6.1820/MAS.453: Mobile and Sensor Computing
aka IoT Systems

https://6mobile.github.io/

Lecture 10: mmWave Sensing and Self-Driving Cars

Slides adapted from Haitham Hassanieh (EPFL)

Course Staff	Announcements
<u>Lecturers</u> Fadel Adib (fadel@mit.edu) Tara Boroushaki (tarab@mit.edu) <u>TAs</u> Waleed Akbar (wakbar@mit.edu) Jack Rademacher (jradema@mit.edu)	1- Lab 2 due today 2- Lab3 out today, due next week 3- Start forming teams

What are we learning today?

Learn the fundamentals, applications, and implications of
mmWave Sensing

1- What are the pros and cons of mmWave vs Vision?

2- What is an mmWave radar? How does it work?

3- How does specularity impact mmWave imaging?

4- Can Generative AI help us with mmWave shortcomings?

Today in IoT + Self-Driving Cars

March 4, 2025

UC Irvine study shines headlights on consumer driverless vehicle safety deficiencies

Project demonstrates the low cost and ease of carrying out ‘sticker attacks’

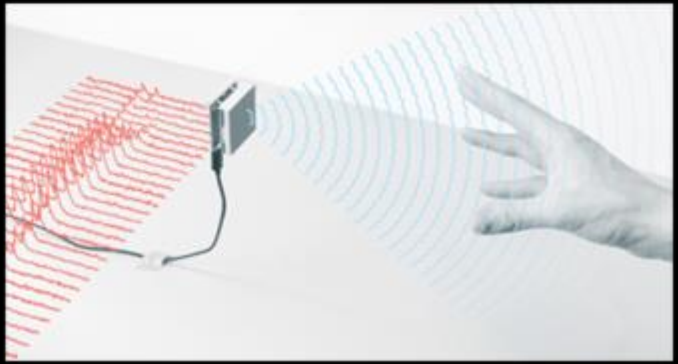
Millimeter Wave Radars

Obstacle Detection

Localization

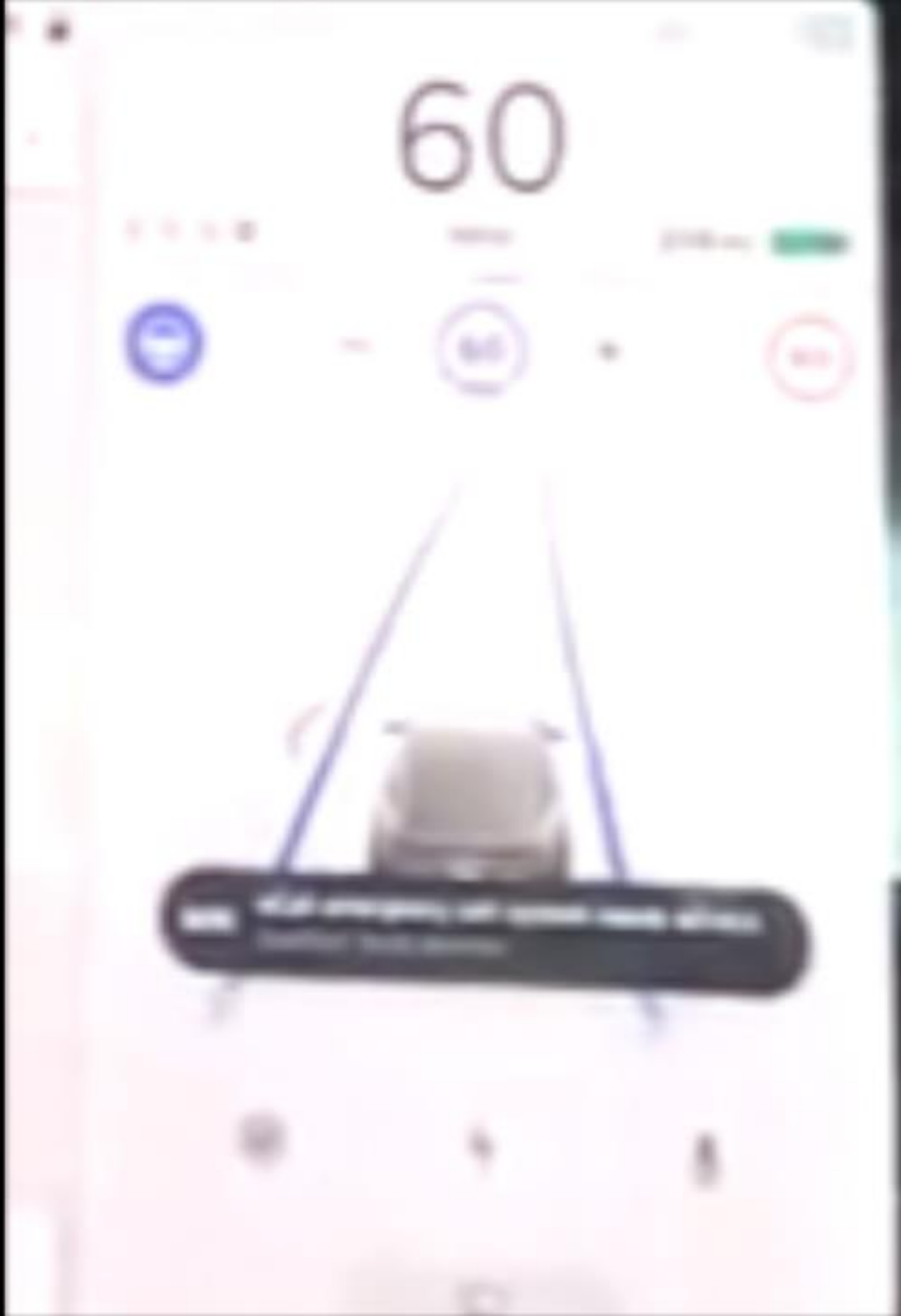
Vital Signs Monitoring

Gesture Recognition

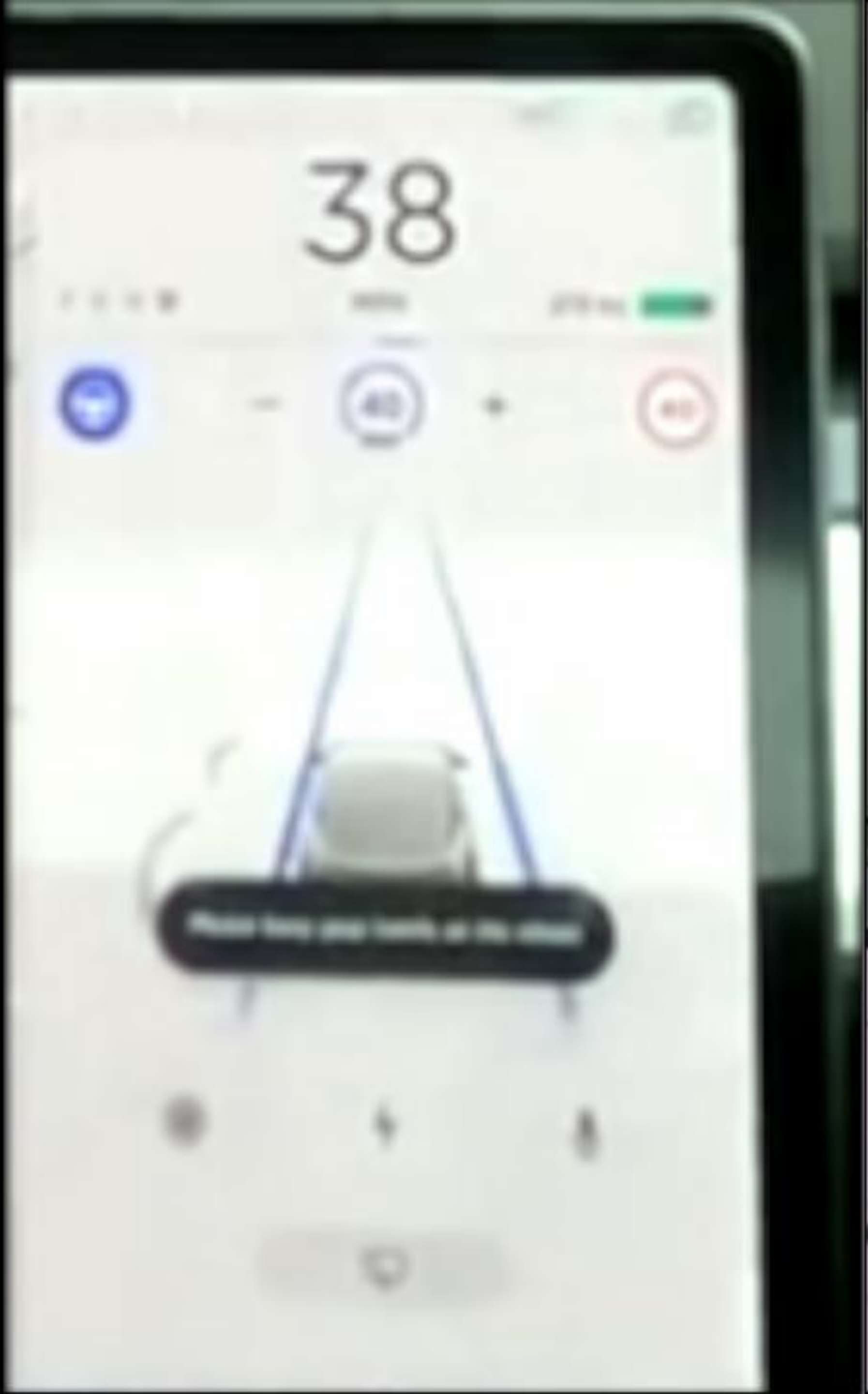


Non-Line-of-Sight Imaging with Millimeter Wave Radars

Tesla in Clear Conditions



Tesla in Fog



Tesla in Fog

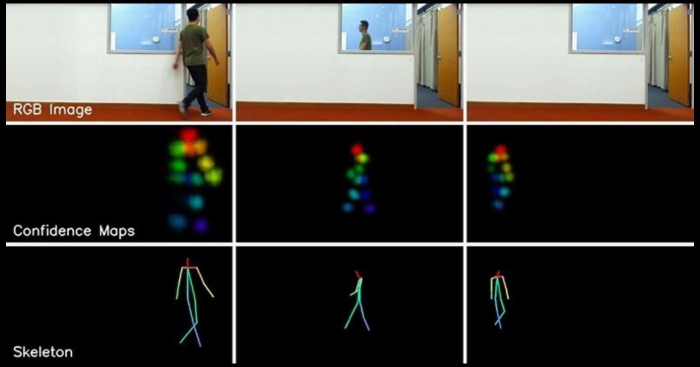
Challenge: Adverse Weather & Low Visibility

Wireless mmWave radars can function reliably in adverse weather and low visibility scenarios where LiDARs and cameras fail.

