Results: 3D F-Score

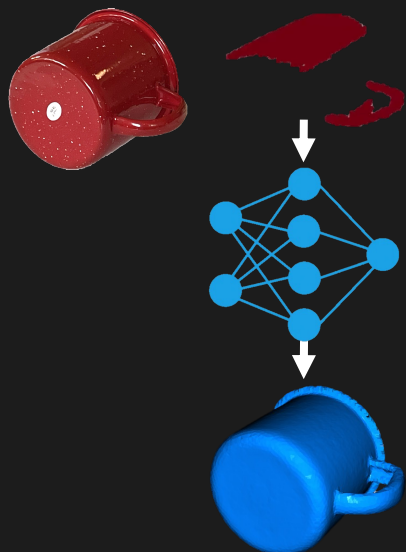
Measured 3D F-Score of each reconstruction relative to ground-truth

Measured across 61 objects in LOS and NLOS



mmNorm Limitations & Future Work

Shape Completion



Novel Downstream Tasks

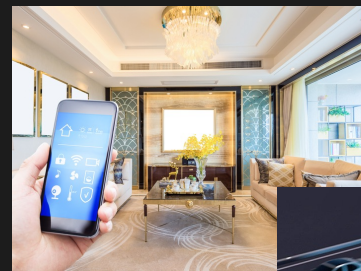


Robotics



Augmented Reality

Large Scale Scenes

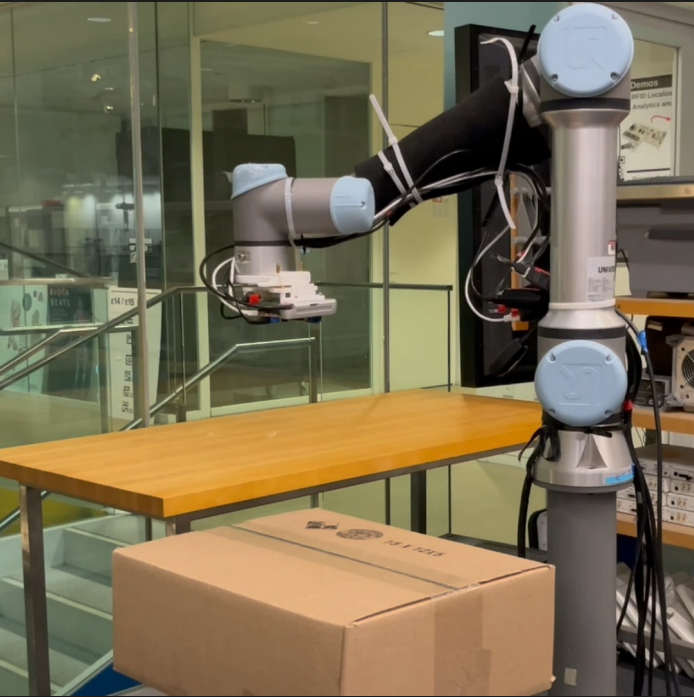


Indoor
Scenes



Autonomous Driving

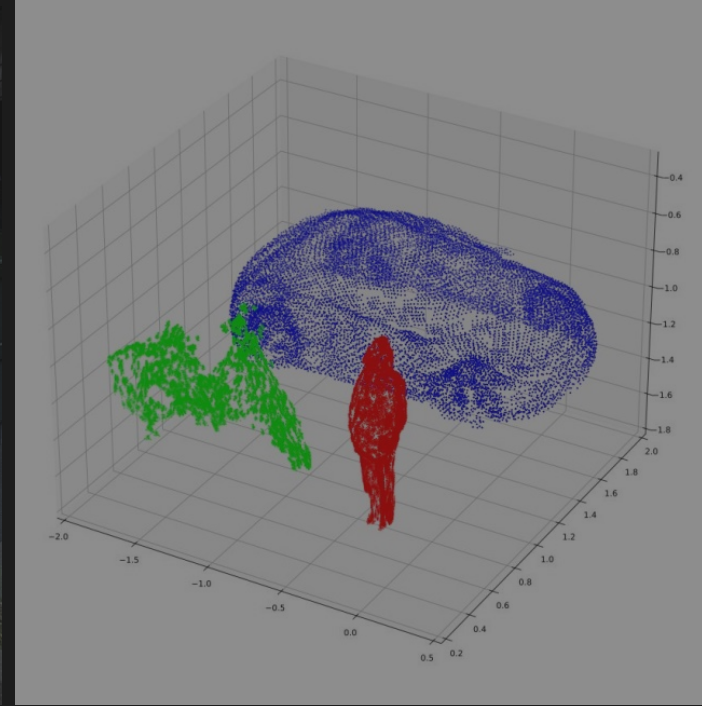
Non-Line-of-Sight Wireless Imaging and 3D Reconstruction



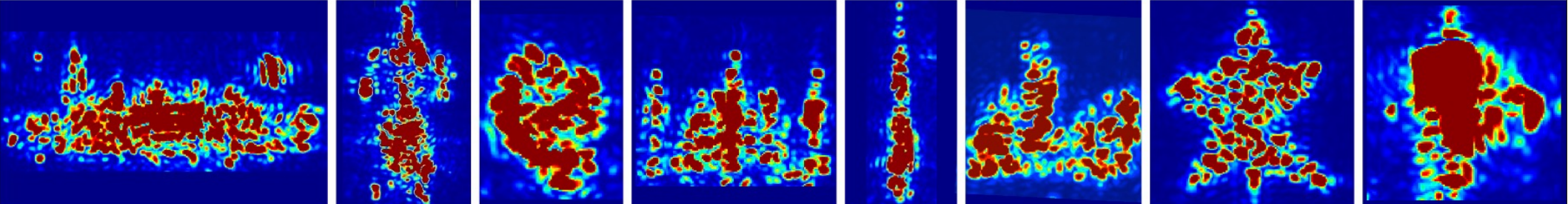
Wireless 3D Reconstruction
Through Boxes



