ECE 598HH: Advanced Wireless Networks and Sensing Systems

Lecture 15: Machine Learning Part 3: RF Imaging

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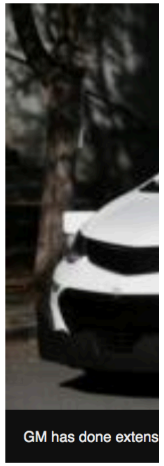
CSL: COORDINATED SCIENCE LAB

Rising Interest in Fully Autonomous Driving

Honda to invest $2.8bn in GM's self-driving car unit

4 October 2018



Honda is to invest
driving unit, GM C
autonomous vehic

Elon Musk to investors: Self-driving will make Tesla a $500 billion company

PUBLISHED THU, MAY 2 2019•6:01 PM EDT | UPD

Lora Kolodny
@LORAKOLODNY

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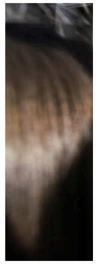
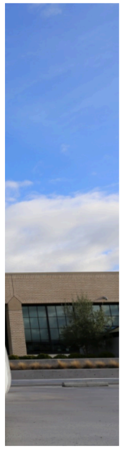


Elon Musk, chief
media outside fe
Natan Dvir | Bloom

Google Has Spent Over $1.1 Billion on Self-Driving Tech

for the
2009 and



Qualcomm eyes self-driving cars with Snapdragon Ride Platform at CES 2020

The company has developed its first system for autonomous vehicles, as well as new offerings for automakers to do things like deliver services.

Shara Tibken Jan. 6, 2020 11:32 a.m. PT ES 0 LISTEN - 03:15

Automotive is a big focus for Qualcomm.

WIRED

Snow and Ice Pose a Vexing Obstacle for Self-Driving Cars

Most testing of autonomous vehicles until now has been in sunny, dry climates. That will have to change before the technology will be useful everywhere.

Forbes

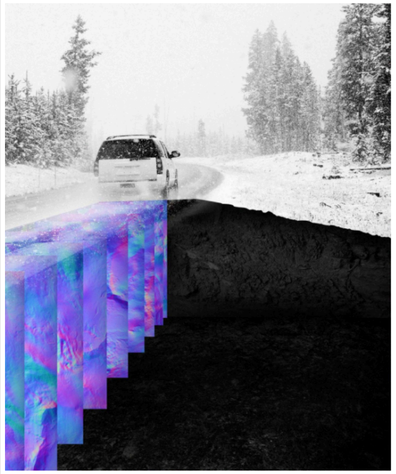
Weather Creates Challenges For Next Generation Of Vehicles

Jim Foerster Contributor
Science

Bloomberg Businessweek

Self-Driving Cars Can Handle Neither Rain nor Sleet nor Snow

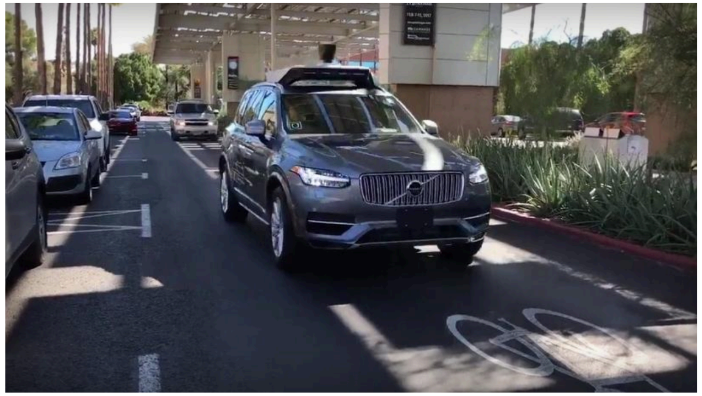
les solve inclement conditions,
that can see below the ground.



ground-penetrating WaveSense radar that can detect various
/ESENSE

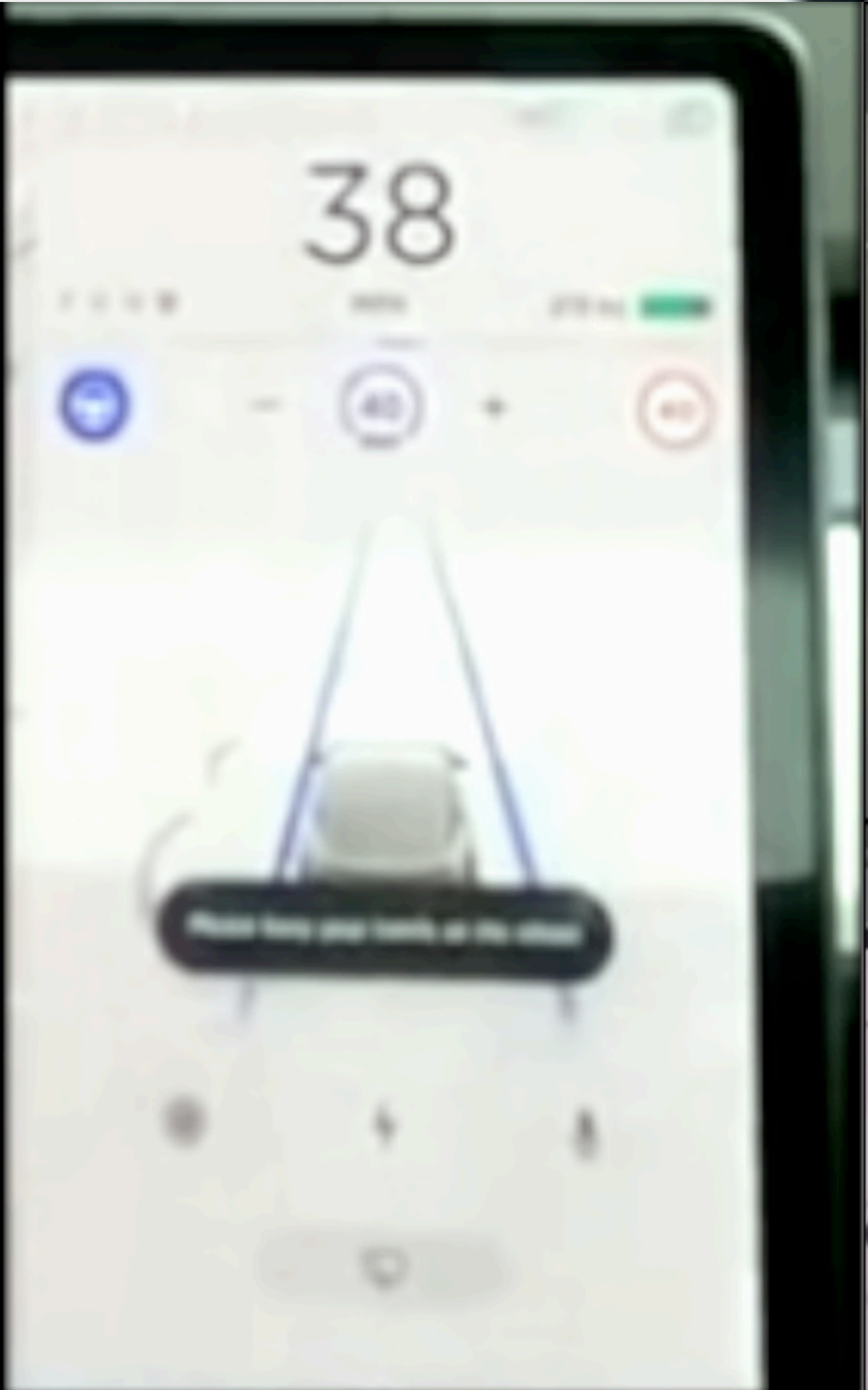
Self-Driving Cars Still Can't Handle Snow, Rain, or Heavy Weather