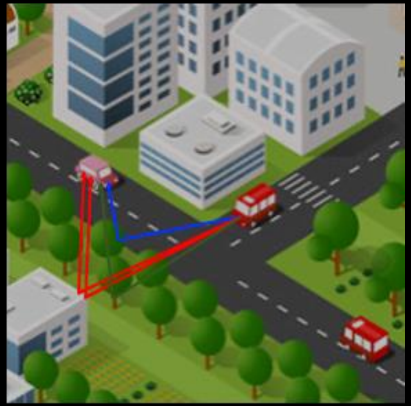
Non-Line of Sight Imaging with Millimeter Wave Radars

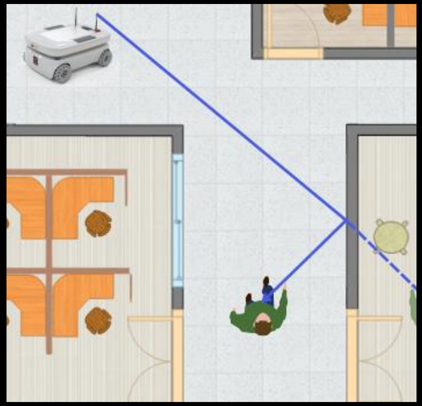
Operate in Bad Weather

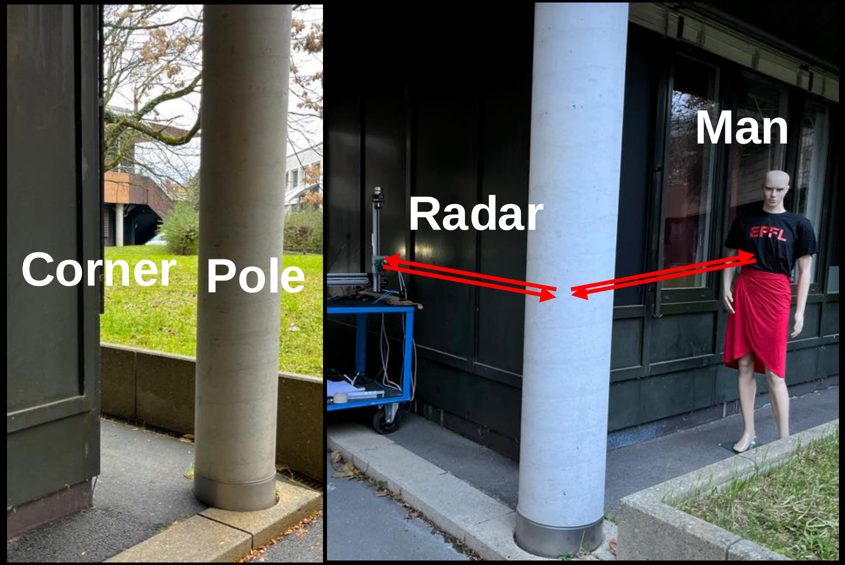
Through Occlusions



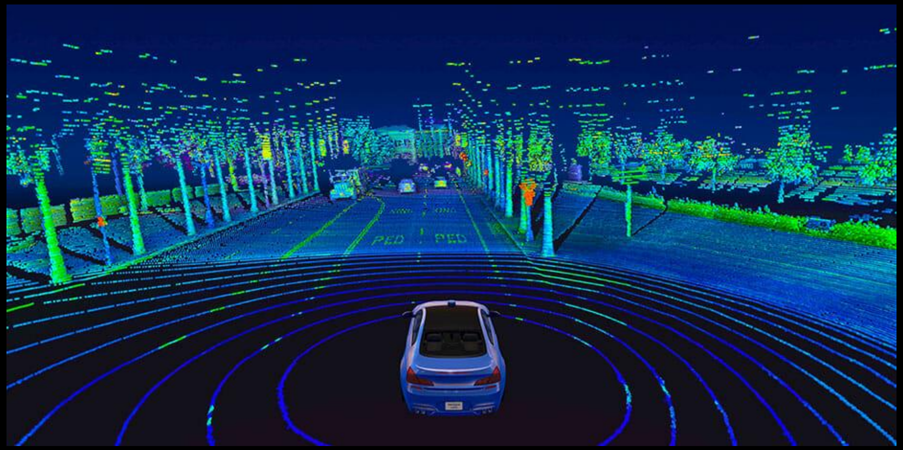
Around Corners



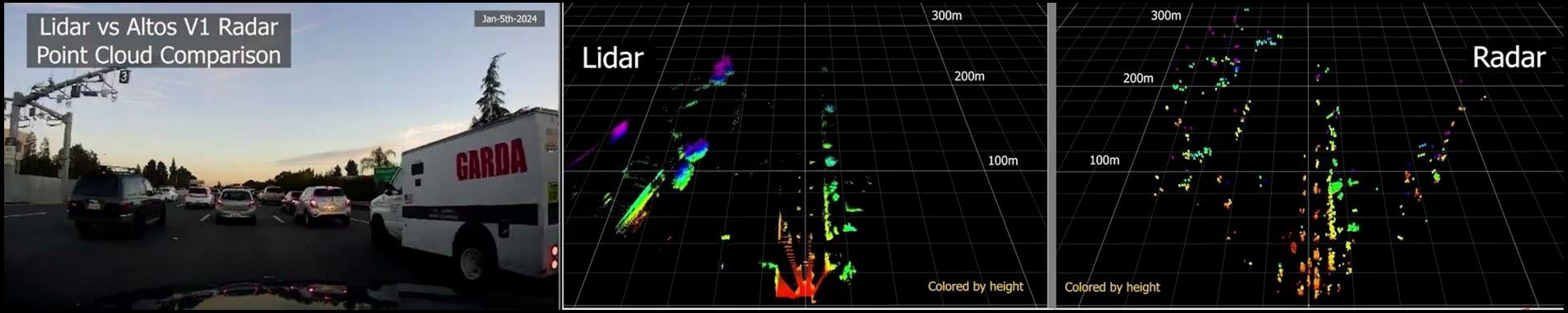




Challenge: Resolution of millimeter wave radar is very low compared to LiDAR and Cameras



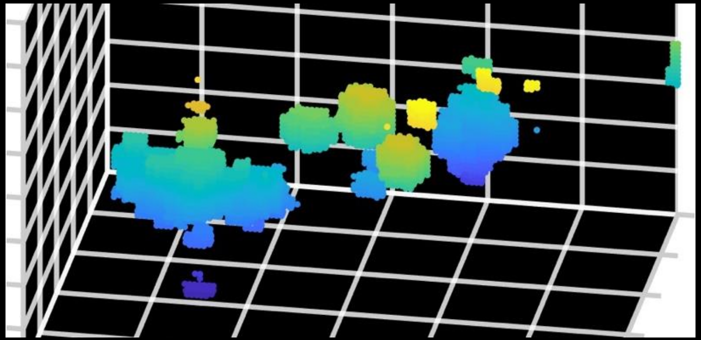
LiDAR with 0.1° Angular Resolution



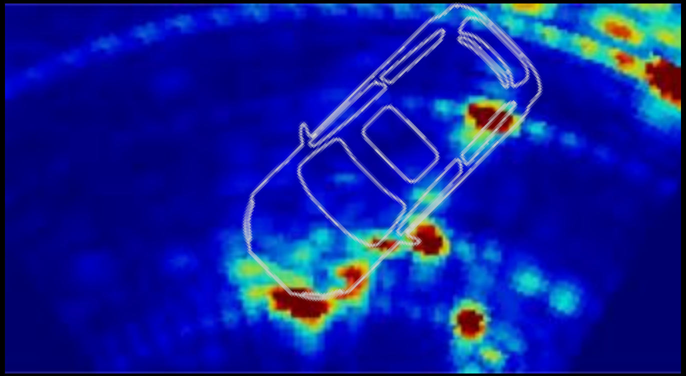
Challenges in Radar Perception

Camera Image

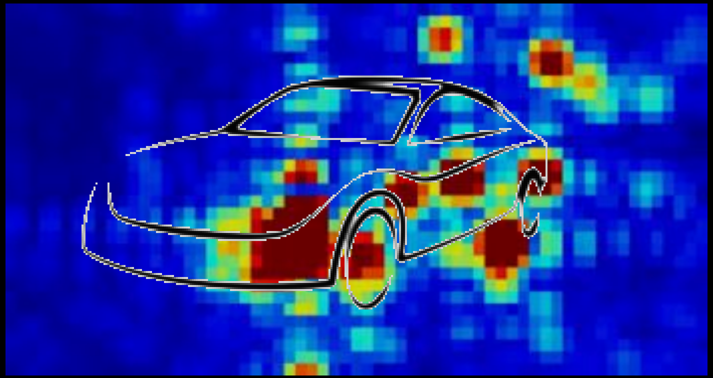
Point Cloud



Top-View



Front-View



Huge Performance Gap Between Radar and Vision!

Challenges in Radar Perception

1. Low Angular Resolution
- Blobs of reflected power
- No sharp boundaries/shapes

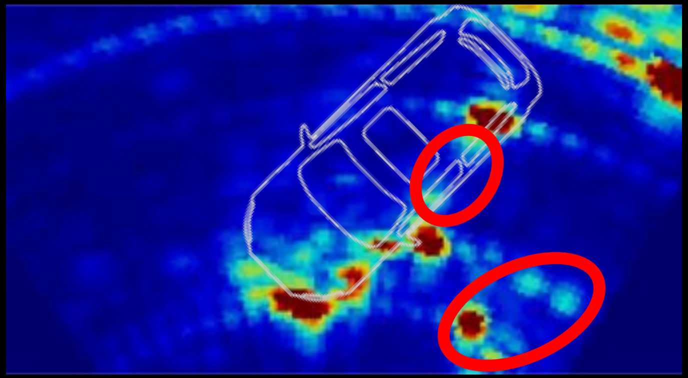
2. Specularity
- Missing major parts of cars