Around-the-Corner
Wireless Imaging



Wireless Reconstruction
In Low Visibility

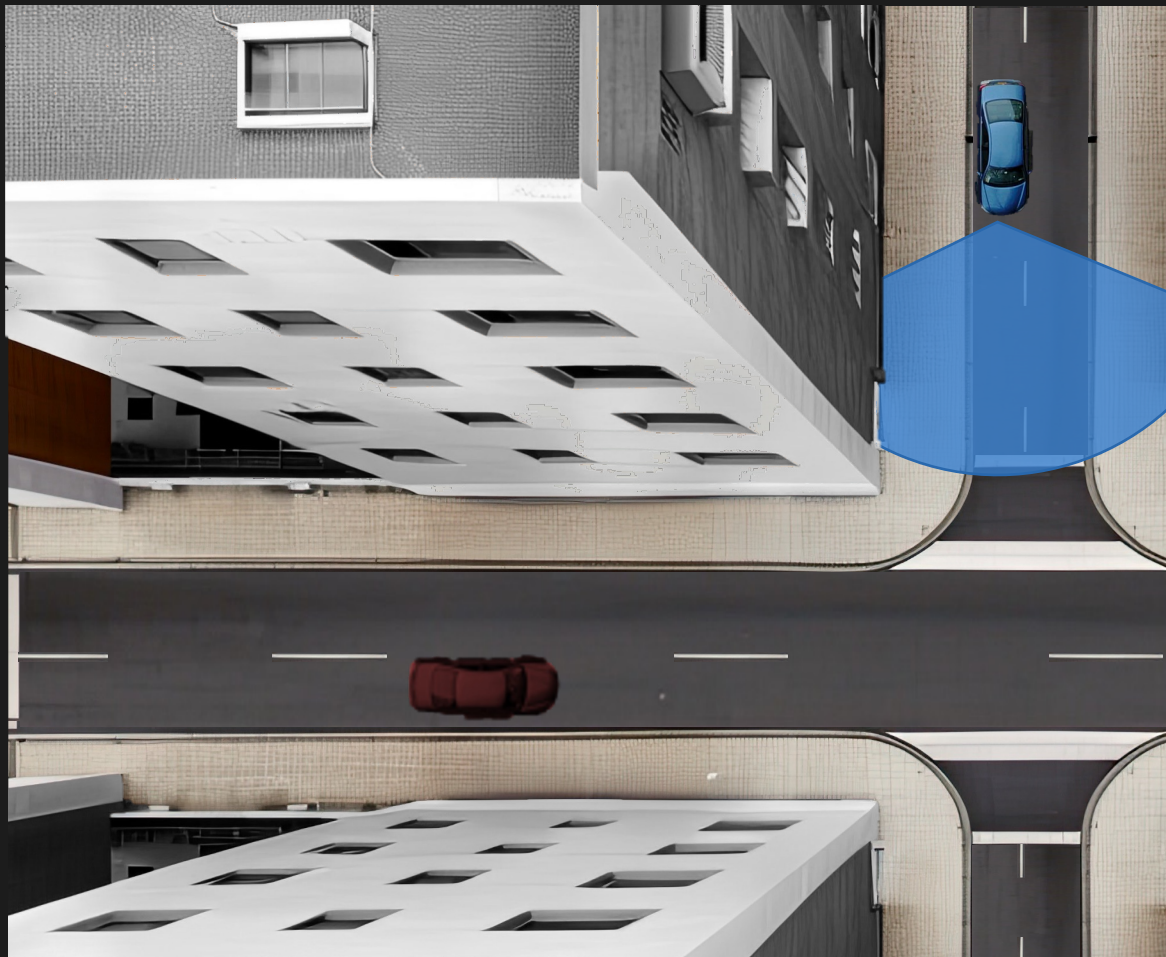


Around-the-Corner mmWave Imaging in Practical Environments

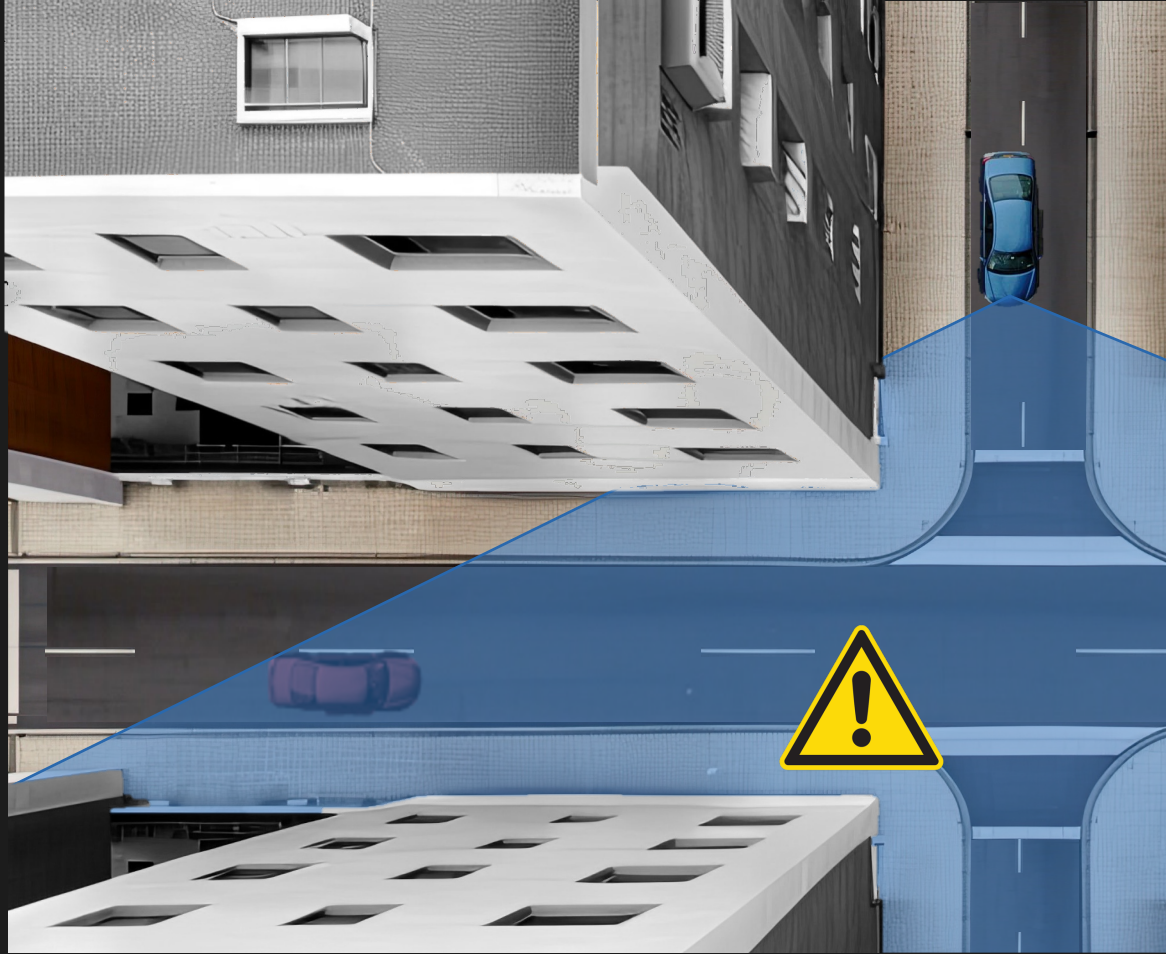
Laura Dodds, Hailan Shanbhag, Junfeng Guan,
Saurabh Gupta, Haitham Hassanieh



Classic Sensing Modalities are Limited to Line-of-Sight



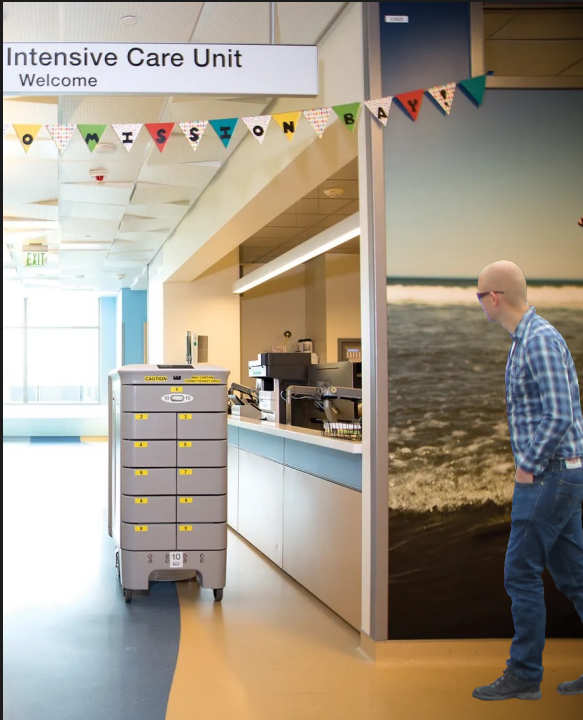
Can We Produce RF Images of Objects Around-the-Corner?



The Ability to Image Around-the-Corner has Many Applications



Autonomous Driving



Robotic Navigation



Search and Rescue

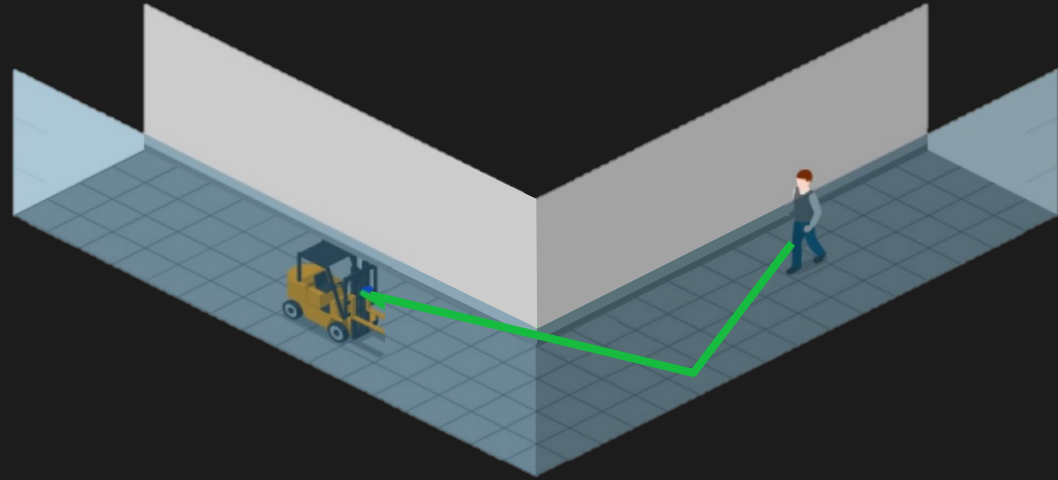
State-of-the-Art RF Non-Line-of-Sight Sensing

RF Through-Occlusion Imaging



✗ Signals Cannot Pass Through All Occlusions (e.g., Metal, Thick Concrete/Brick, etc)

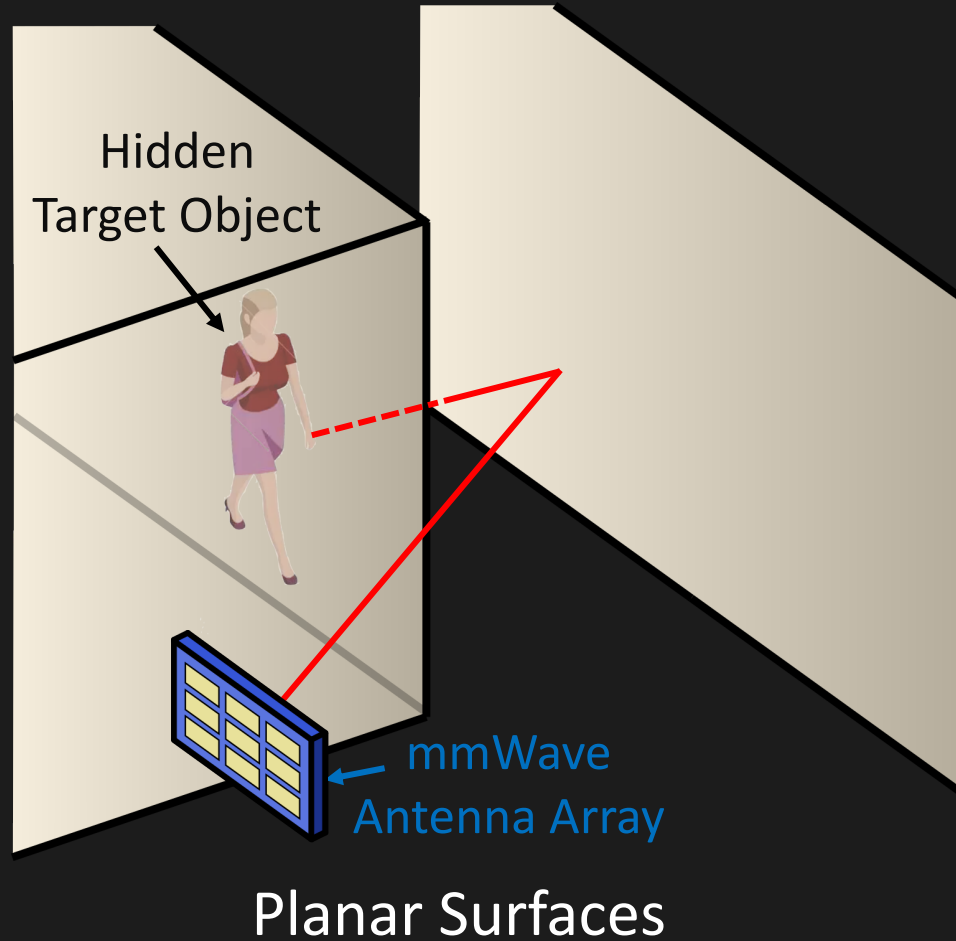
RF Around-the-Corner Sensing



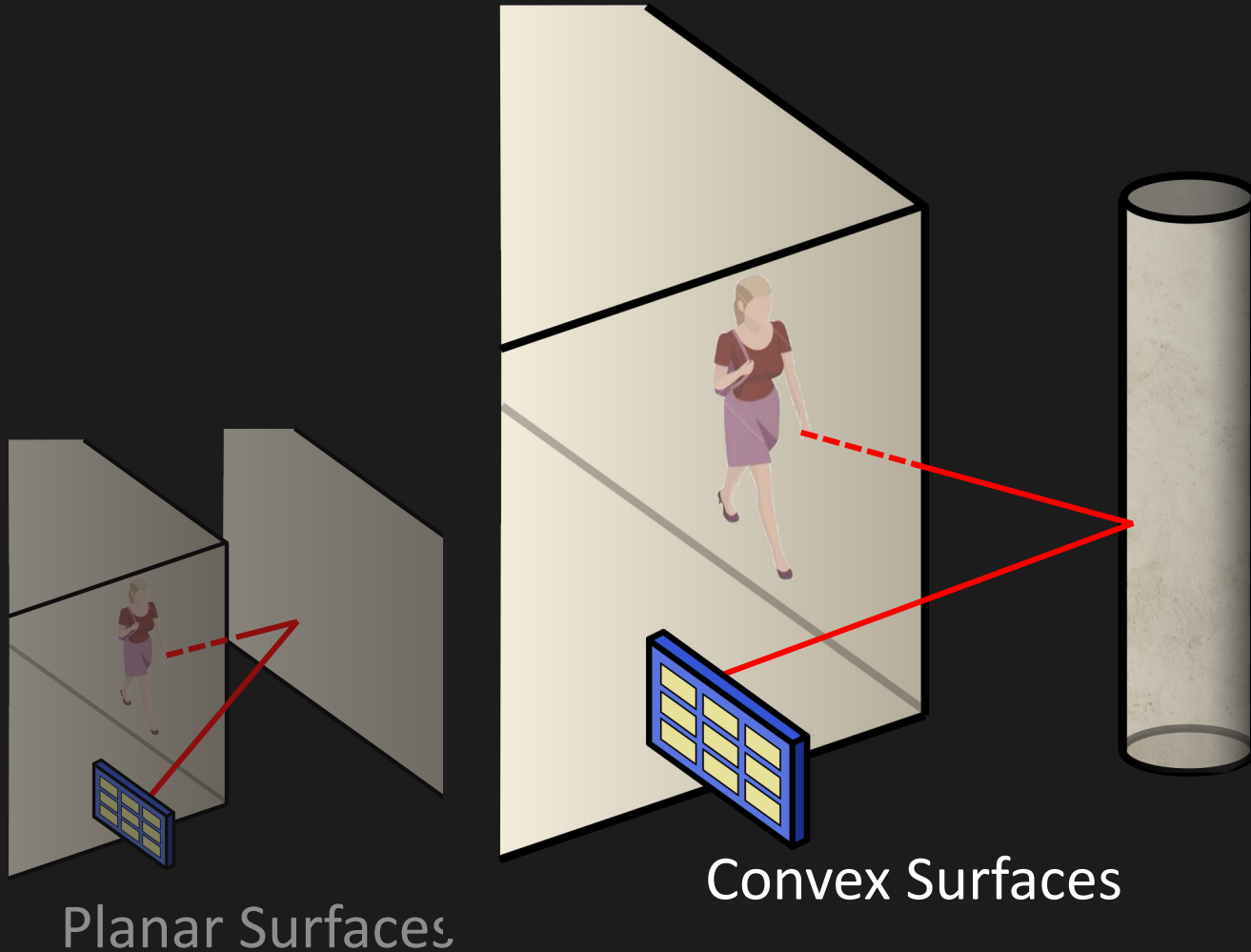
✗ Limited to Localization AND/OR
✗ Restricted to Specific Environments