By Joel Hruska on October 30, 2018 at 4:53 pm | 88 Comments



If you listen to the companies deploying self-driving vehicle technology, the date for full deployment and L5 capability (full self-driving, no need for driver intervention at all) is just

Tesla in Fog



Millimeter Wave Radar

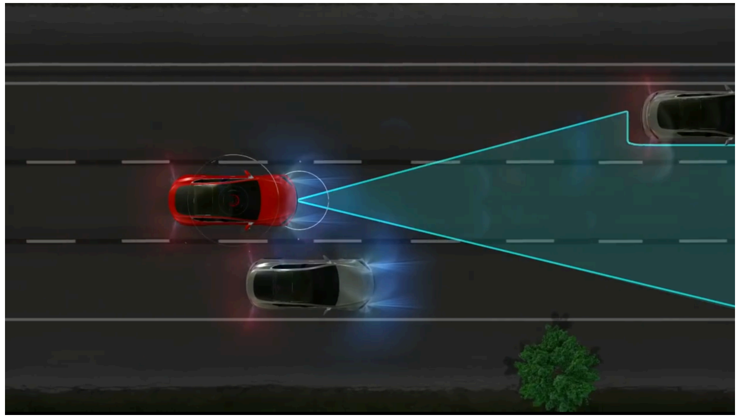
Radar can function in adverse conditions

Millimeter Wave Radar

Radar can function in adverse conditions

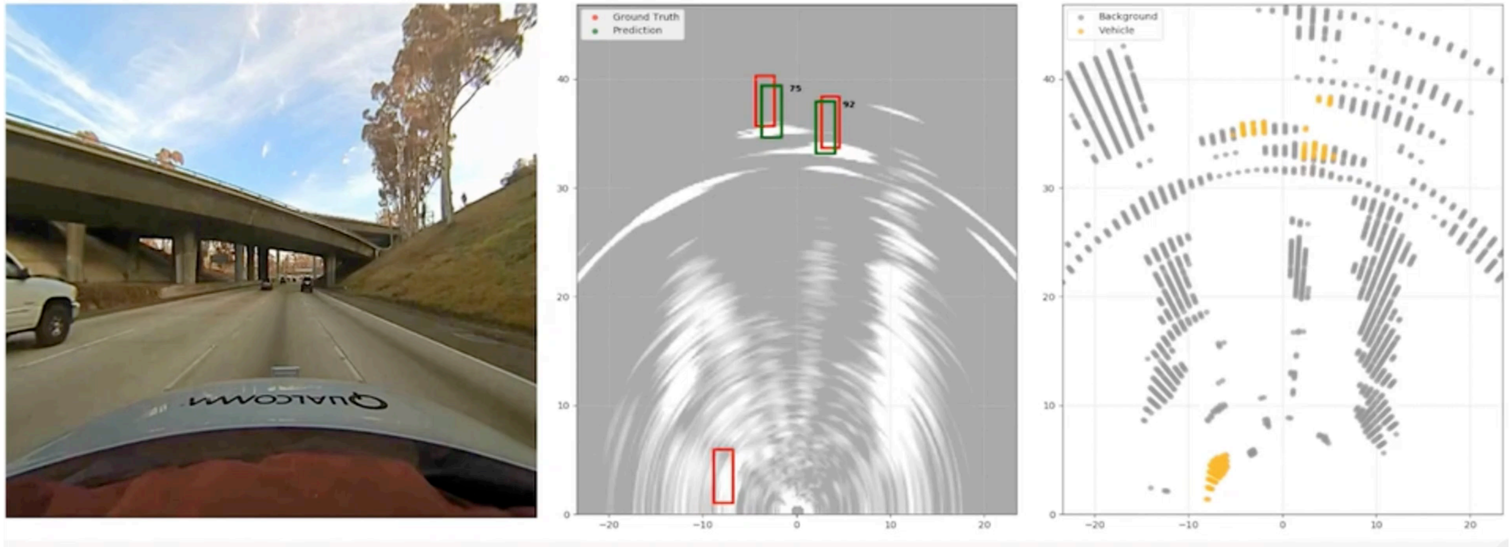
Can we use millimeter wave radars in scenarios where LiDARs and cameras fail?

State of the Art Millimeter Wave Radars



Automotive Radars mainly used for 1D Ranging & Speed estimation

Recent works extend it to 2D Ranging & Object detection



Qualcomm snapdragon ride platform

Can we use millimeter wave radars for 3D imaging and not just ranging?

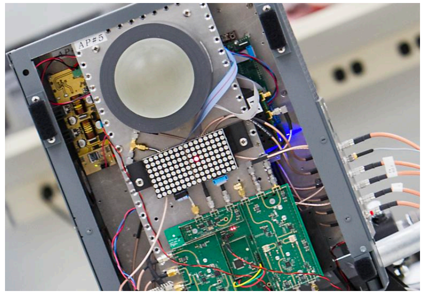
Millimeter Wave Radar:

- Uses FMCW for ranging and antenna arrays for 2D ranging.
- Operates at very high frequencies around 24 GHz and 77 GHz.
- Called millimeter wave since wavelength is in millimeter scale.
- Huge bandwidth available at high frequency:
  - Large sweep bandwidth → Accurate ranging.
  - E.g. 2 GHz → resolution $= c/2B = 7.5$ cm

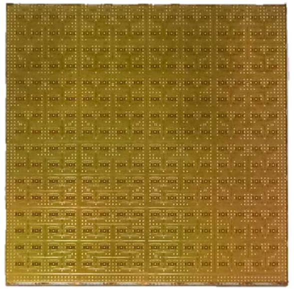
Can we use millimeter wave radars for 3D imaging and not just ranging?

Need 2D Phased Arrays!