3. Multipath
- Spurious Reflections

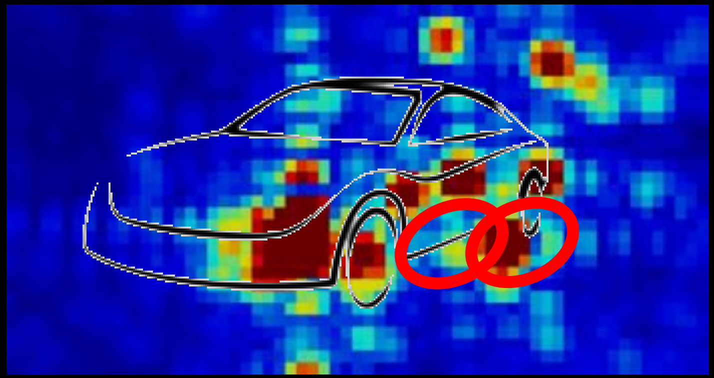
Camera Image

Point Cloud

Top-View



Front-View



Accurate Bounding Box Detection using Radar

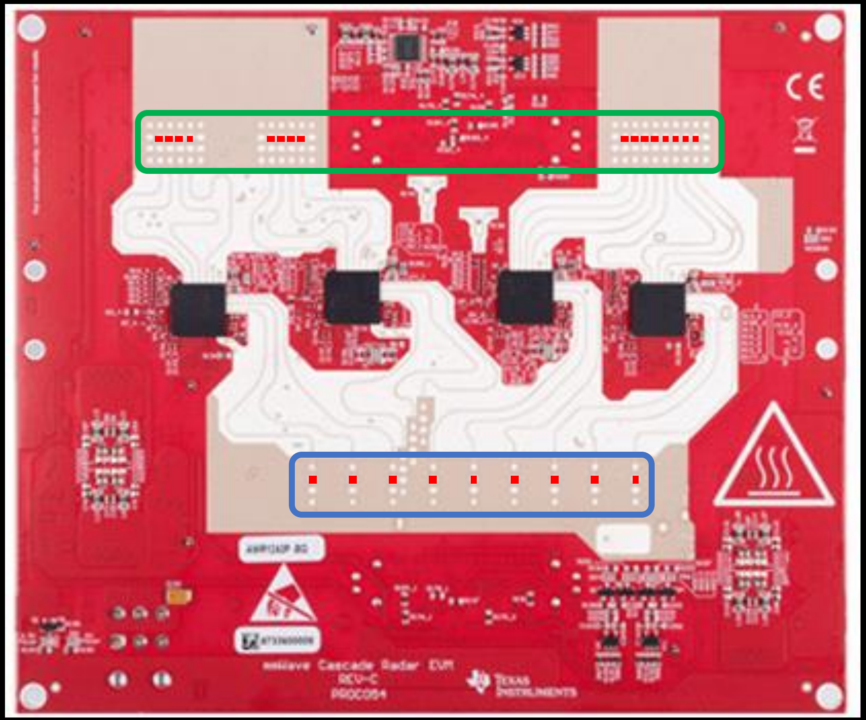
Scene **Radar Heatmap**

Red: Predicted bounding box

Car silhouette: Ground truth car location

Cascaded MIMO Radar

Receiver Array
(16 elements)

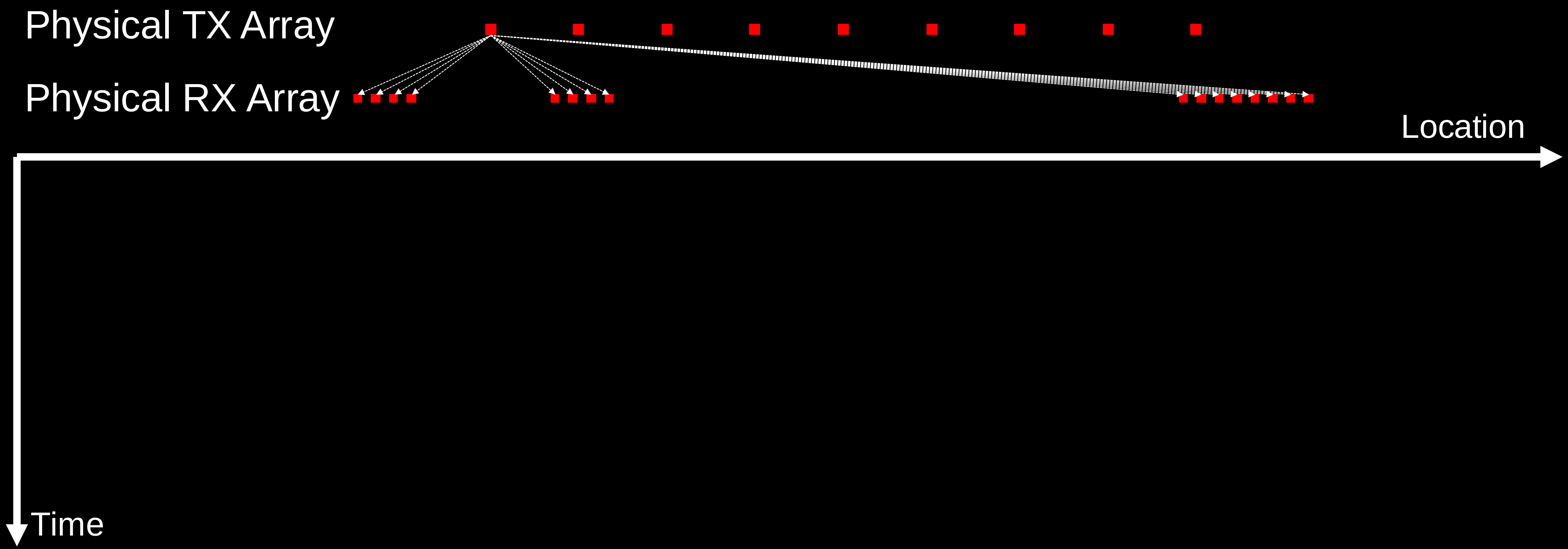


Transmitter Array
（9 elements）

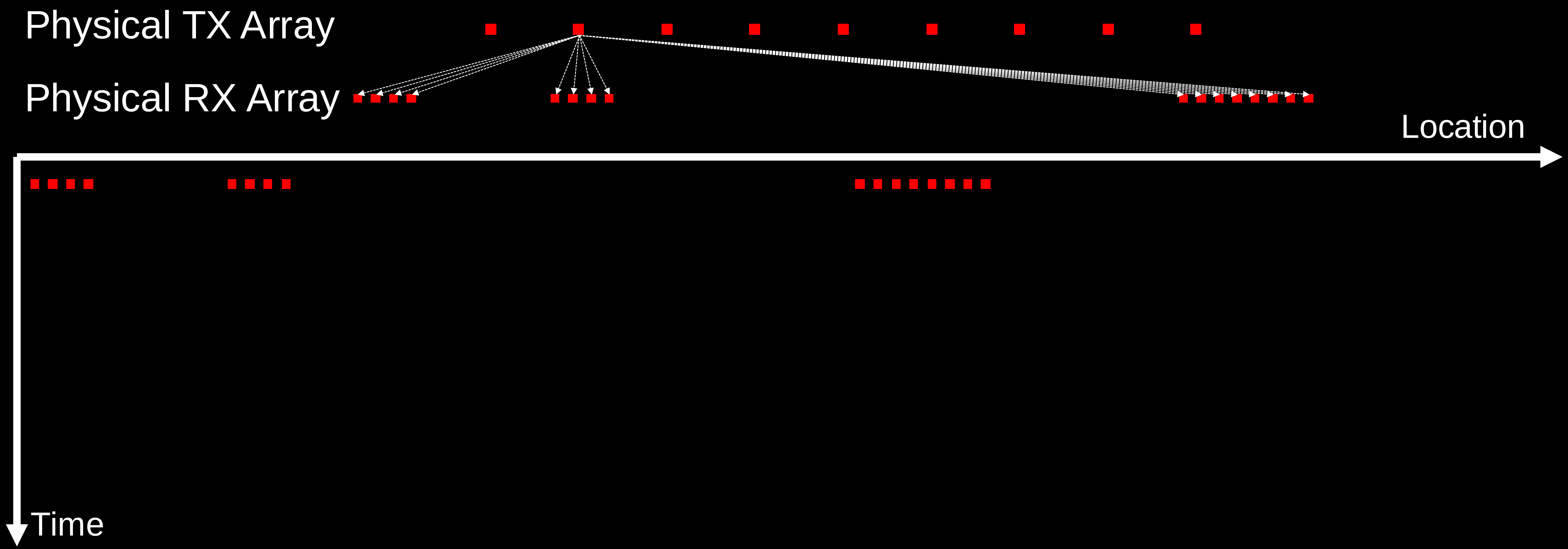
TI MIMO Radar

Angular resolution of radar is proportional to antenna array size.