Problem:
Practical Environments Contain a
Variety of Reflecting Surfaces

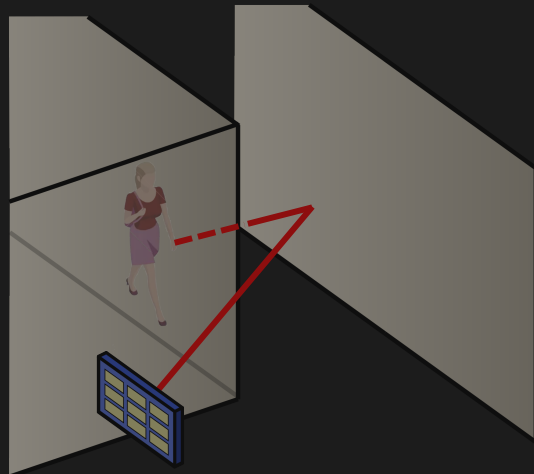
Practical Environments Contain a Variety of Reflecting Surfaces



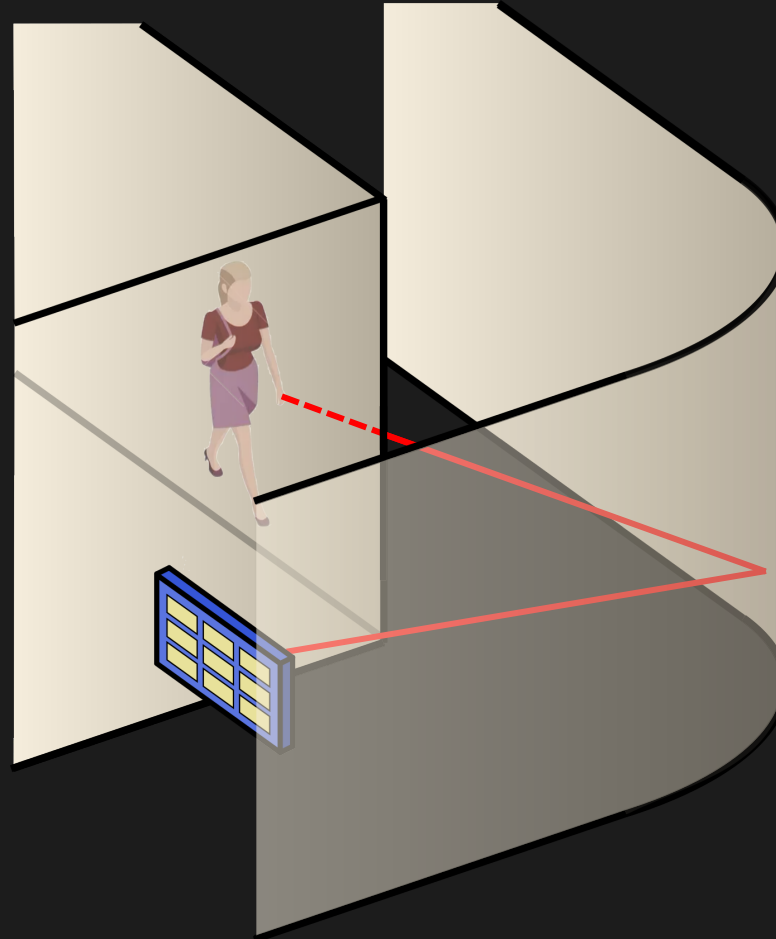
Practical Environments Contain a Variety of Reflecting Surfaces



Practical Environments Contain a Variety of Reflecting Surfaces

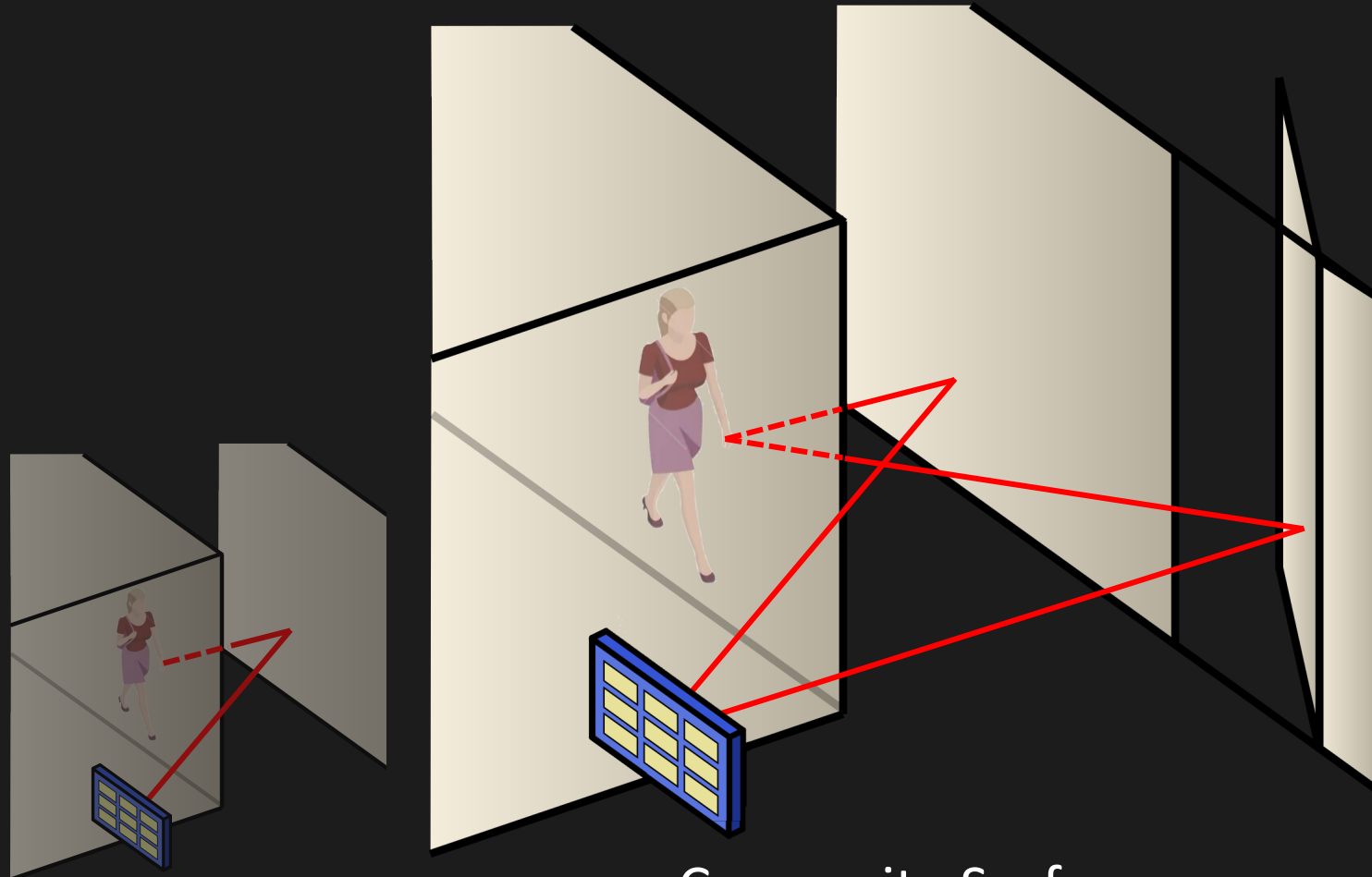


Planar Surfaces



Concave Surfaces

Practical Environments Contain a Variety of Reflecting Surfaces

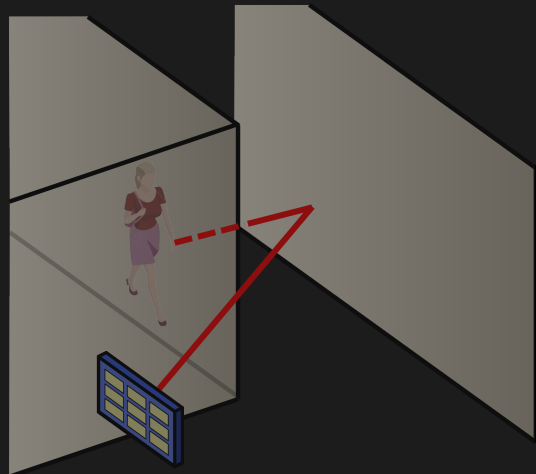


Planar Surfaces

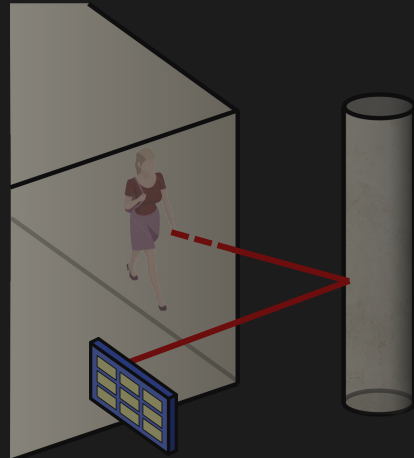
Composite Surfaces

Concave Surfaces

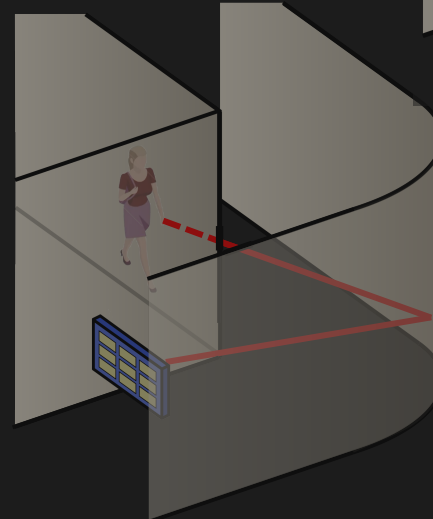
Practical Environments Contain a Variety of Reflecting Surfaces