5G pushing research into delivering large 2D millimeter wave phased arrays

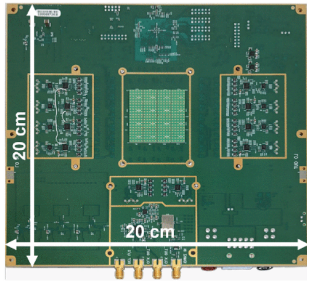


Nokia & National Instruments

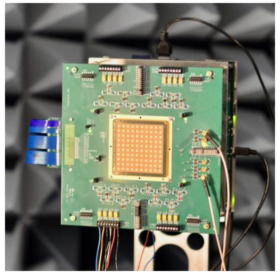


UCSD
256 elements

UCSD
64 elements

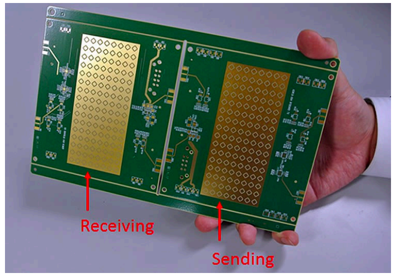


Bell Labs
384 elements



Anokiwave
256 elements

IBM
64 elements

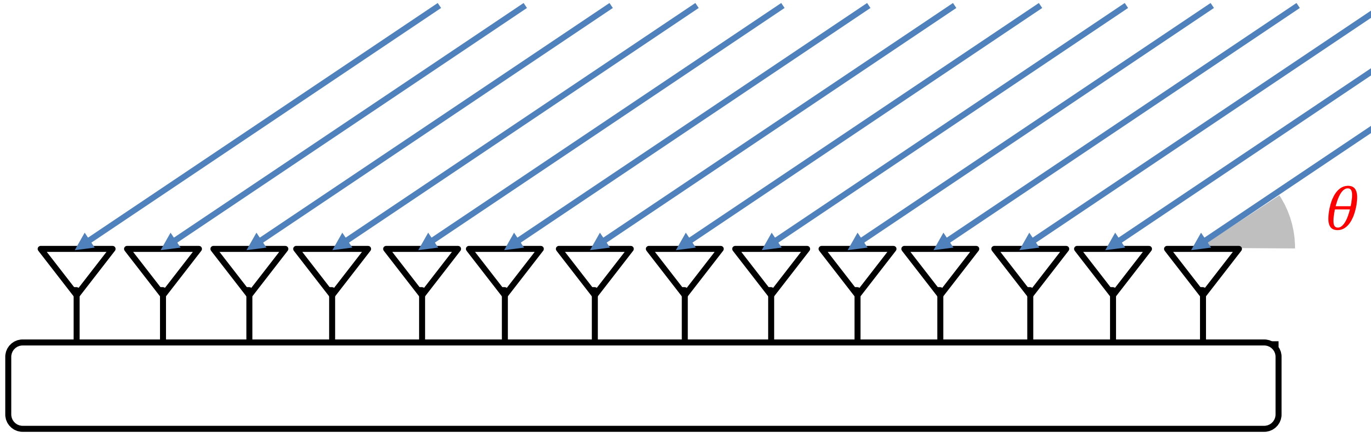


Fujitsu
64 elements

Small wavelength enables thousands of antennas to be packed into small space

→ Extremely narrow beams

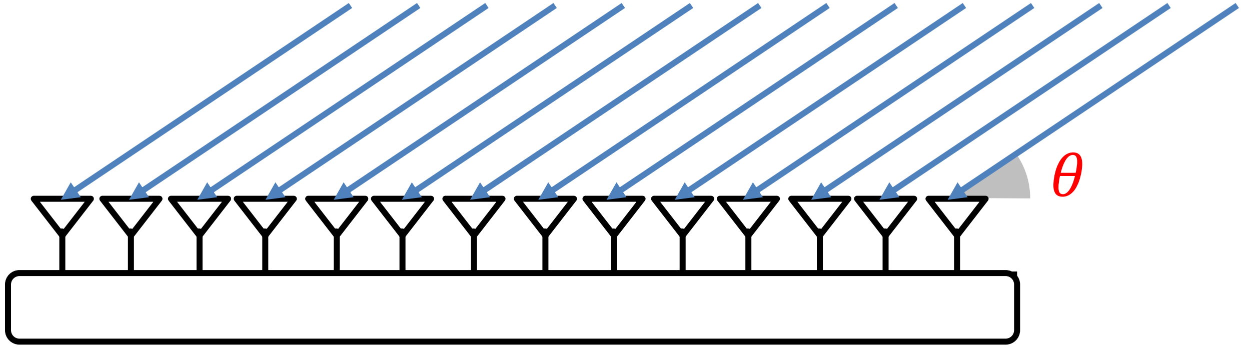
Phased Arrays Primer



$$h_k = \alpha_1 e^{-j2\pi\frac{d_1 - k\, s \cos\theta_1}{\lambda}}$$

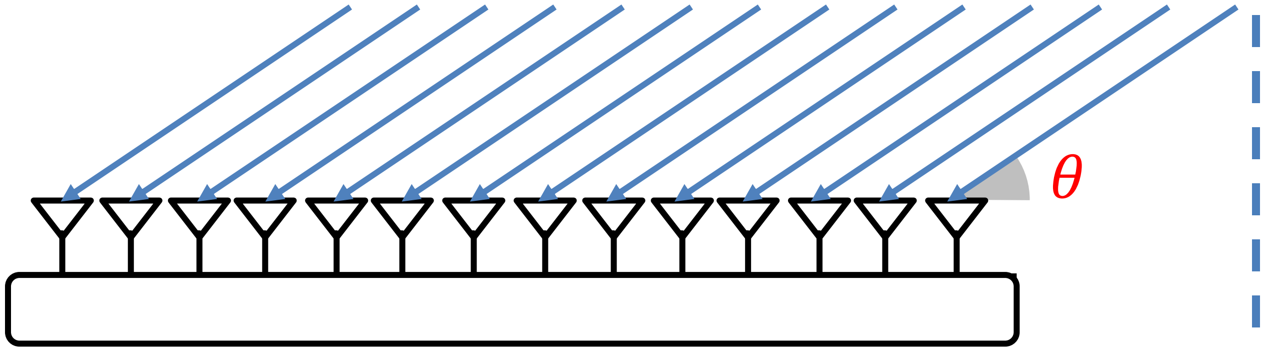