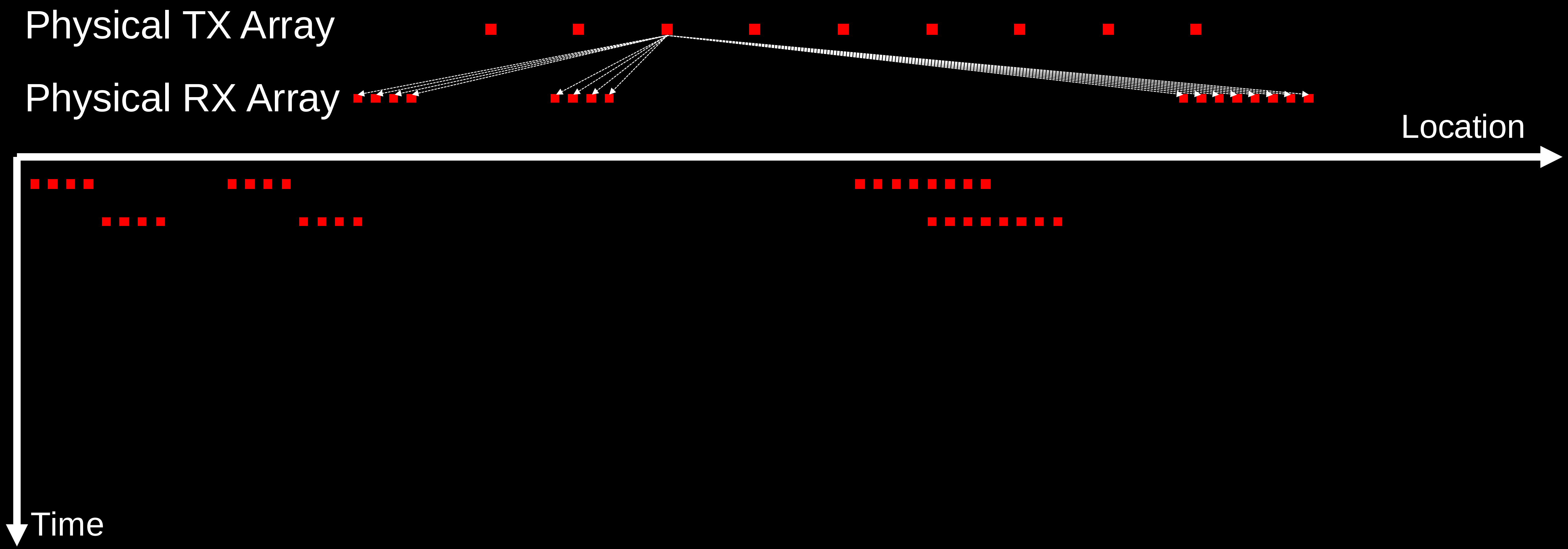
Virtual Antenna Array



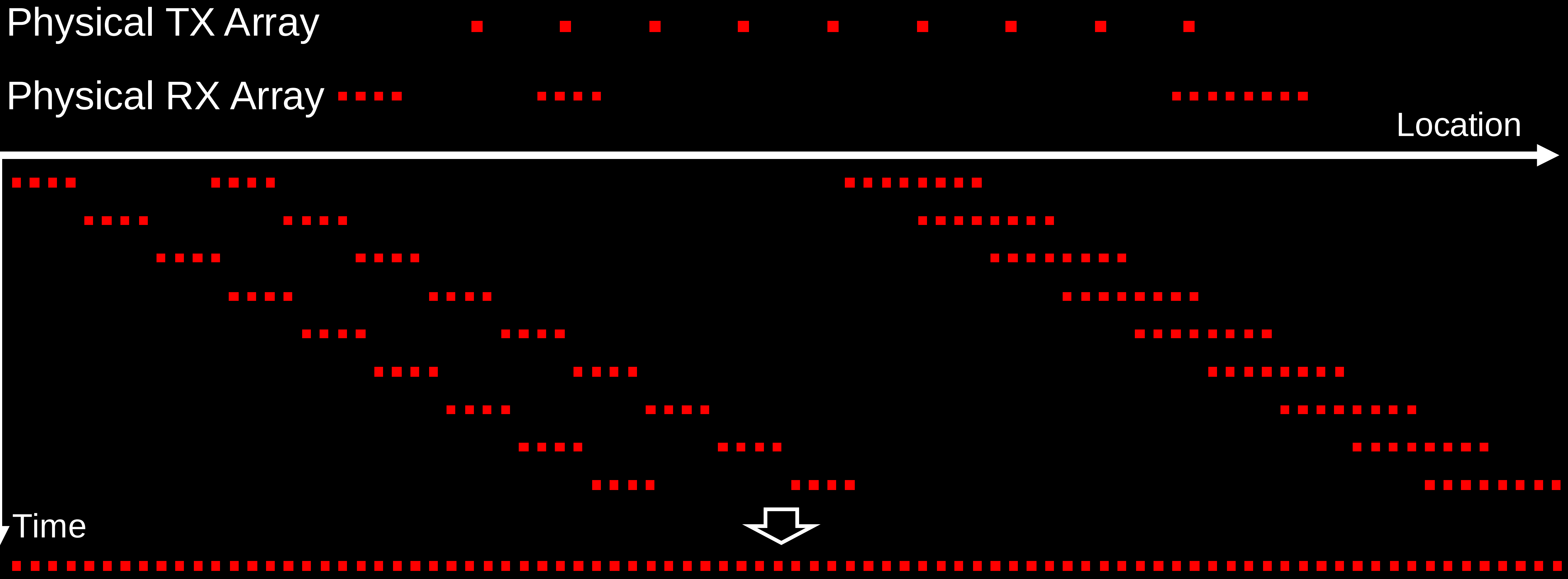
Virtual Antenna Array



Virtual Antenna Array



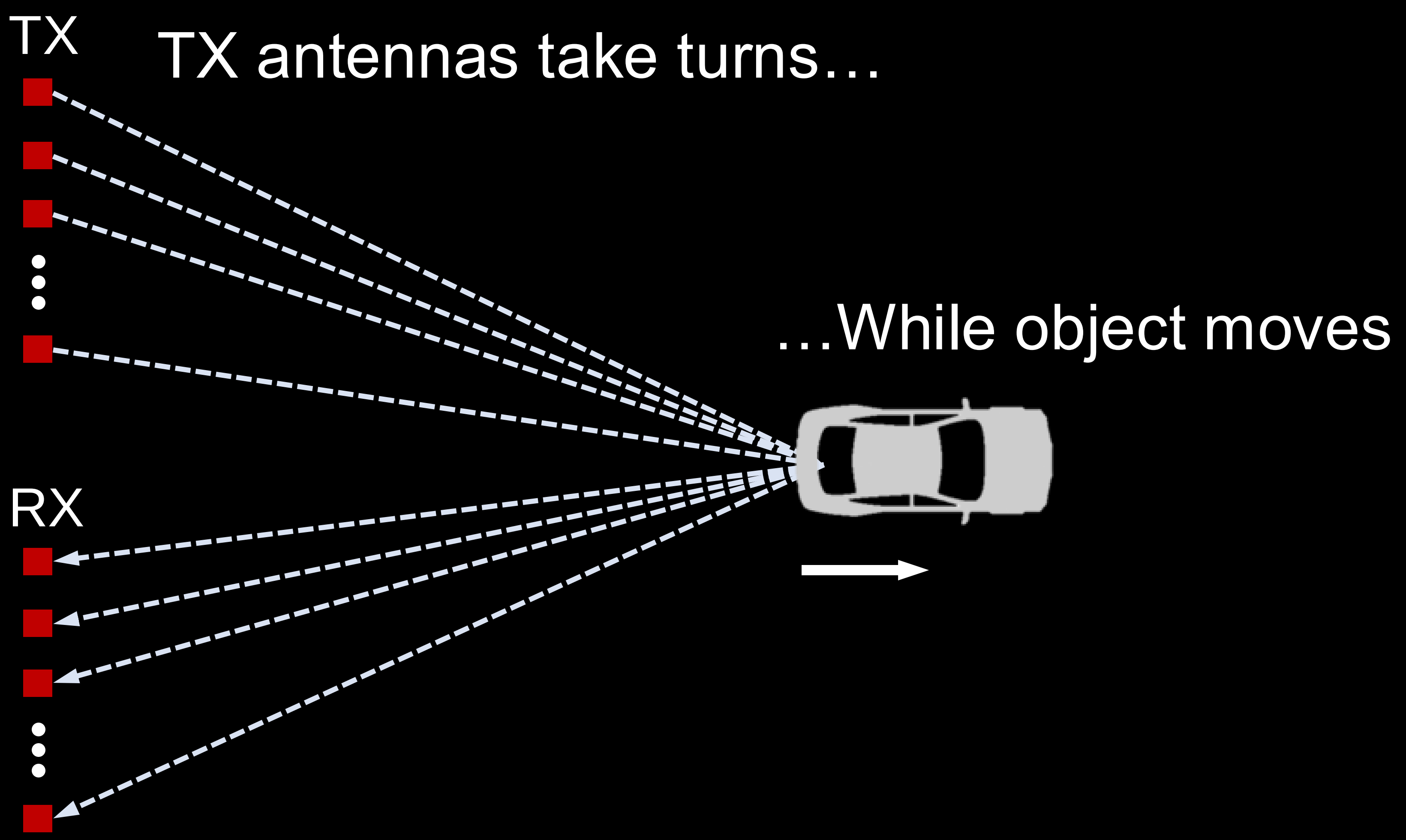
Virtual Antenna Array



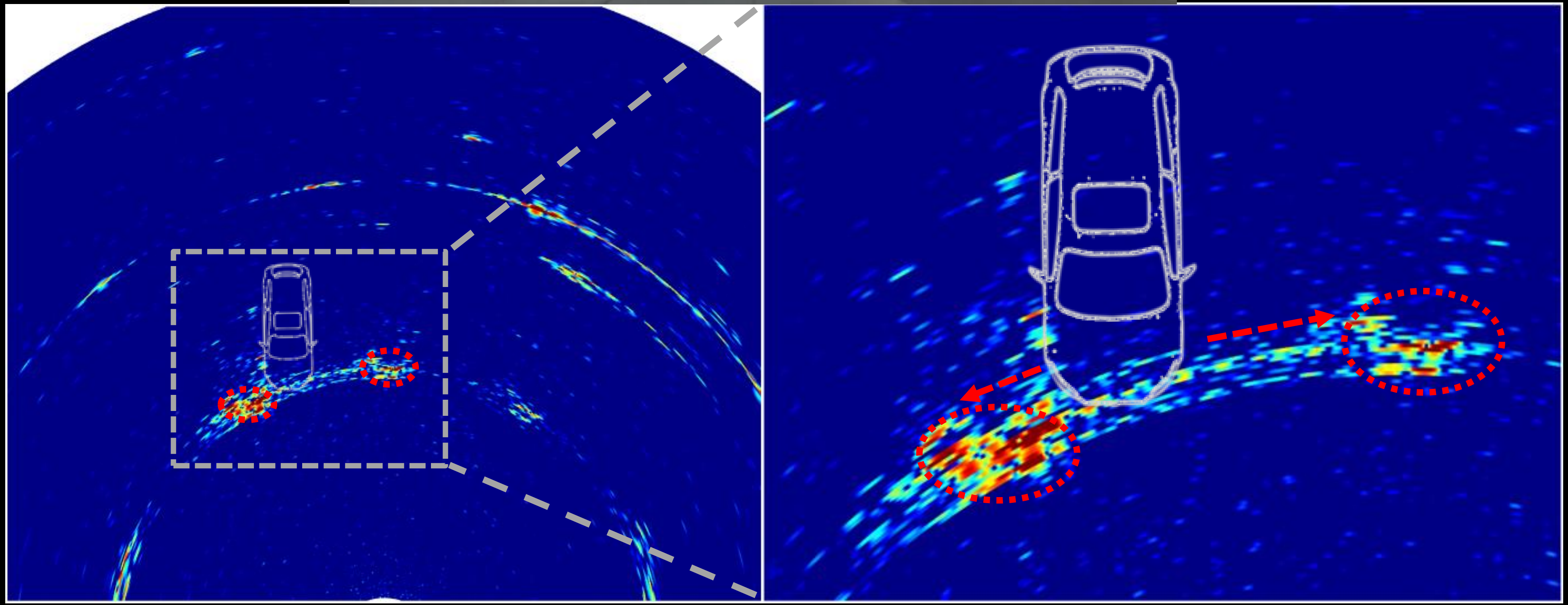
86-element array

1.8º azimuth resolution 10x higher than single-chip radars

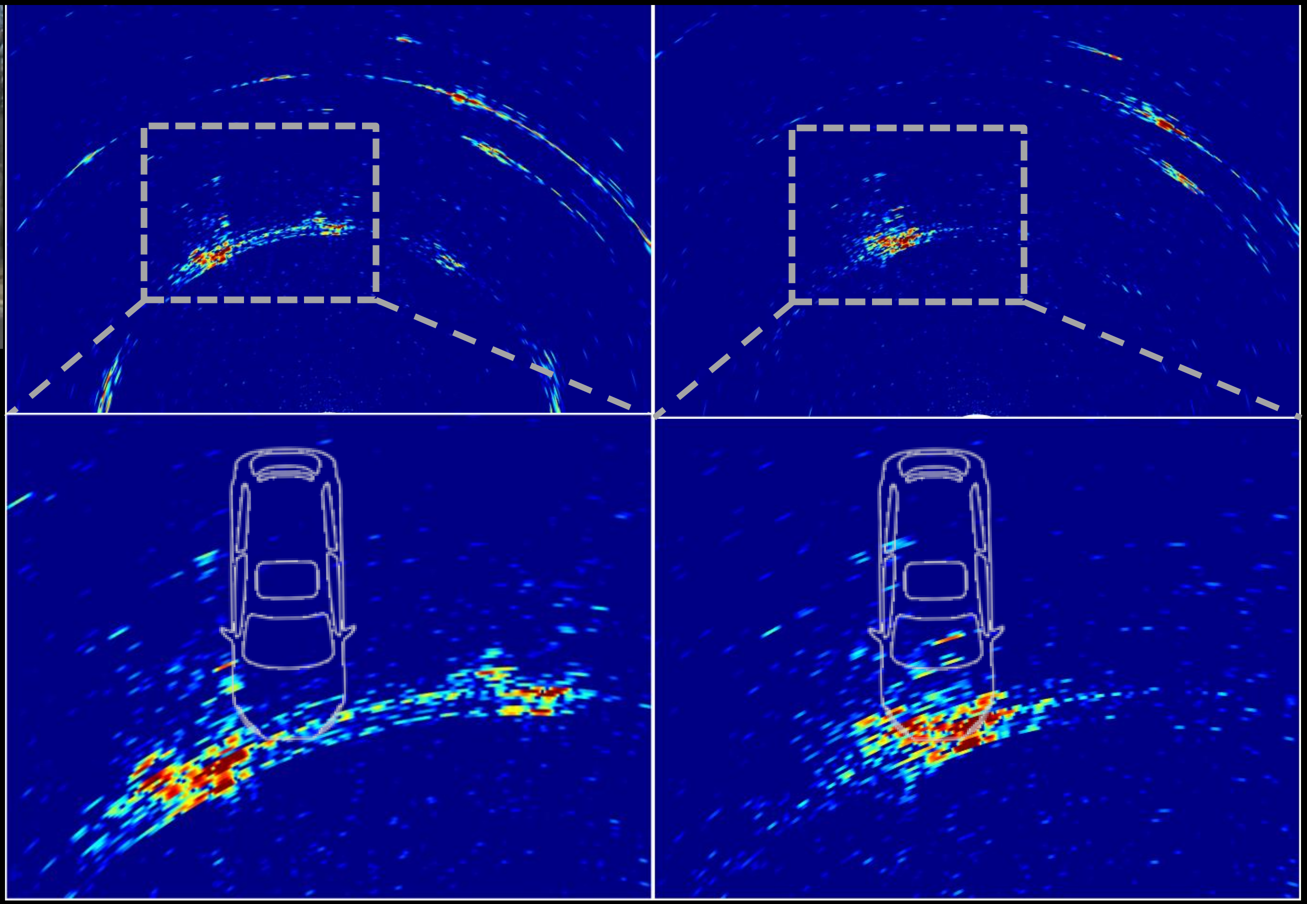
High-resolution cascaded MIMO radar suffers from *motion smearing* in highly dynamic scenes!