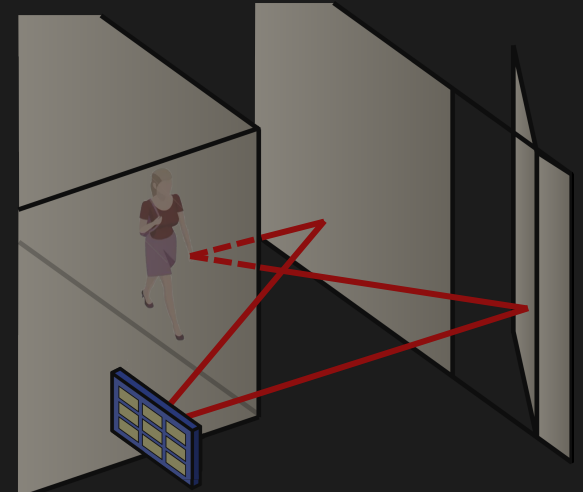
Planar Surfaces



Convex Surfaces

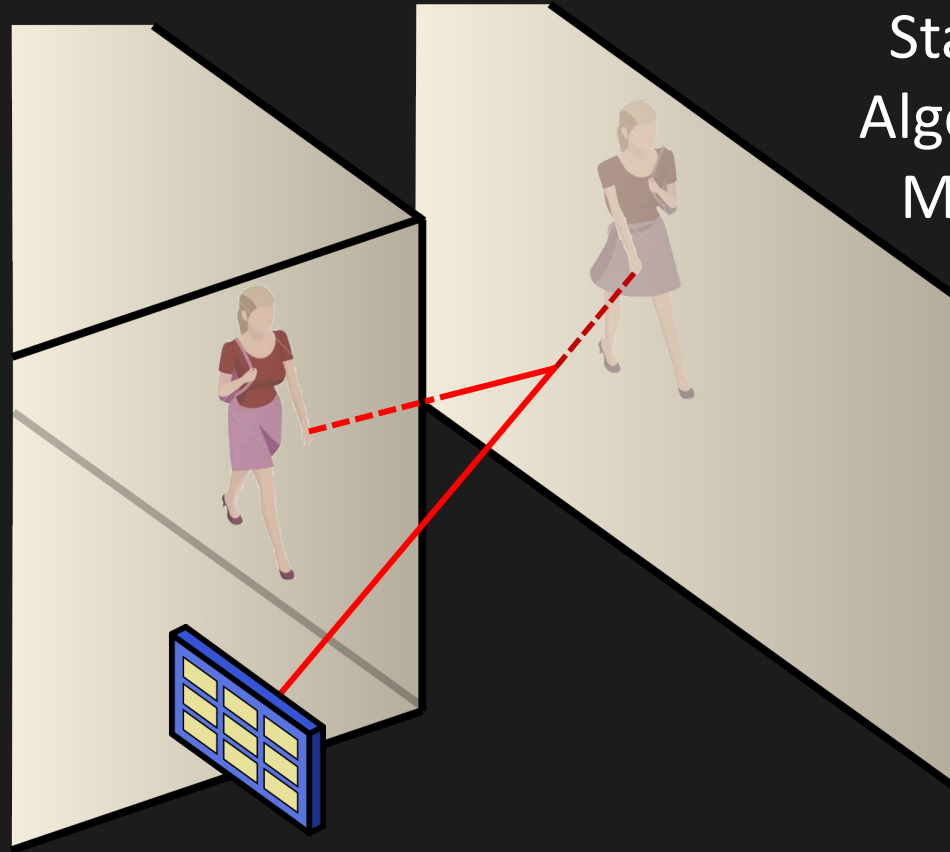


Concave Surfaces



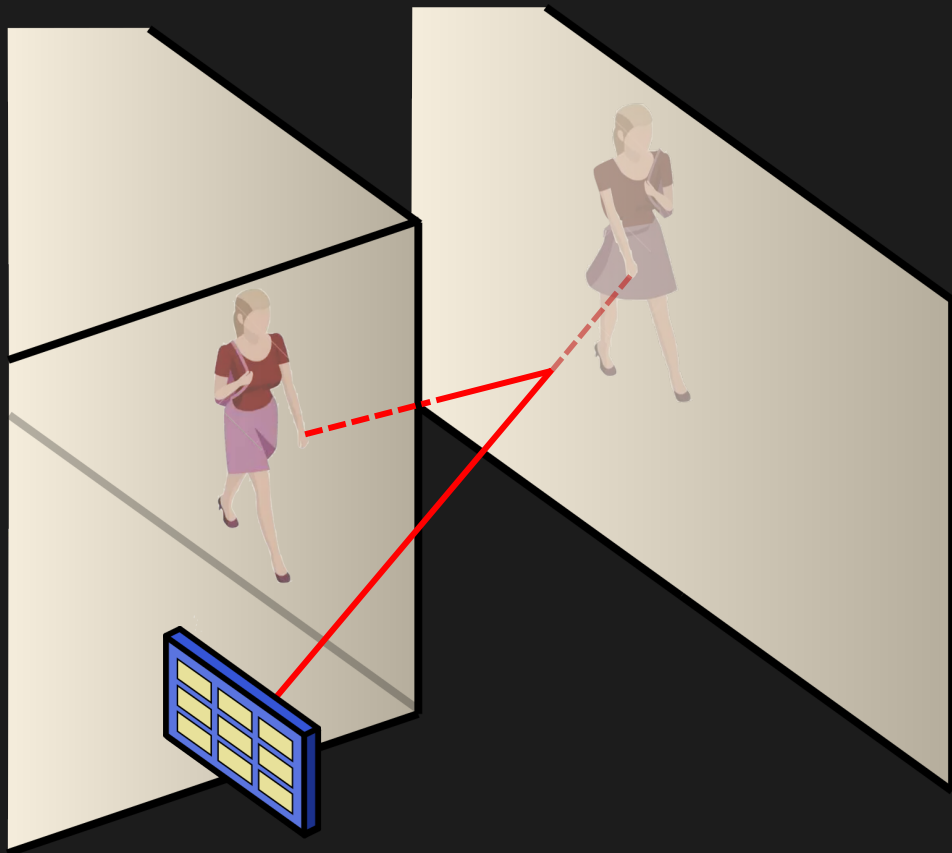
Composite Surfaces

How Can We Image off Planar Surfaces?

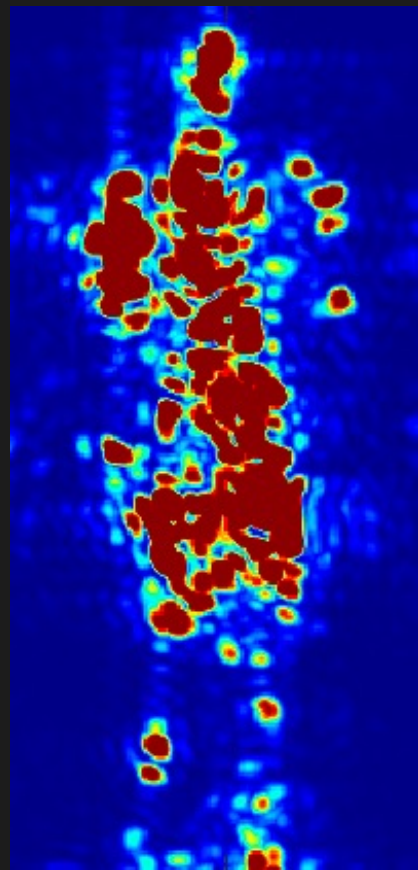


Standard Imaging
Algorithms Produce
Mirrored Images

How Can We Image off Planar Surfaces?



Target



Rflect

Can We Use the Same Approach for More Complex Surfaces?



Complex environments require more sophisticated modeling techniques



Convex Building Column



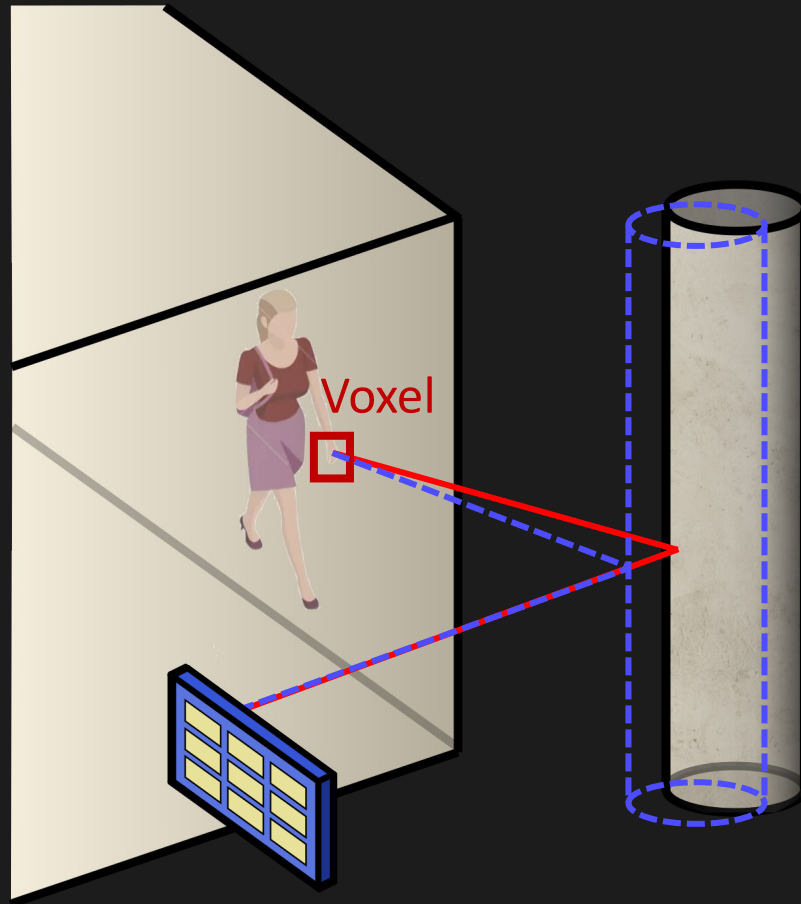
Image When Using Standard Imaging Algorithms

How can we know the **geometry and location** of the reflecting surface?

How can we accurately model reflections to enable **coherent imaging**?

What is the theoretical **resolution & coverage** for different reflectors?

What Happens When There Are Errors In The Reflector Mapping?

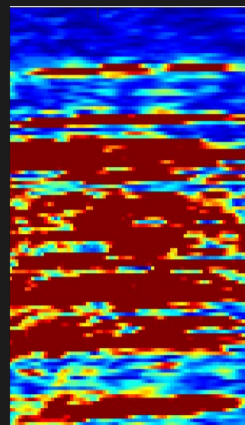
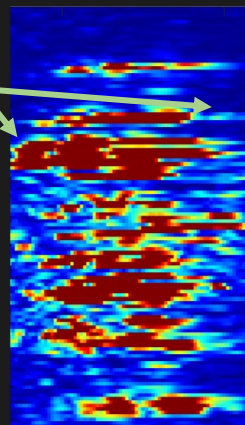
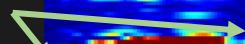


Impact of Reflector Mapping Accuracy

Produce images with RFlect's Non-Linear Imaging Algorithm
With Small Error in Convex Reflector Location



Image Distortions



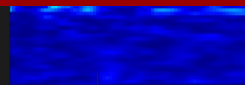
High-accuracy reflector mapping is key to producing
accurate around-the-corner images



Target

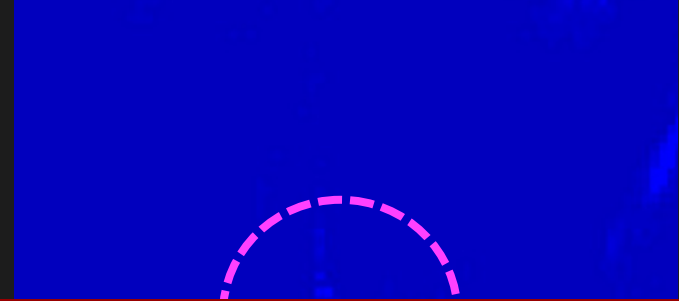
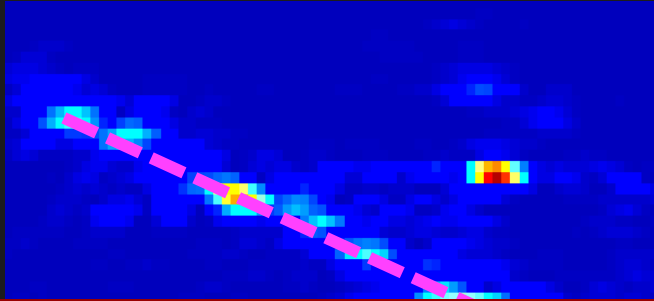


3 cm



5 cm

Can We Leverage Line-of-Sight Images for Reflector Mapping?