Phased Arrays Primer

Digital Phased Arrays



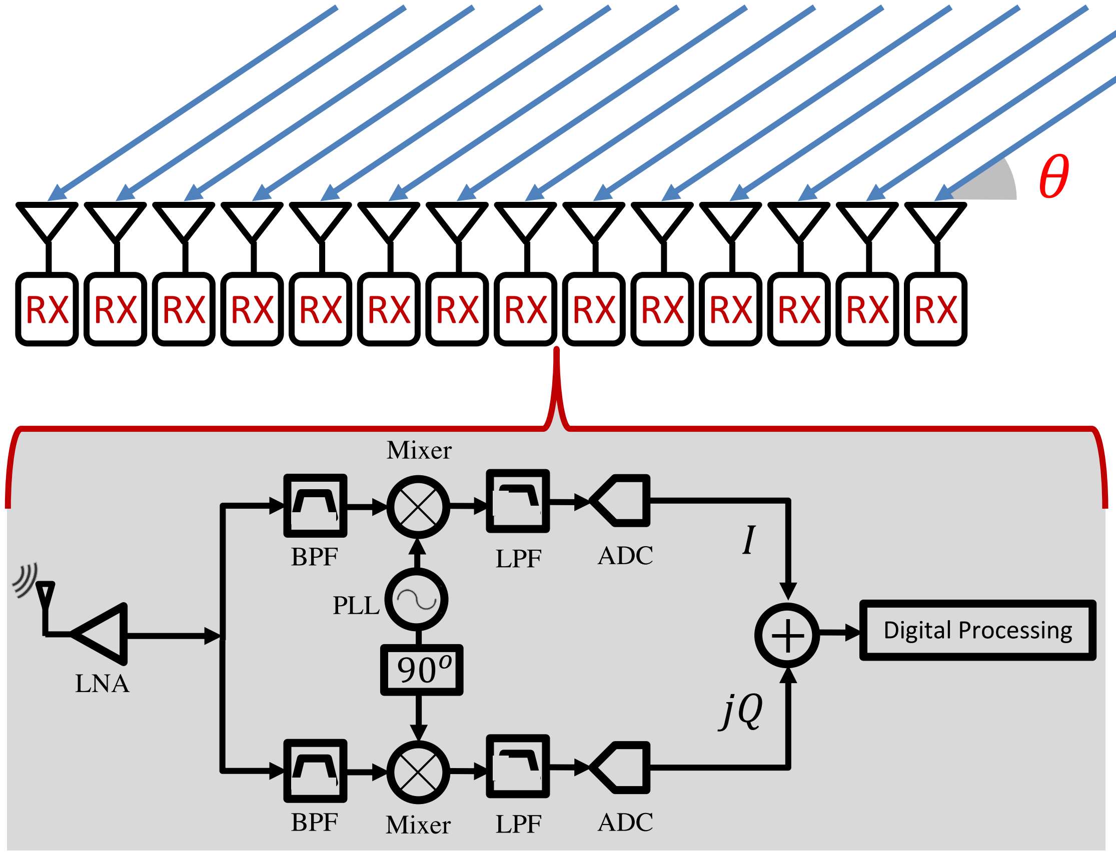
Phased Arrays Primer

Digital Phased Arrays



Phased Arrays Primer

Digital Phased Arrays

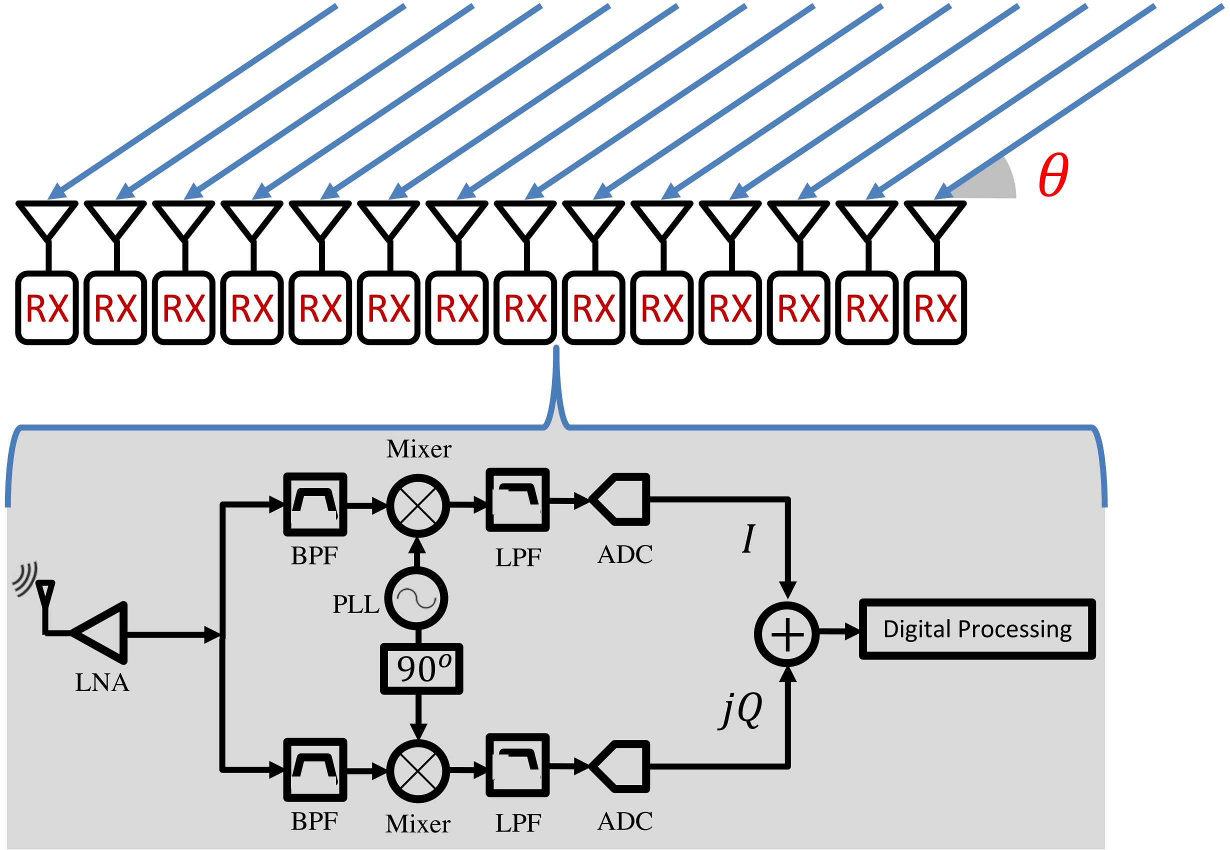


Every antenna connected to full fledged RX

Sample & Process Signals in Digital

Phased Arrays Primer

Digital Phased Arrays

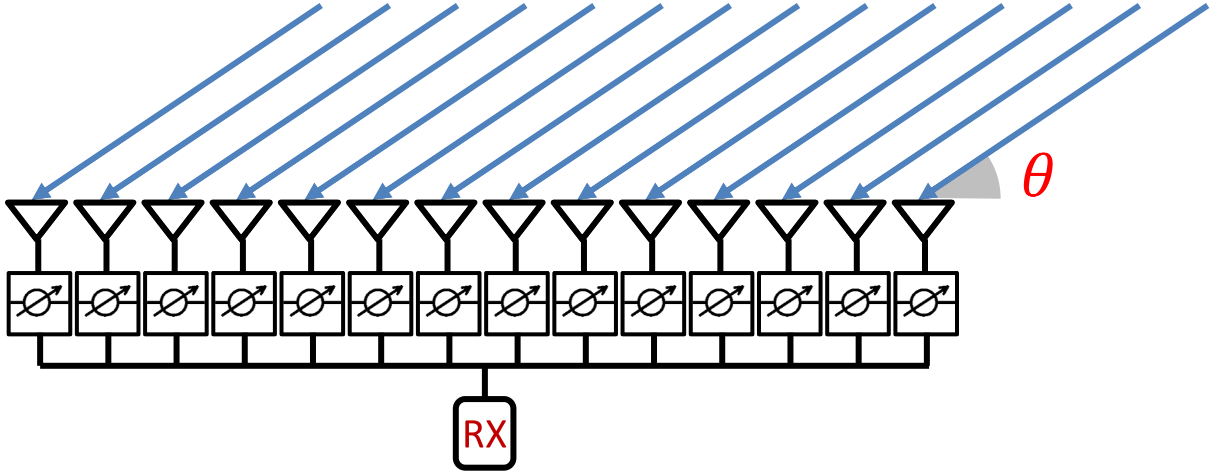


Every antenna connected to full fledged RX

Sample & Process Signals in Digital

Very expensive and high power for large arrays & mmWave

Analog Phased Arrays

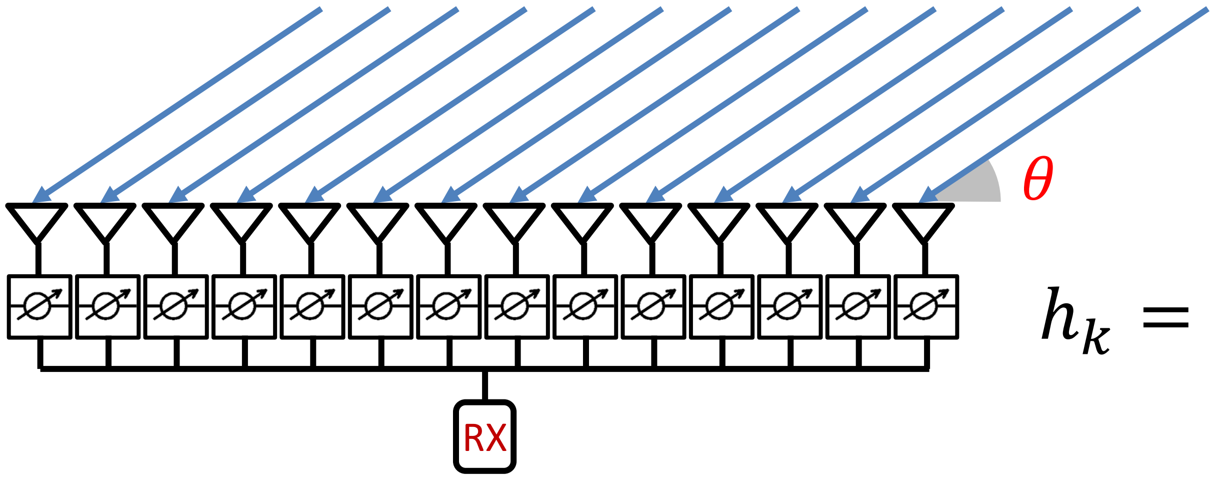


All antennas connected to a single receiver

- Each antenna connected to a phase shifter.