Challenge: Motion Smearing



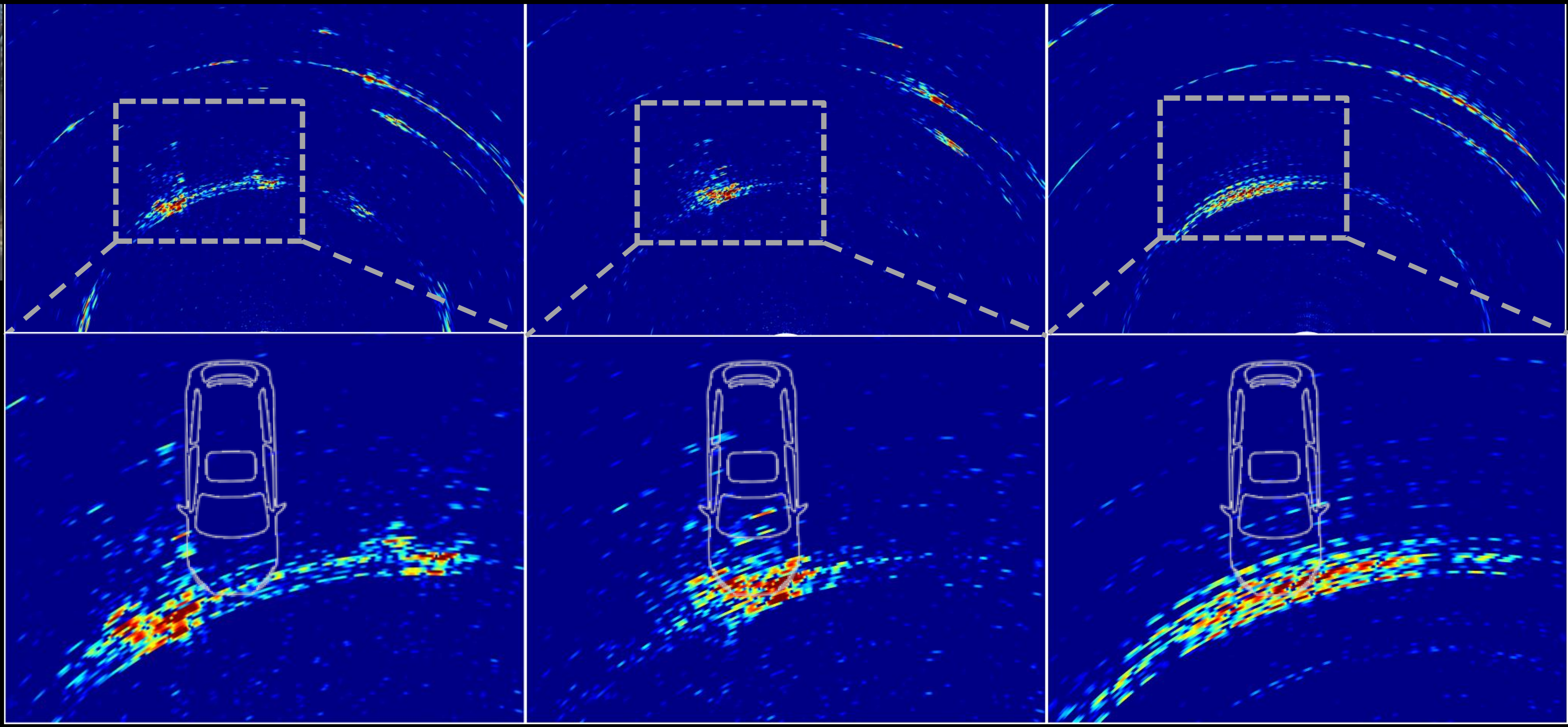
Resolving Motion Smearing



Motion Smearing in Radar Heatmap

High-Resolution After Compensation

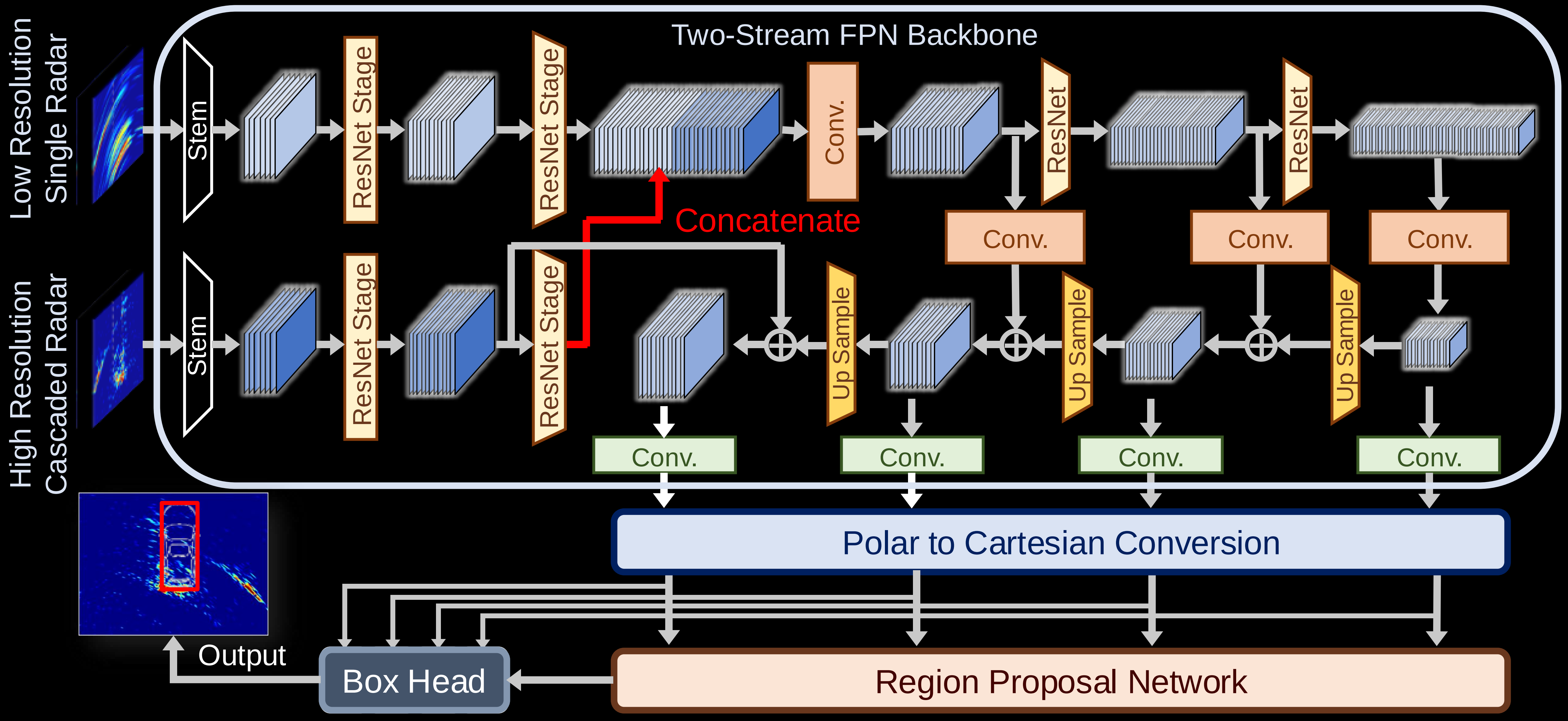
Deep Learning



Motion Smearing in Radar Heatmap | High-Resolution After Compensation | Low-Resolution Single Transmitter

Jointly leverage high- and low-resolution radar heatmaps.