Line-of-Sight images are not sufficient for mapping complex reflectors

Our Solution: Design a non-linear reflector mapping algorithm leveraging line-of-sight reflections

Line-of-Sight Overhead view

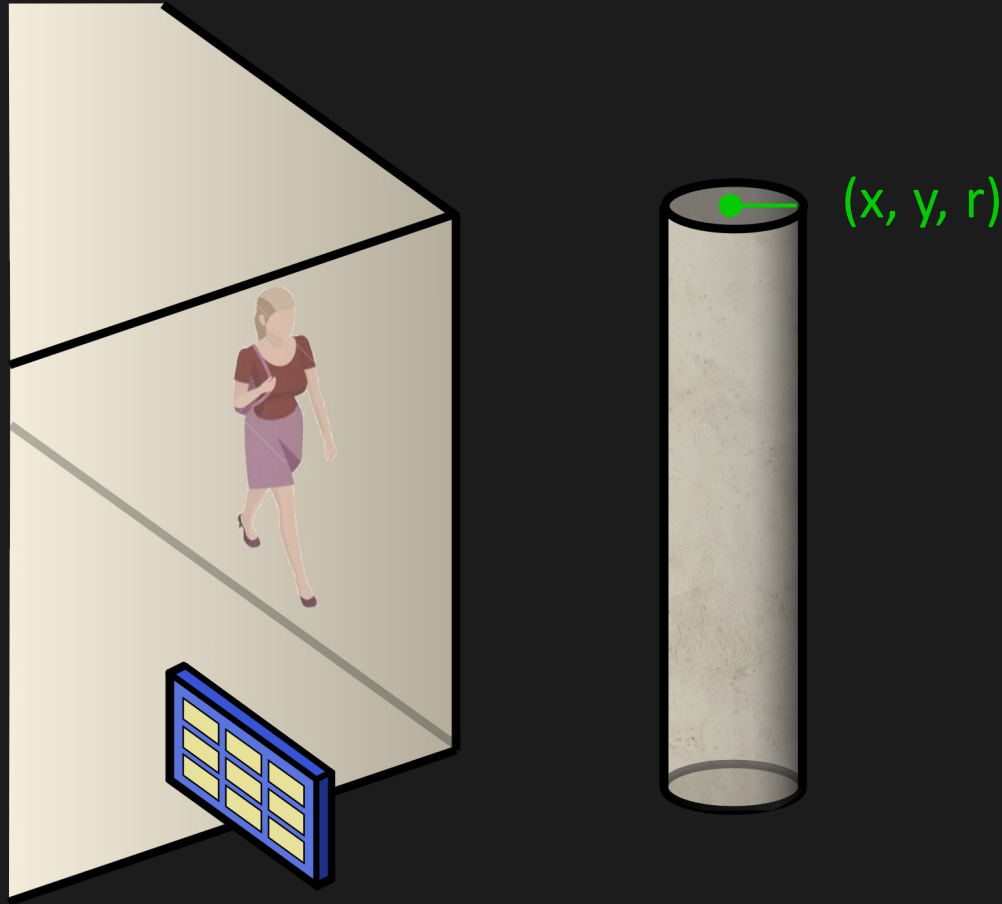
Planar Reflector

Line-of-Sight Overhead view

Convex Reflector

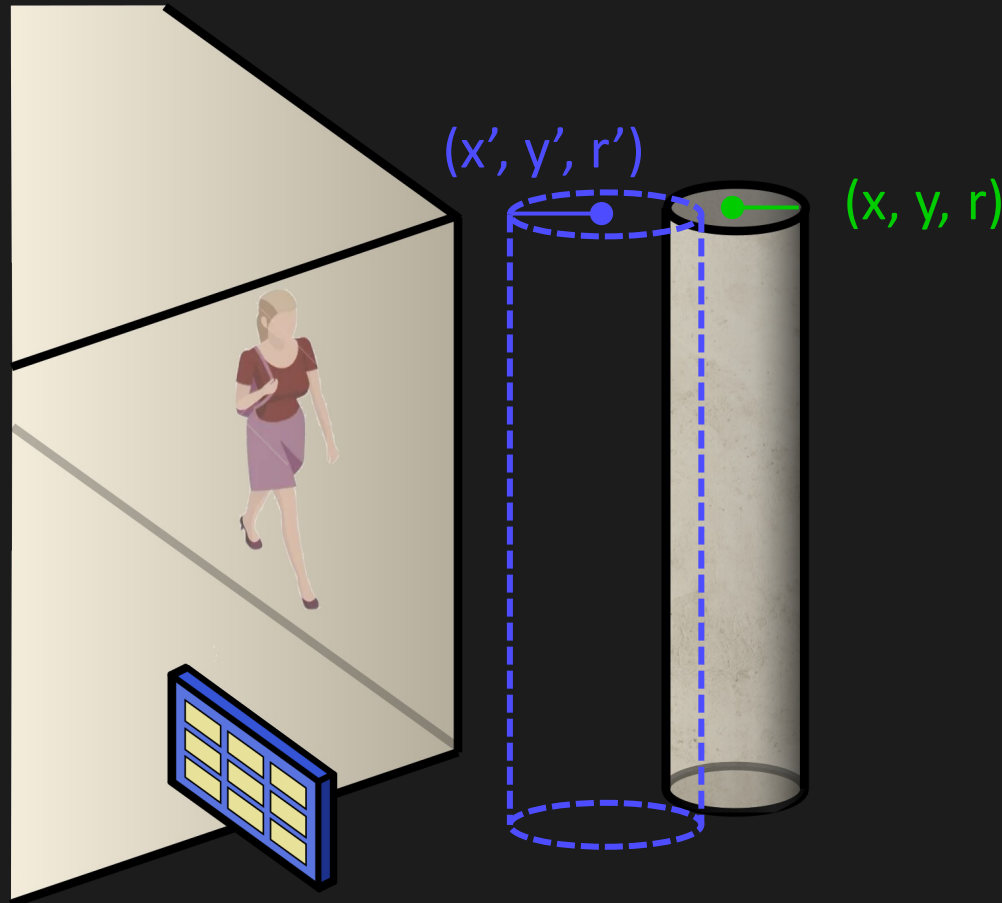
Solution: Non-Linear Reflector Mapping Algorithm

Step 1: Reduce reflectors to low-dimensional model



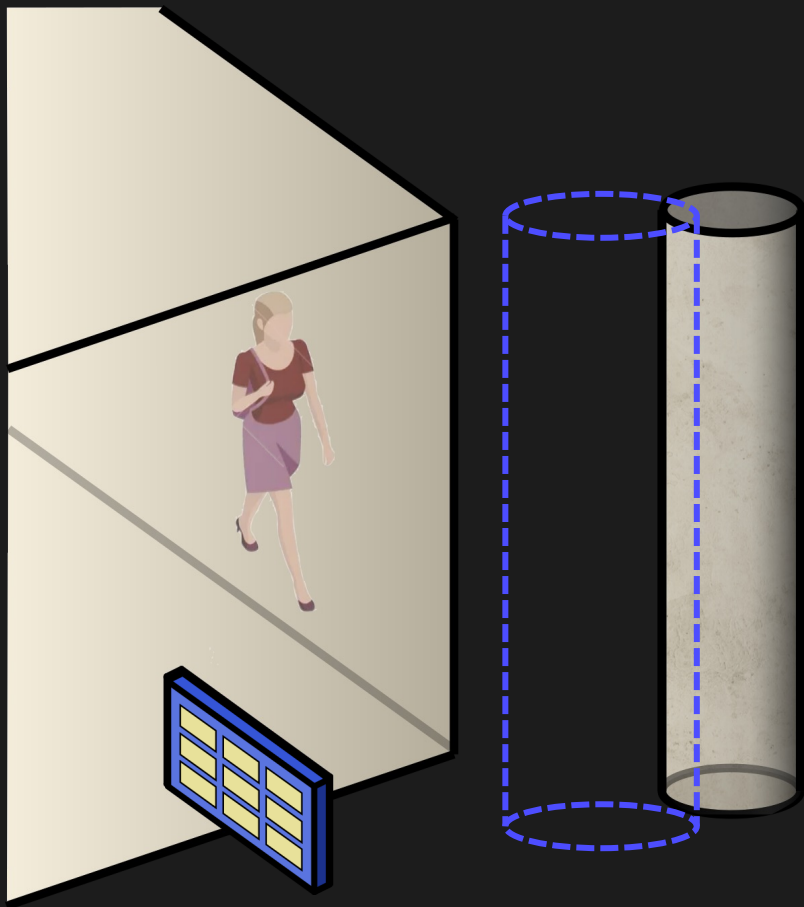
Solution: Non-Linear Reflector Mapping Algorithm

Step 2: Generate Candidate Surface and Evaluate its Match

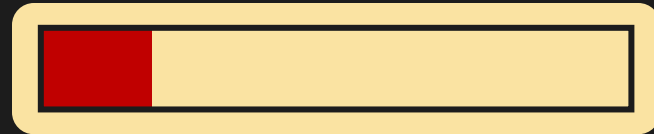


Solution: Non-Linear Reflector Mapping Algorithm

Step 2: Generate Candidate Surface and Evaluate its Match



Candidate Surface Score

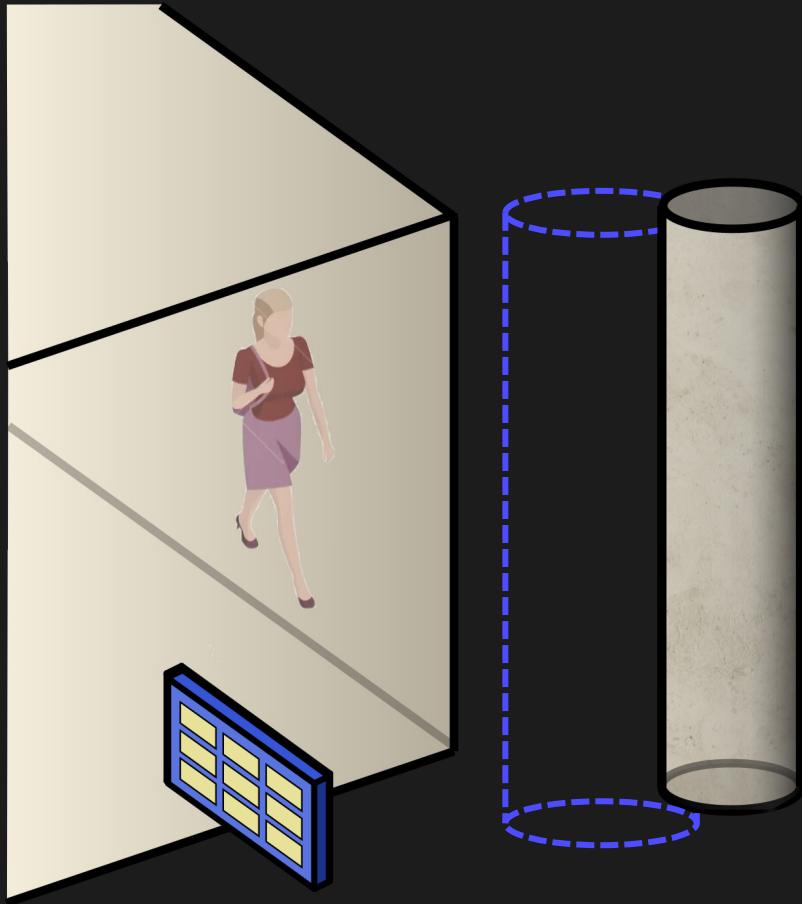


RFlect produces
candidate scores by
comparing received
line-of-sight reflections
with the **candidate model**