- Phase shifter changes the phase of the signal on each antenna by multiplying with $e^{j\phi}$.
- Steer the beam electronically by changing the phases of the signals.
- Get the sum along a certain direction.

Cheap & low power but requires scanning

Analog Phased Arrays



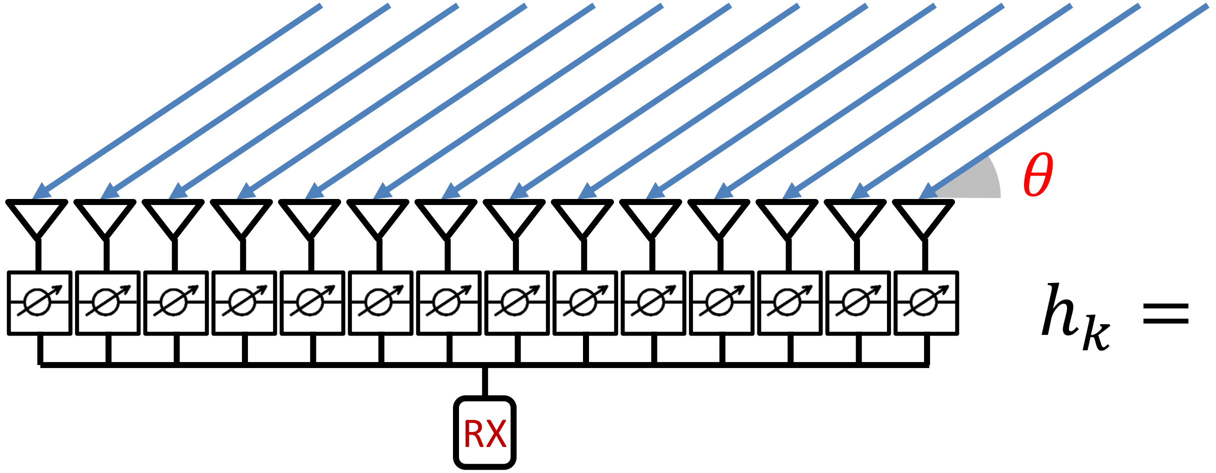
$$h_k = \alpha e^{-j2\pi\frac{d-k\,s\cos\theta}{\lambda}}$$

$$y(t) = \sum_{1}^{N} y_k(t)e^{j\phi_k} = \sum_{1}^{N} h_k x(t)e^{j\phi_k} = \sum_{1}^{N} \alpha e^{-j2\pi\frac{d-k\,s\cos\theta}{\lambda}} x(t)e^{j\phi_k}$$

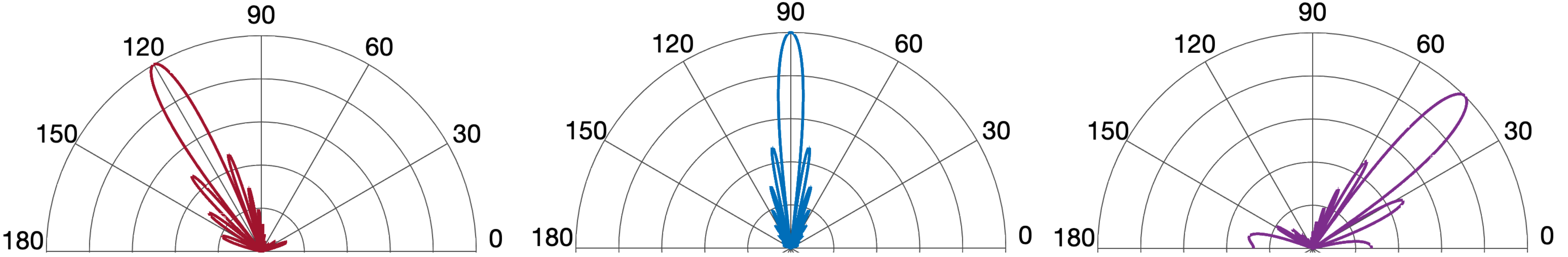
$$= x(t)\alpha e^{-j2\pi\frac{d}{\lambda}} \sum_{1}^{N} e^{j\pi k\ \cos\theta} e^{j\phi_k}$$