Object Detection Network Architecture

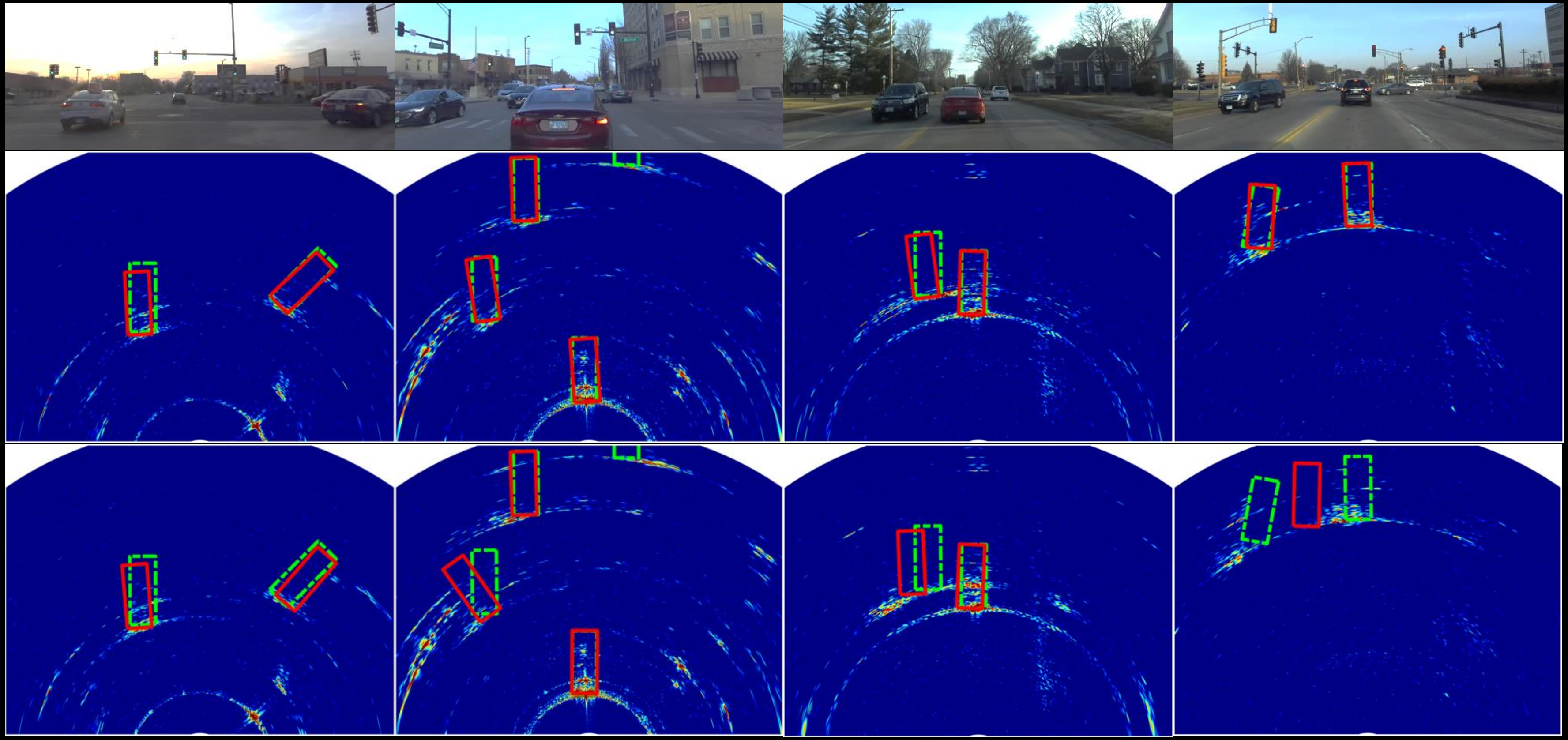


Results

Scene

Radatron

Cascaded Baseline



Green: ground truth car location

Red: predicted bounding box

Demo Video

No Temporal Post Processing

Frame to frame detection in the range of 25 meters.

Can we go beyond 2D object detection to full-fledged 3D imaging using radar?

Challenges in Radar Perception

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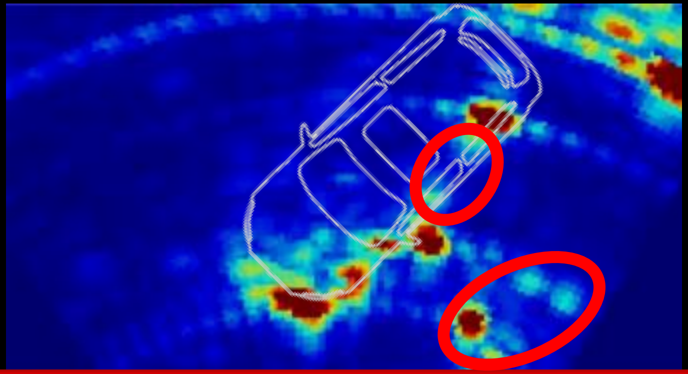
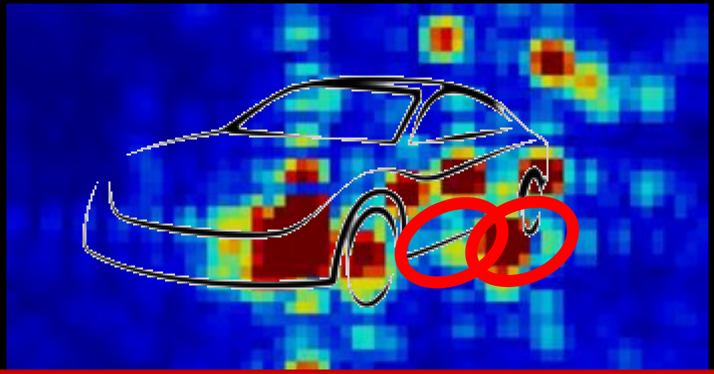
Camera Image

Point Cloud

Top-View



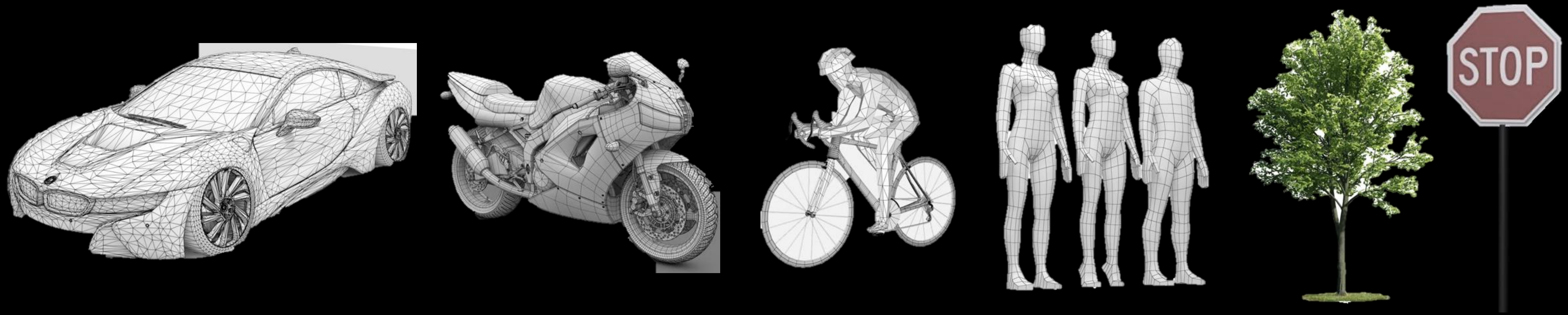
Front-View



Cast mmWave Radar Perception as a Learning Problem

Our Solution

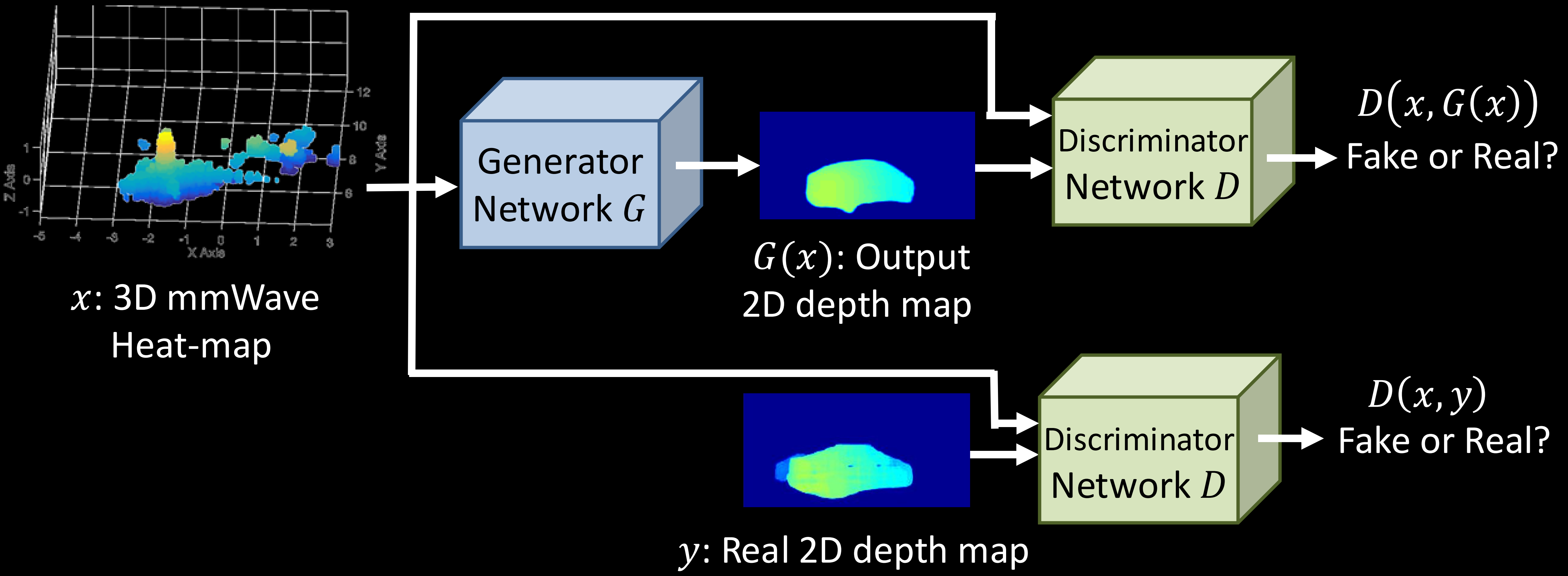
Learning *geometric priors* on structures of commonly found streetside objects.



Generative Adversarial Network (GAN) is effective for various computer vision tasks: super-resolution, learning image prior, image style transformation, etc.