$$S(x, y, r) = \sum_{i=1}^A \sum_{j=1}^N s(n, i) e^{j2\pi d_i (f+kn)/c}$$

Solution: Non-Linear Reflector Mapping Algorithm

Step 3: Search Across Candidate Surfaces



Candidate Surface Score



Solution: Non-Linear Reflector Mapping Algorithm

Step 3: Search Across Candidate Surfaces



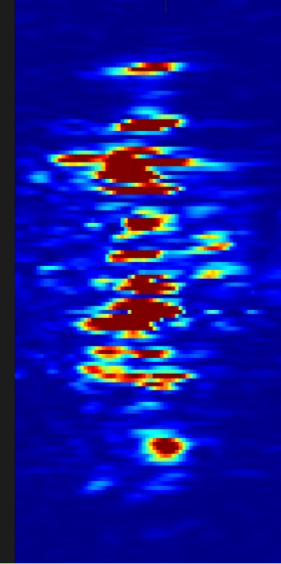
Candidate Surface Score



Choose the surface with
the highest score
& apply RFlect's
non-linear imaging
algorithm

Solution: Non-Linear Reflector Mapping Algorithm

Step 3: Search Across Candidate Surfaces



RFlect's reflector mapping algorithm enables high-accuracy around-the-corner imaging



Target



RFlect

How can we know the geometry and location of the reflecting surface?

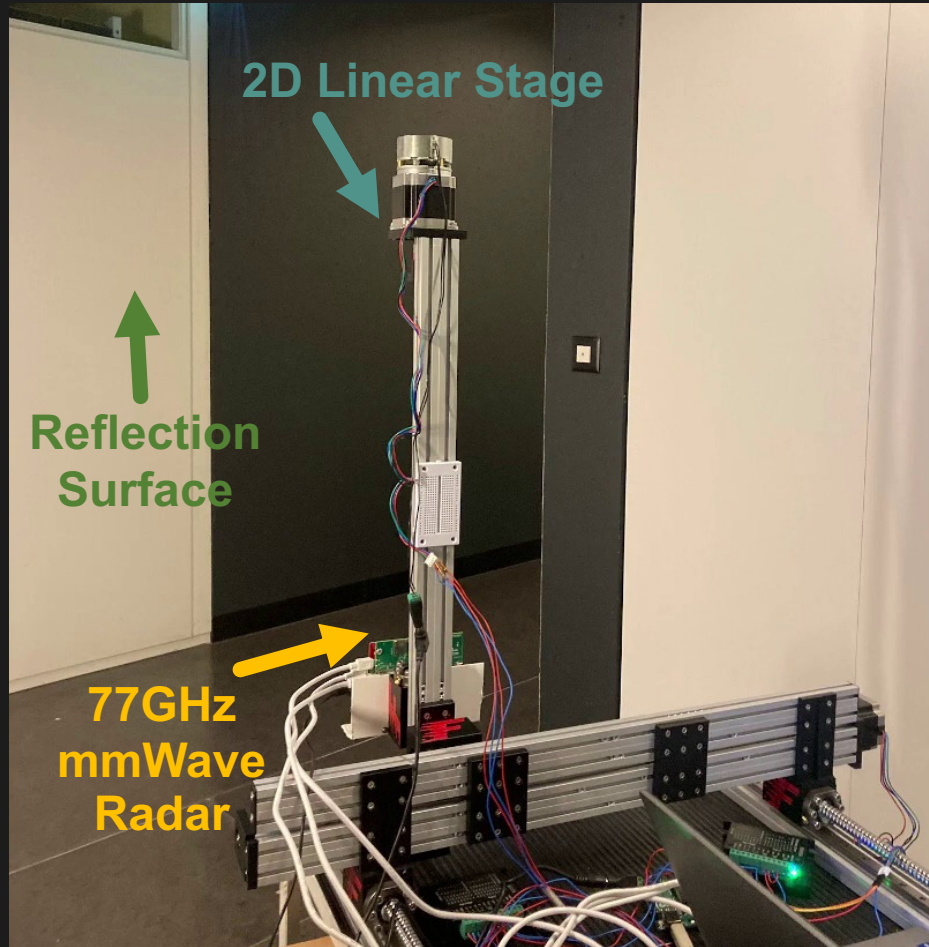


Introduce **Non-Linear Reflector Mapping**

How can we accurately model reflections to enable coherent imaging?

What is the theoretical resolution & coverage for different reflectors?

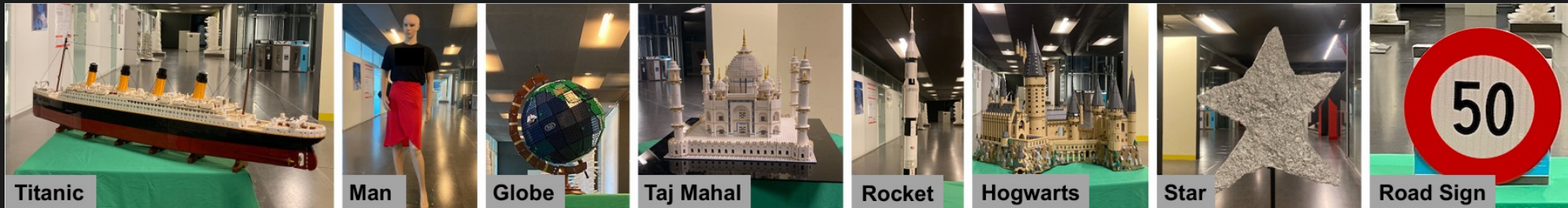
Implementation



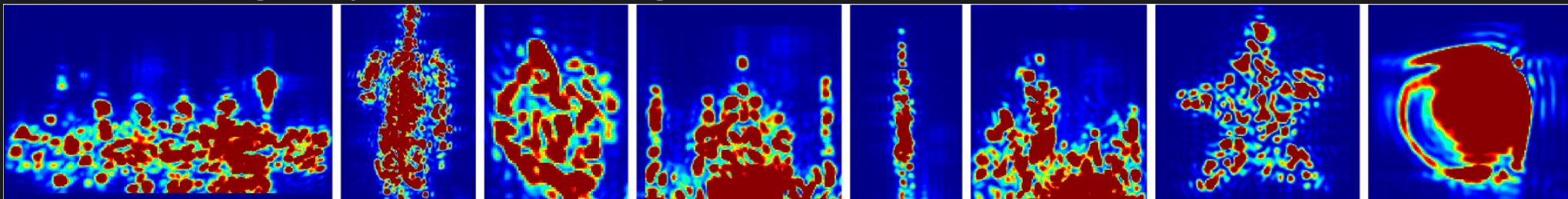
- TI AWR1843Boost 77GHz mmWave Radar
- 2D Linear Stage to create a synthetic aperture
- Leveraged reflectors with various materials (concrete, wood, glass, metal, plastic)

Planar Imaging Results

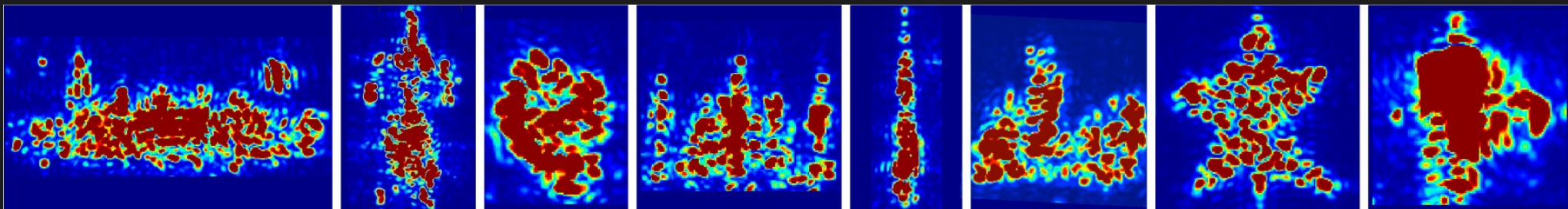
Target Objects



Baseline: Image objects in line-of-sight of radar



RFlect Around-the-Corner Imaging off Planar Surfaces

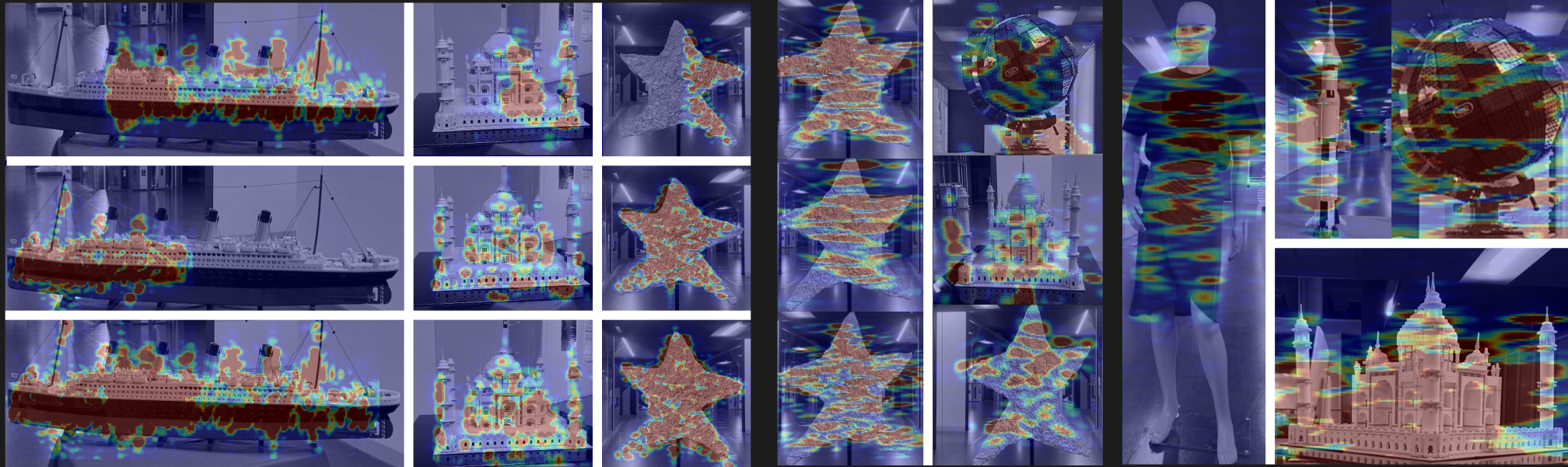


Complex Imaging Results

Composite Surfaces
(Door and Wall)

Concave Surface
(Computer Monitor)

Convex Surfaces
(Building Column)