To get signal along direction θ_1, set the phases on the phase shifters to $\phi_k = -\pi k\cos\theta$

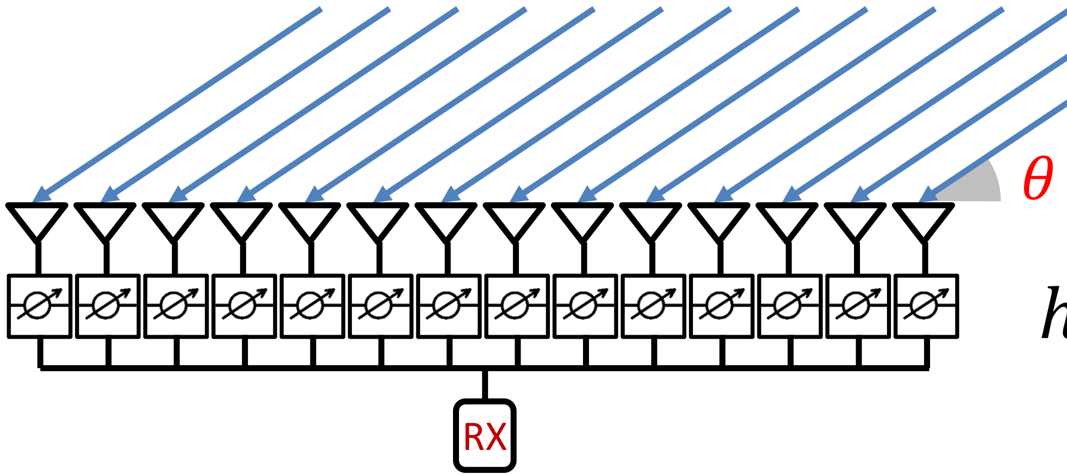
Analog Phased Arrays



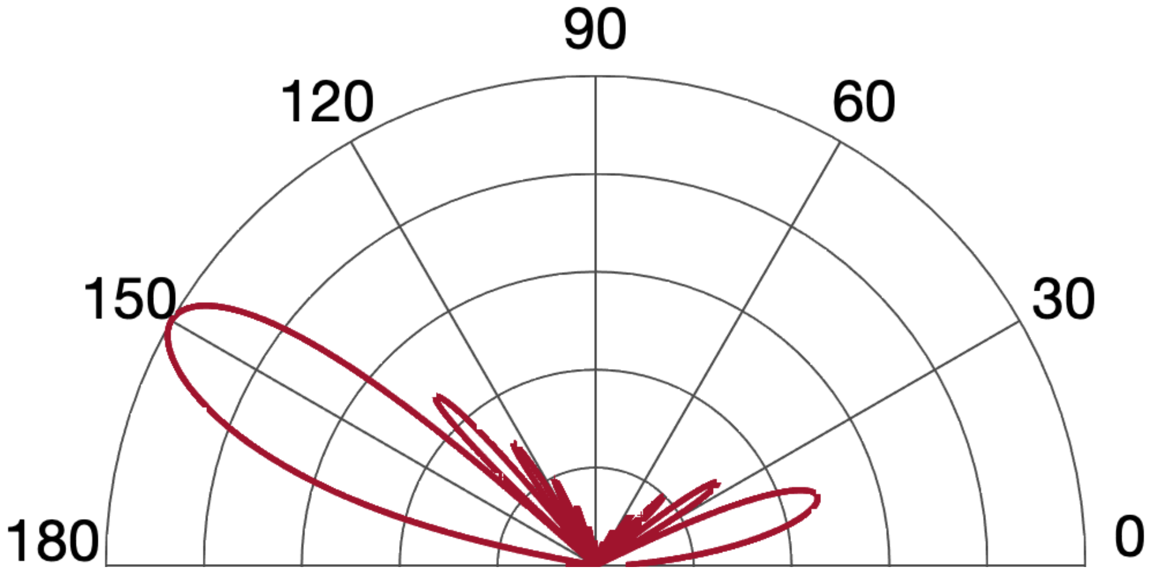
$$h_k = \alpha e^{-j2\pi \frac{d - k\, s \cos\theta}{\lambda}}$$



Analog Phased Arrays



$$h_k = \alpha e^{-j2\pi \frac{d - k\, s \cos\theta}{\lambda}}$$



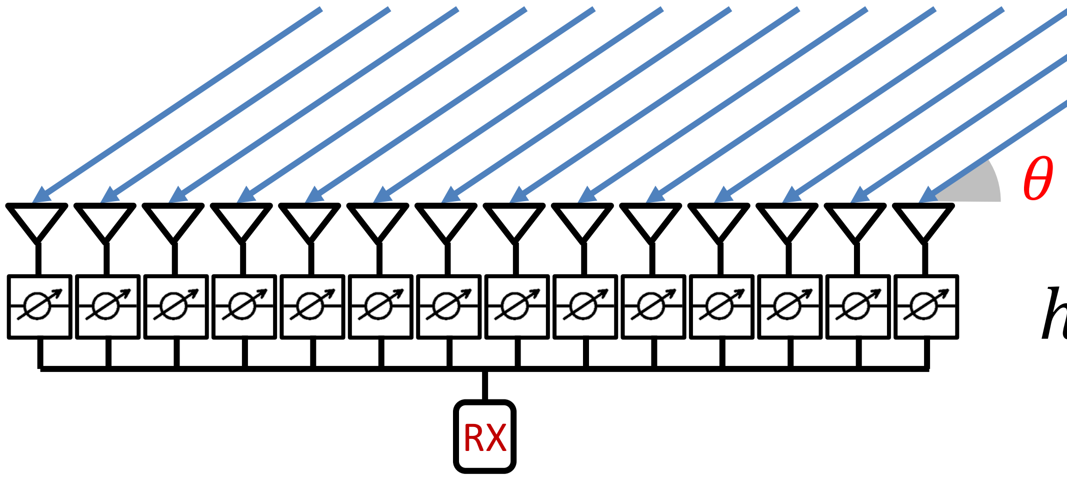
(1) Set the phase shifters to receive signals from a given direction.

(2) Send FMCW signals.

(3) Receiver FMCW reflections, down convert, sample and compute range FFT.