Conditional Generative Adversarial Network (cGAN)

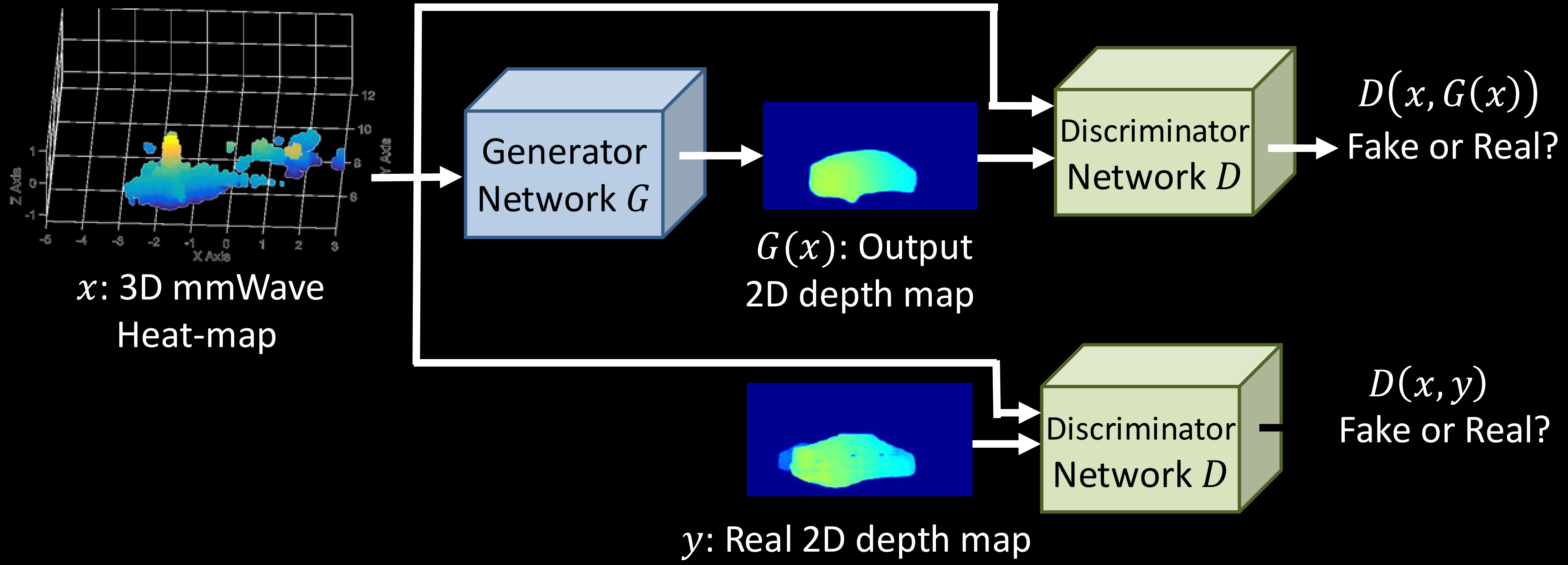
- Generator takes 3D radar heatmap as input and outputs high resolution depth map.
- Discriminator tries to guess is the high resolution depth map is real or fake.
- Generator's goal is to fool the discriminator into thinking this is real



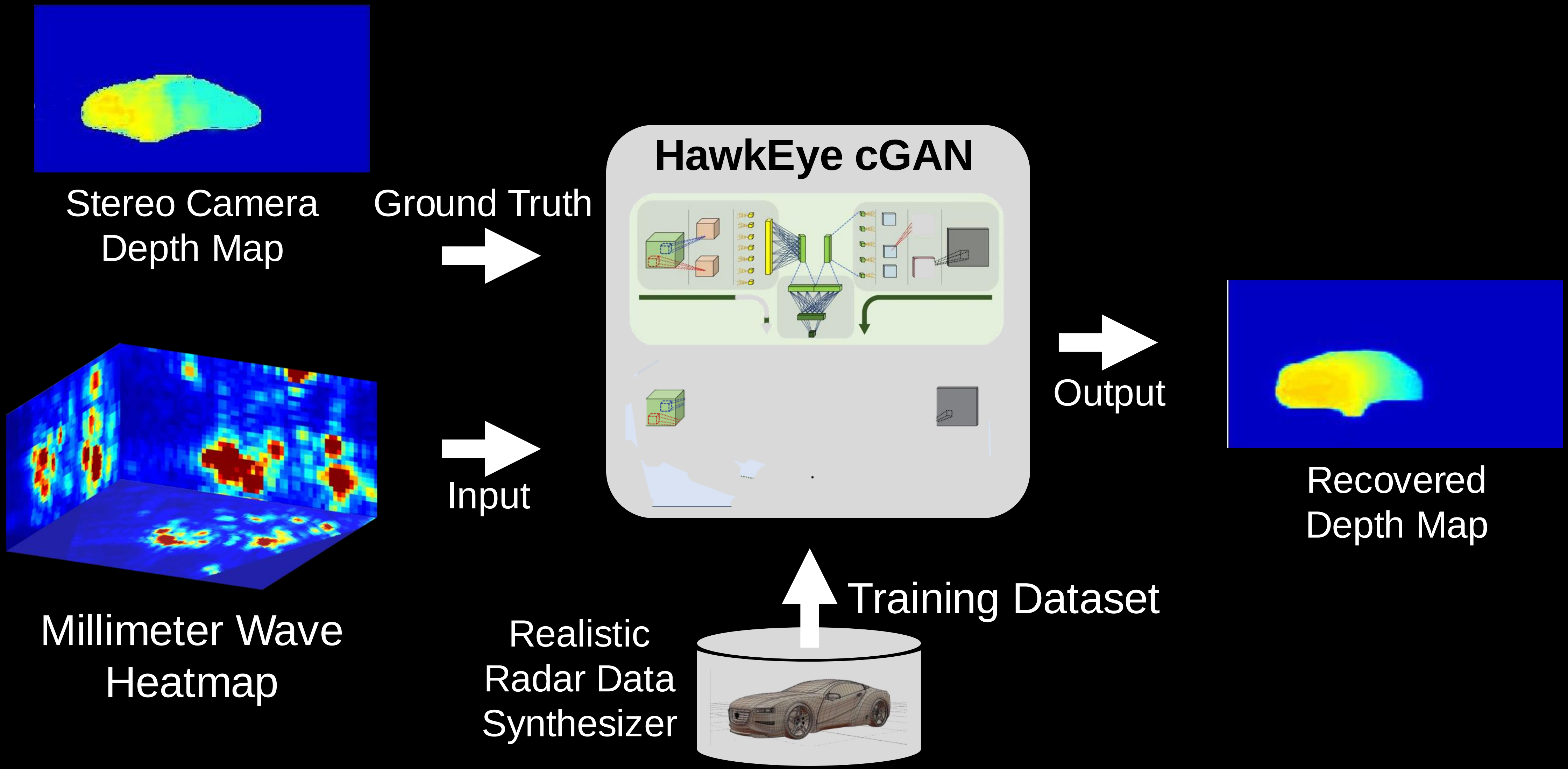
Conditional Generative Adversarial Network (cGAN)

- Train neural networks in Generator and Discriminator to optimize for the GAN loss

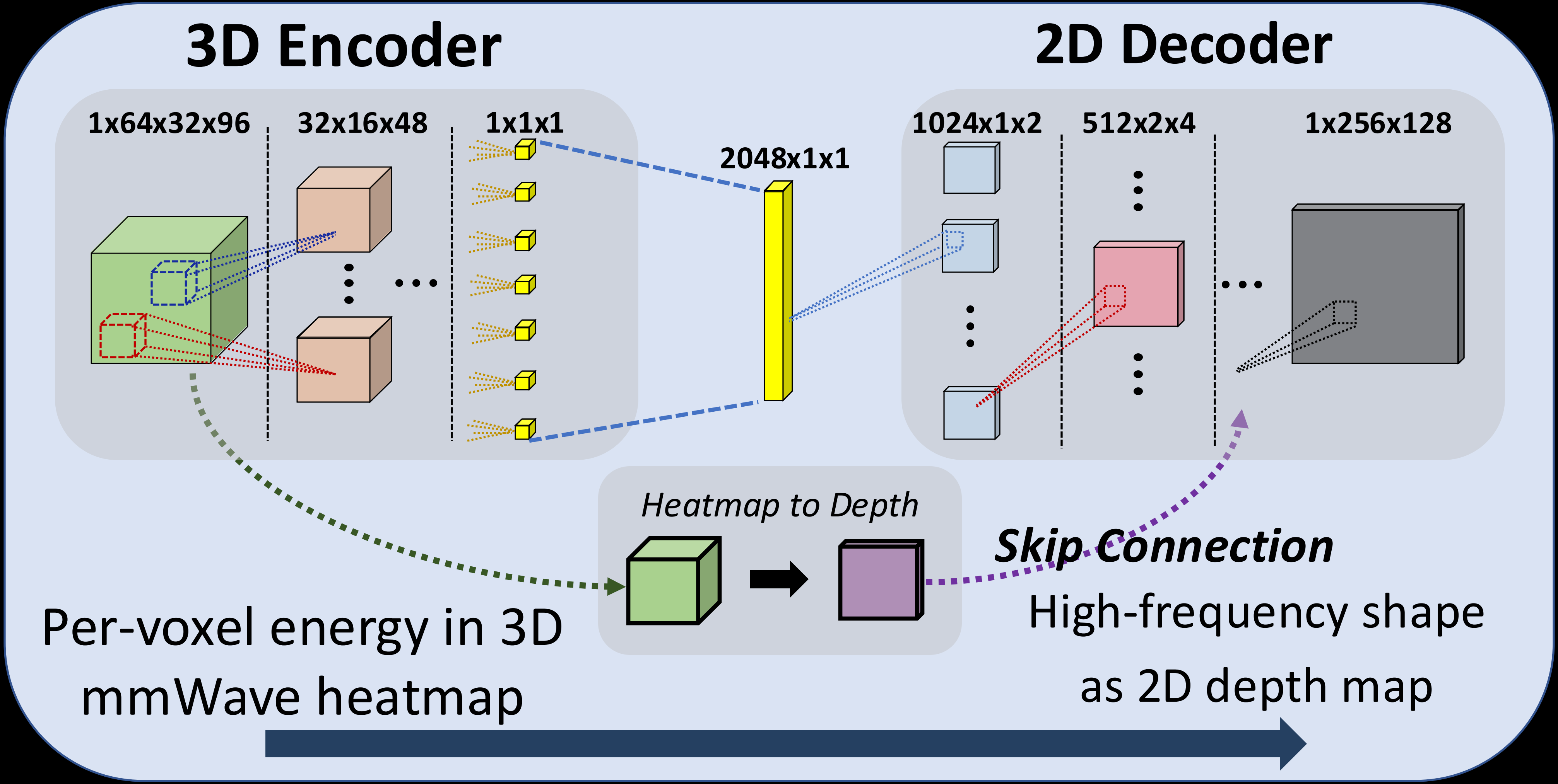
$$\min_{G}\left(\max_{D}\left(\mathbf{E}_y\left[\log D(x,y)\right]+\mathbf{E}_x\left[\log\left(1-D(x,G(x))\right)\right]\right)\right)$$