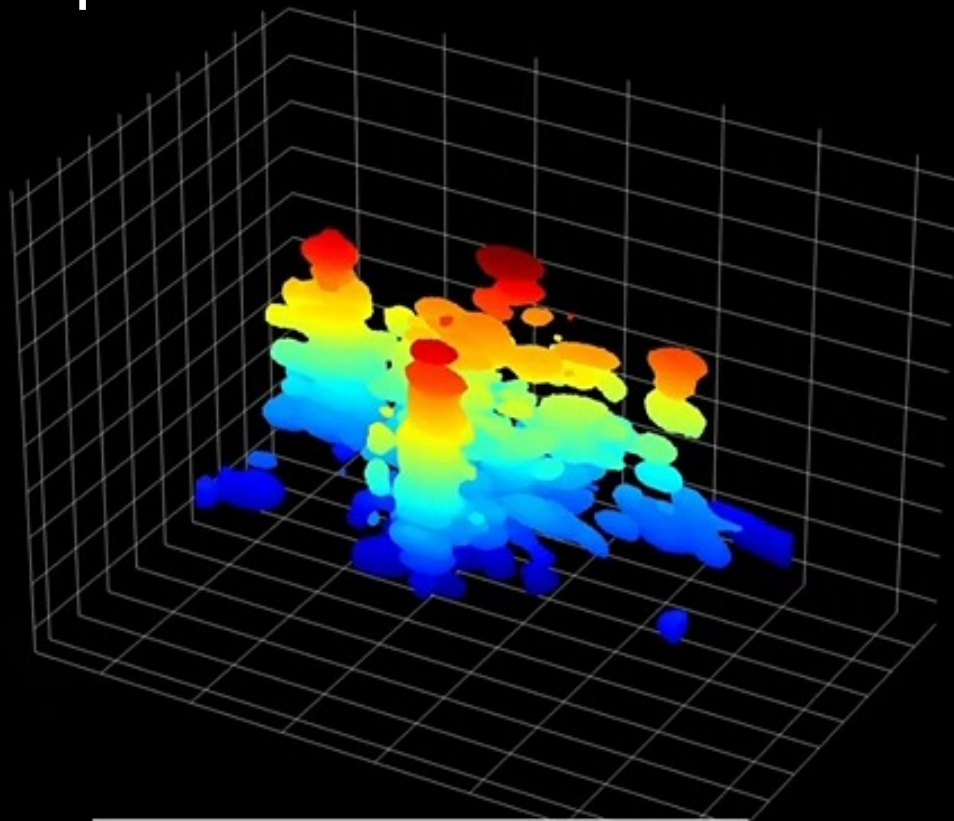


Qualitative Results: Concave Reflectors

Curved Computer Monitor



TAJ MAHAL



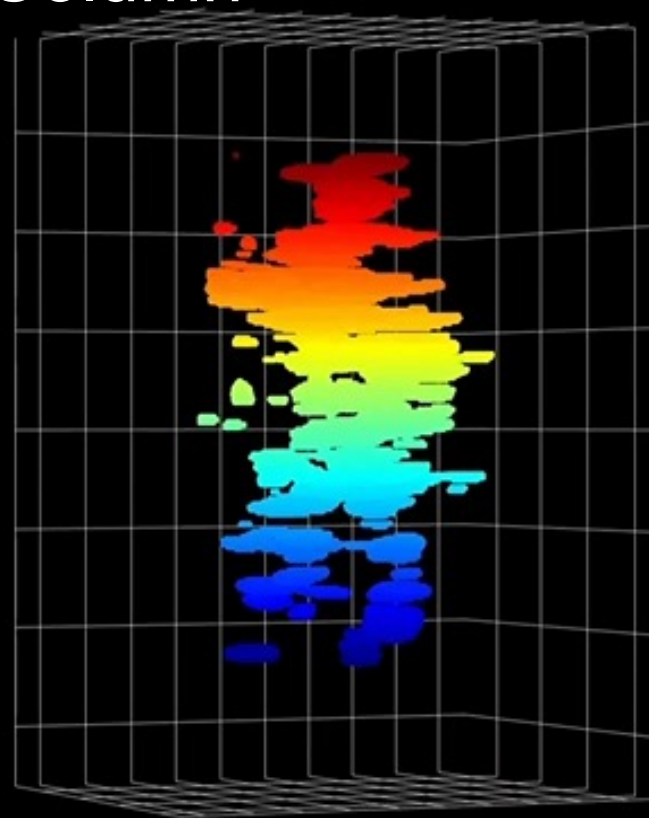
NLOS 3D Reconstruction
Concave Reflection

Qualitative Results: Convex Reflectors

Building Column



MANNEQUIN



NLOS 3D Reconstruction
Convex Reflection

RFlect Limitations & Future Work

Limitations:

- Can only image if there is a reflecting surface (of a given geometry)
- Scanning time of SAR
- Range is limited (at some point, the surface mapping begins to fail)

Future Work:

- Extending to other reflecting surface geometries
- Extending modeling to include non-specular reflections
- Integrating into full systems: self-driving cars, autonomous robots, etc

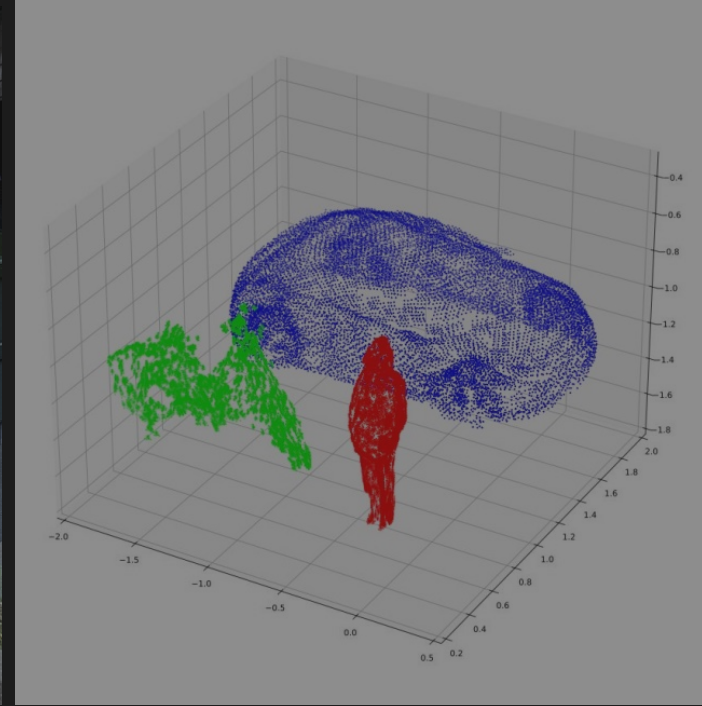
Non-Line-of-Sight Wireless Imaging and 3D Reconstruction



Wireless 3D Reconstruction
Through Boxes



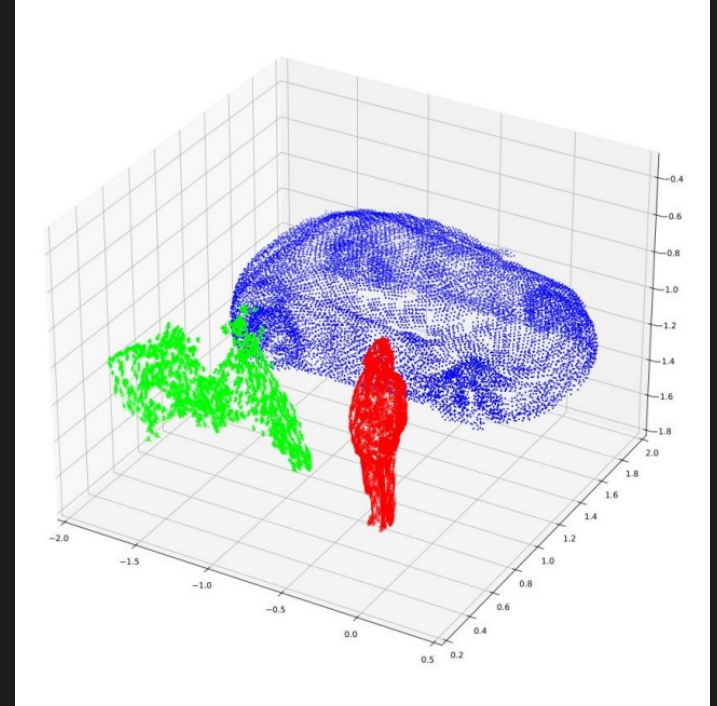
Around-the-Corner
Wireless Imaging



Wireless Reconstruction
In Low Visibility

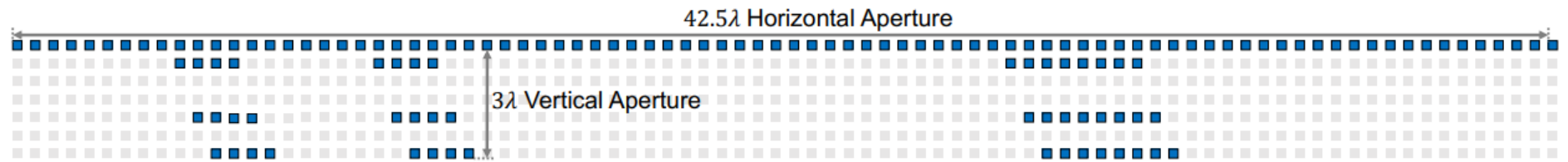
3D Object Reconstruction with mmWave Radars

Samah Hussein, Junfeng Guan,
Swathi Narashiman, Saurabh Gupta,
Haitham Hassanieh

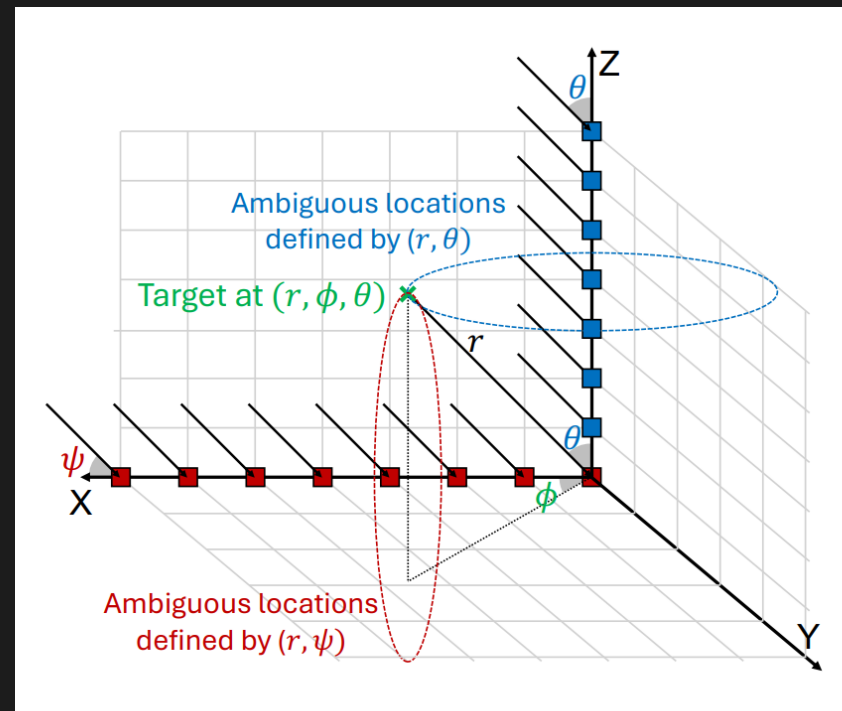


Can we enable wireless 3D reconstruction for
self-driving cars?