(4) Repeat until you get 2D range image: AoA + Range

Analog Phased Arrays



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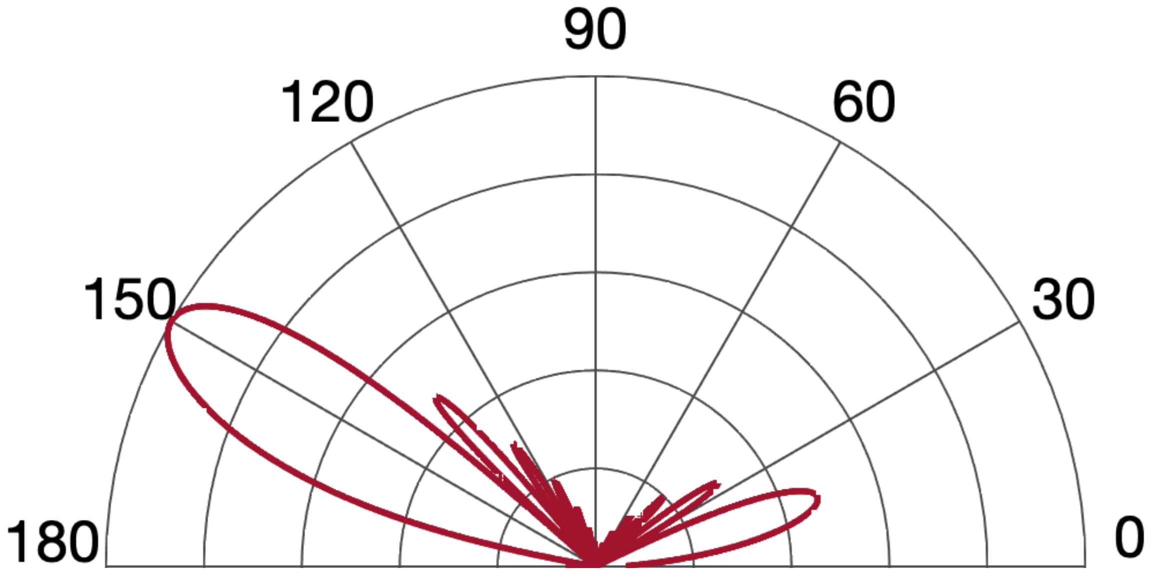
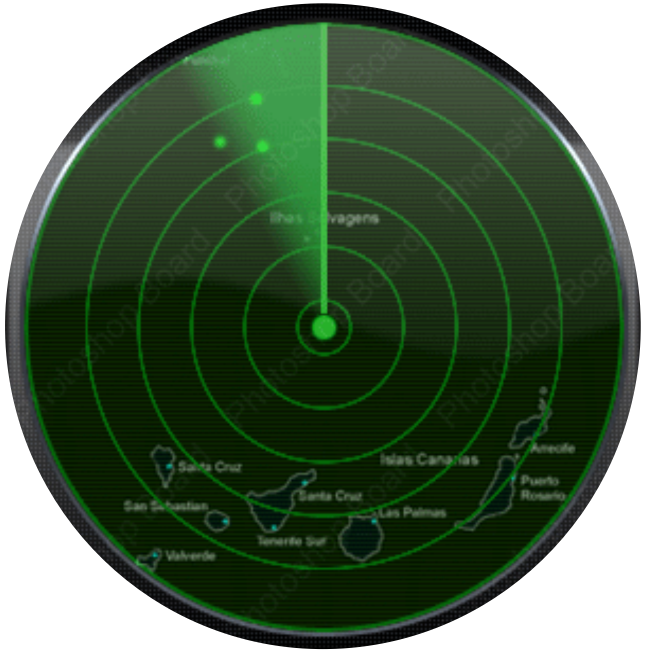
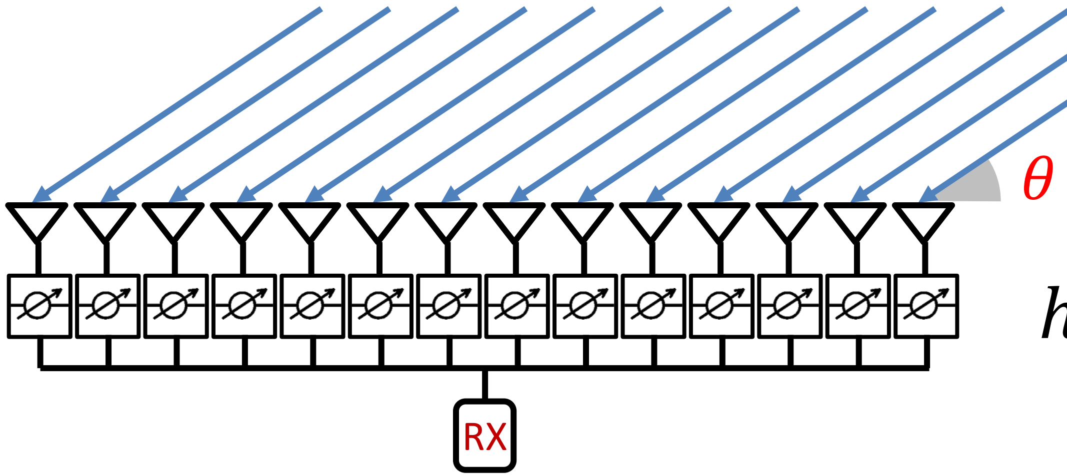