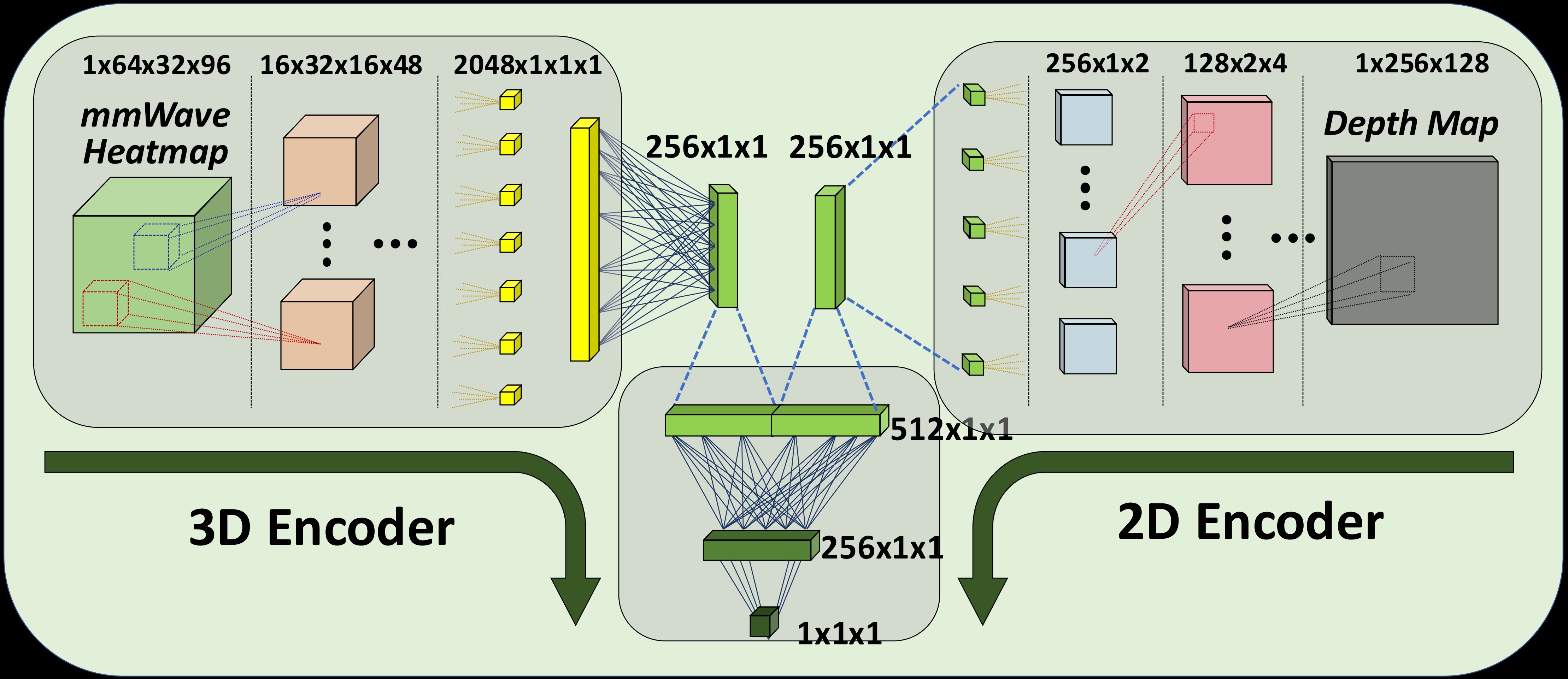
Hawkeye Overview



Generator Architecture



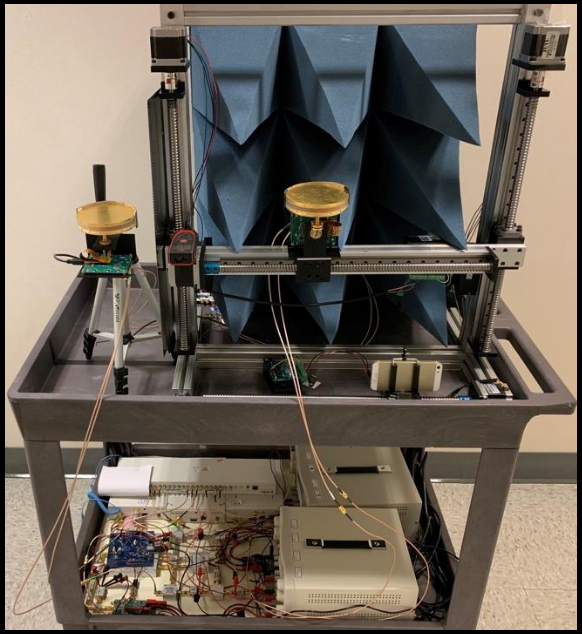
Discriminator Architecture



HawkEye[CVPR 2020]

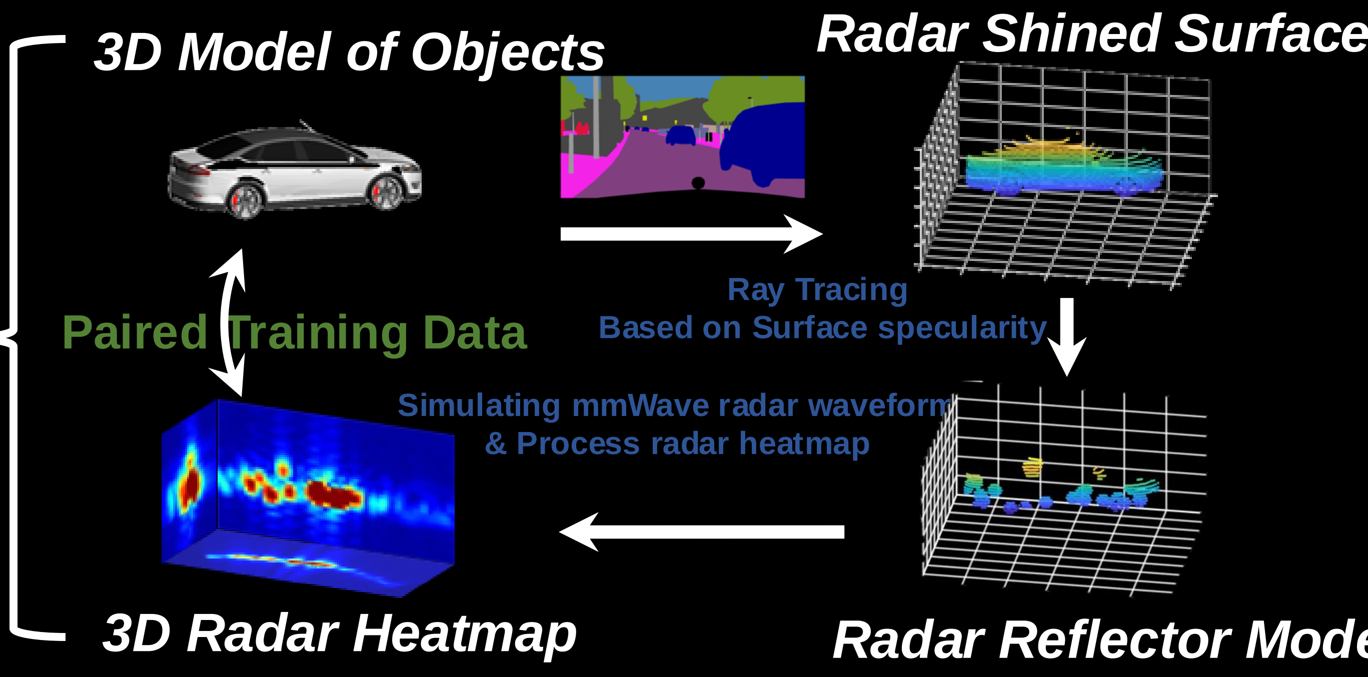
High Resolution Through Fog 3D Millimeter Wave Imaging Using cGANS

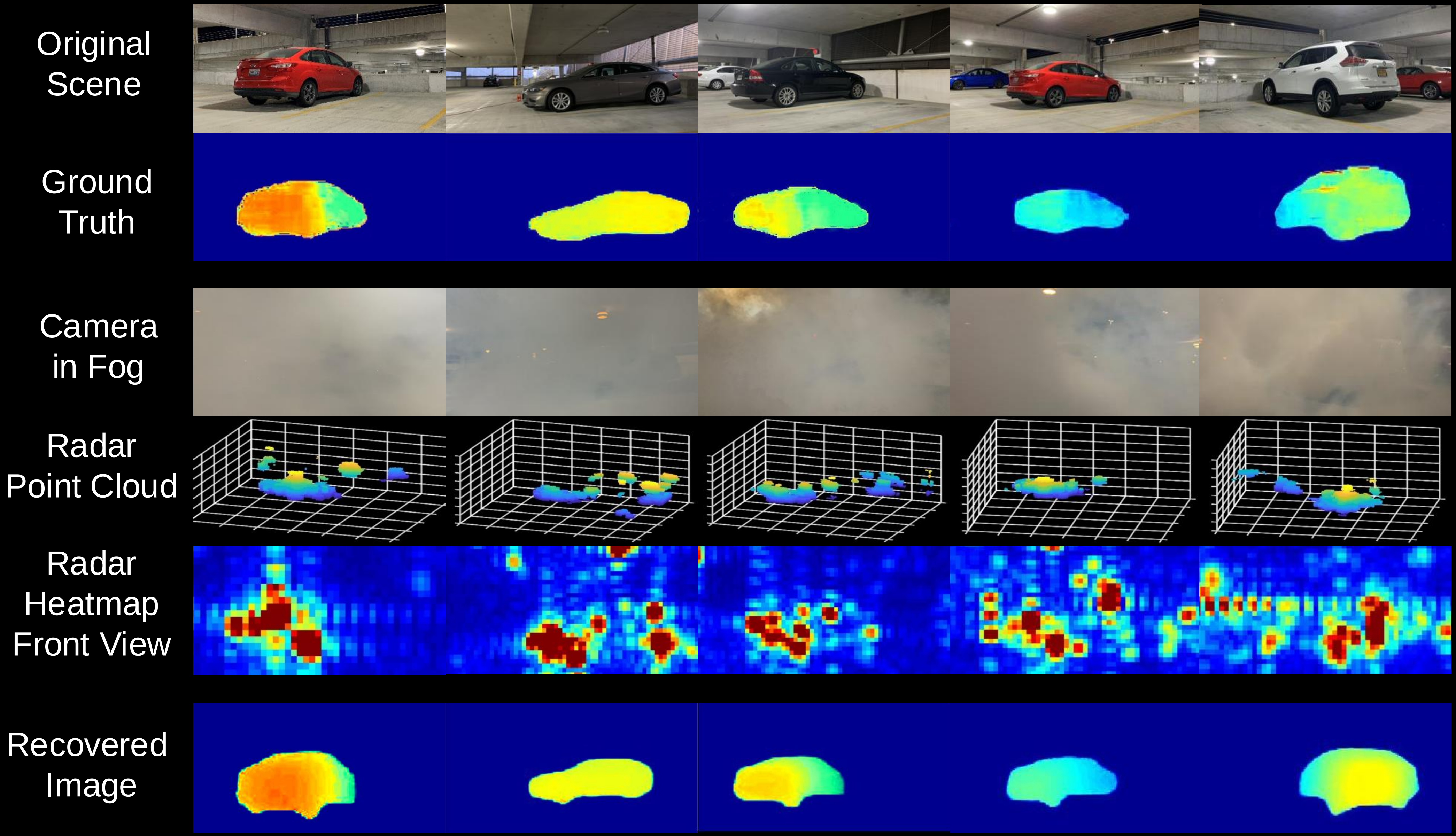
Training done using simulated data and tested using real data



mmWave FMCW Imaging Platform

Radar Data Synthesizer





Trained using simulated data and tested using real data.

What did we cover today?

Learn the fundamentals, applications, and implications of
mmWave Sensing

1- What are the pros and cons of mmWave vs Vision?

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3- How does specularity impact mmWave imaging?

4- Can Generative AI help us with mmWave shortcomings?

TODO:

1- Lab 2 due today

2- Lab3 out today, due next week

3- Start forming teams