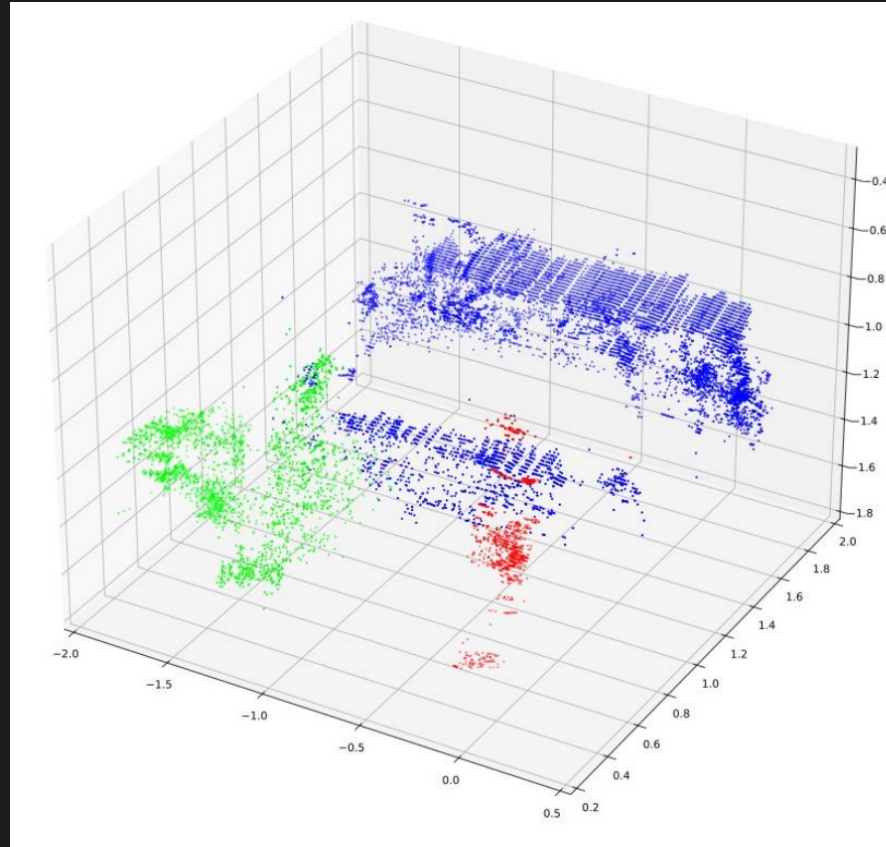
Challenge #1: Lack of 3D Information



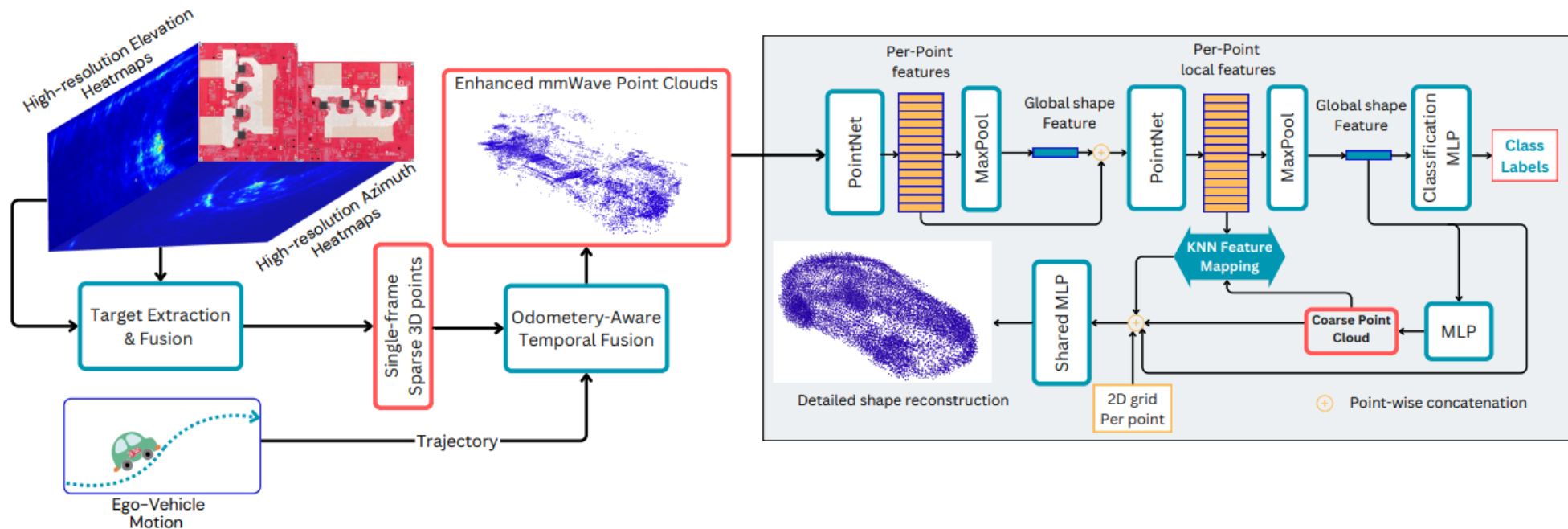
Solution: Combine Information from Perpendicular Radars



Challenge #2: Limited and Noisy Point Clouds Due to Specularity, Radar Artifacts, etc



RFConstruct

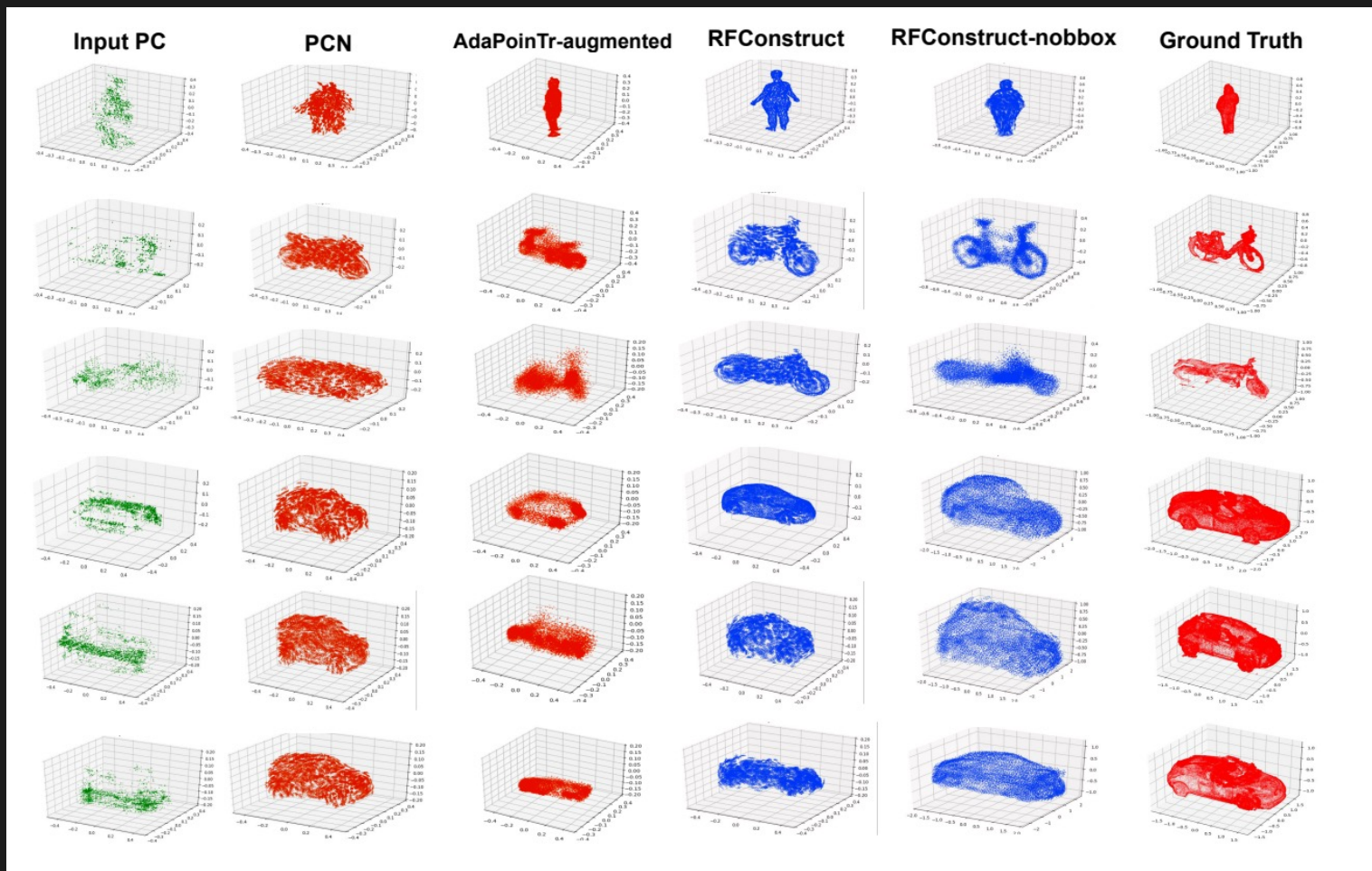


Implementation



- Two perpendicular TI MMWCAS radars
- ZED 2i depth camera for trajectory tracking
- All radars and camera synchronized through software trigger
- Leverage a mobile platform to simulate car motion
- Ground-truth shapes scanned with mobile phone using PolyCam app
- Dataset consists of real-world, synthetic, and simulated data

Qualitative Results



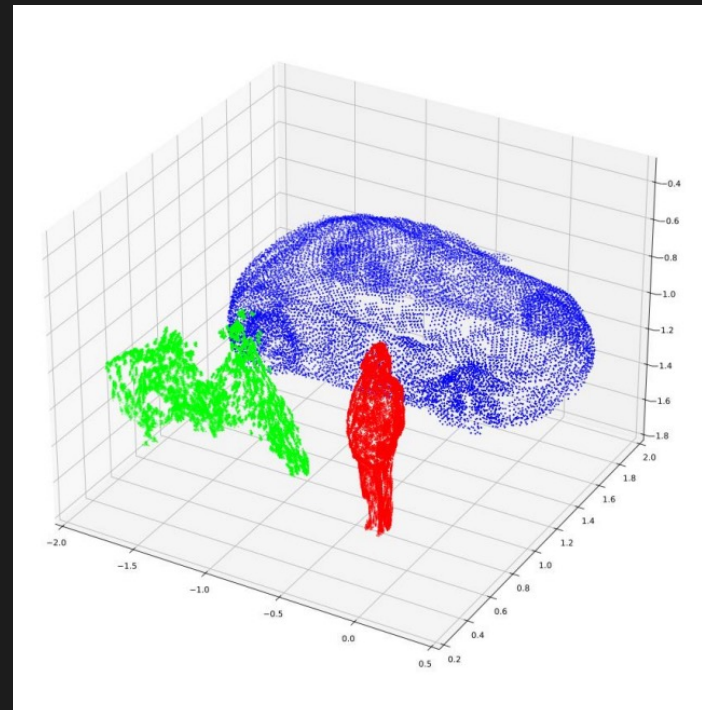
Non-Line-of-Sight Wireless Imaging and 3D Reconstruction



Wireless 3D Reconstruction
Through Boxes



Around-the-Corner
Wireless Imaging



Wireless Reconstruction
In Low Visibility