Analog Phased Arrays



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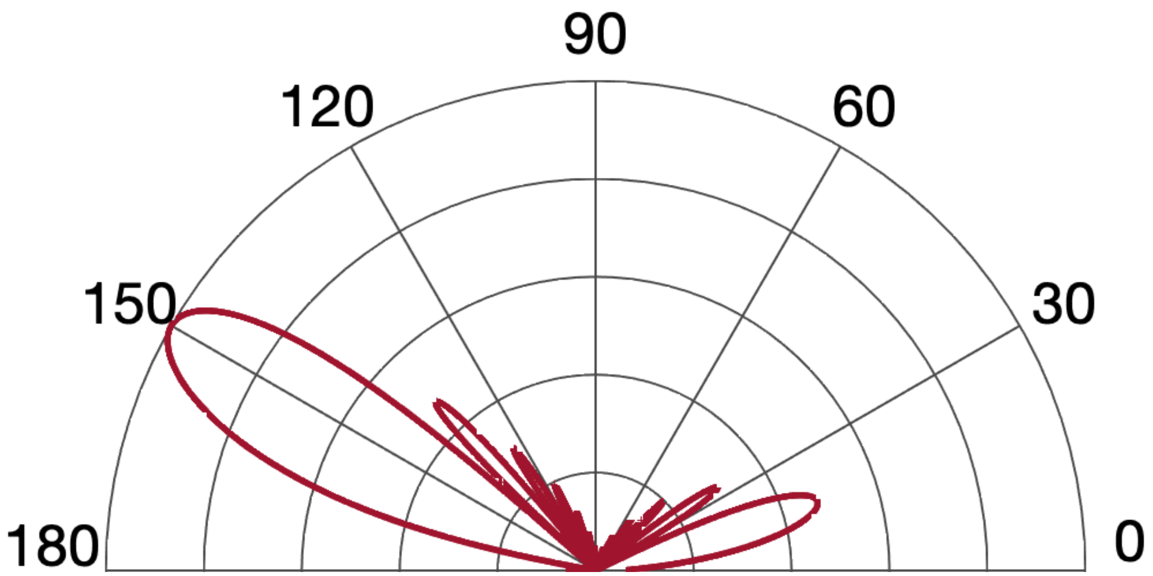
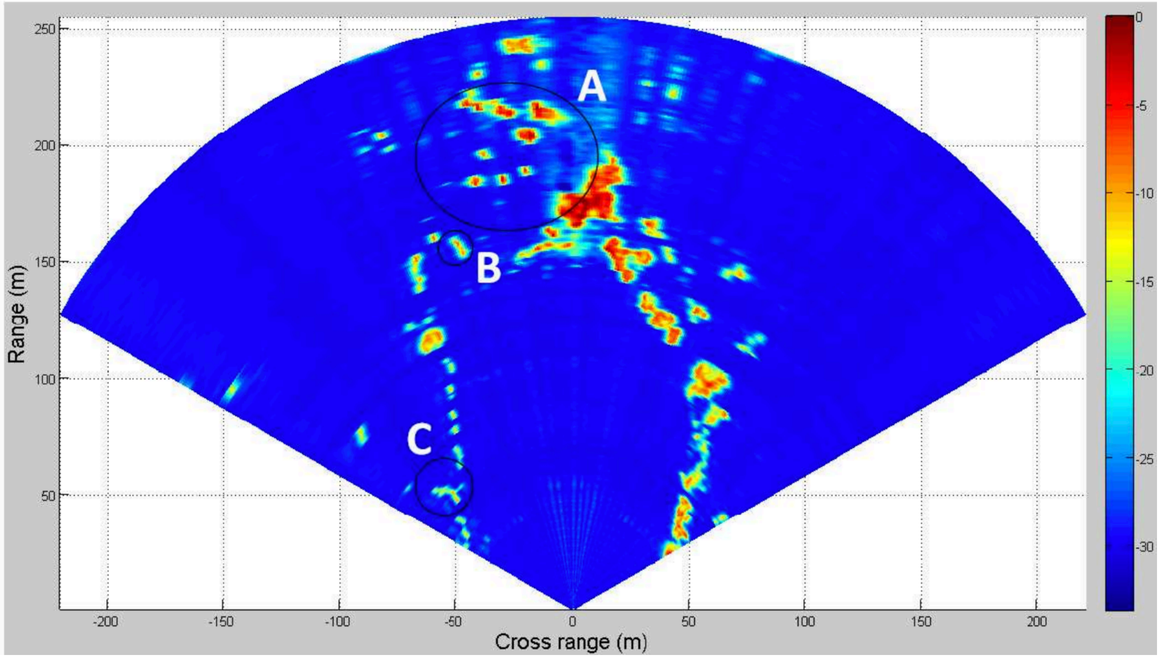
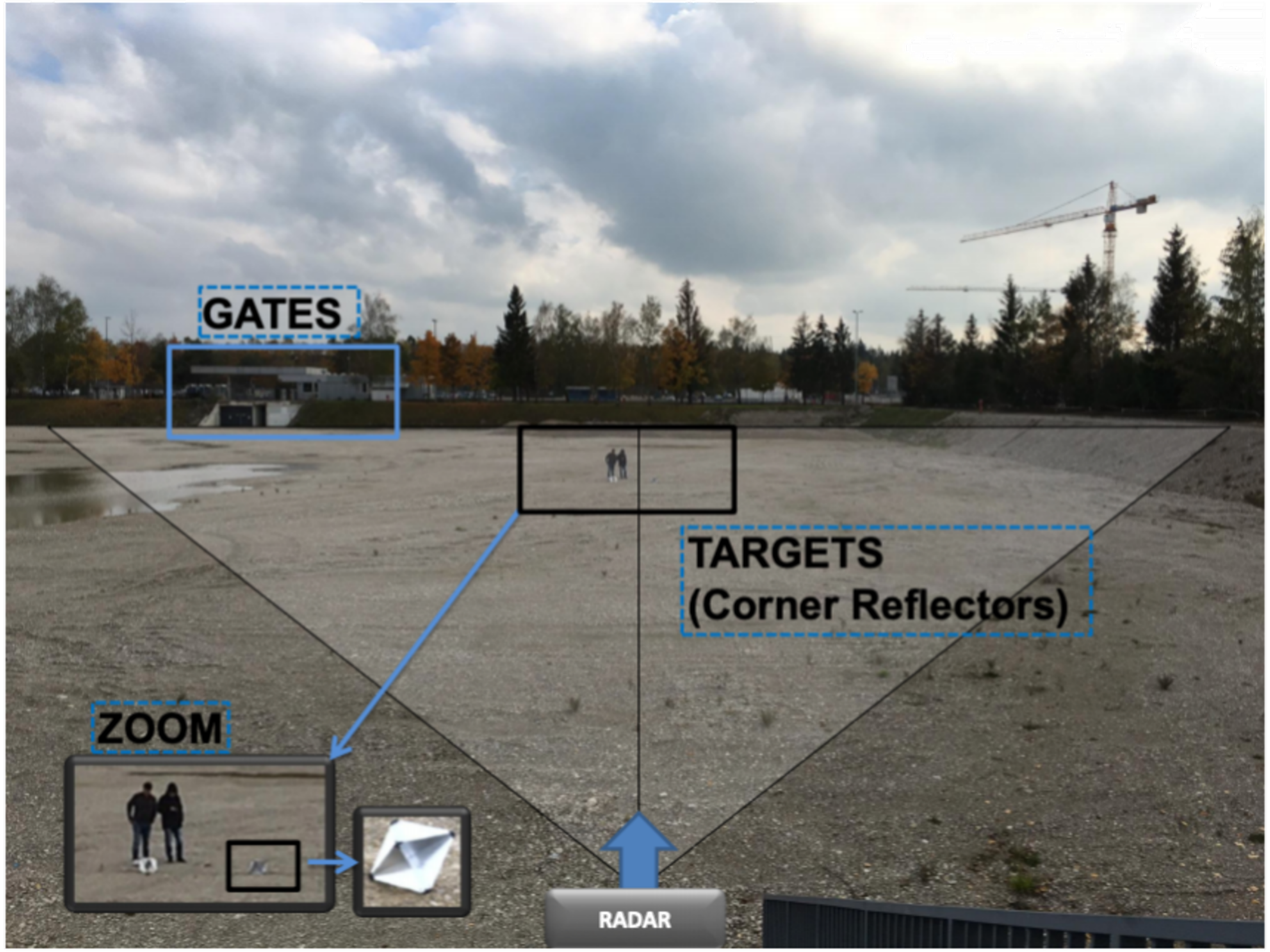
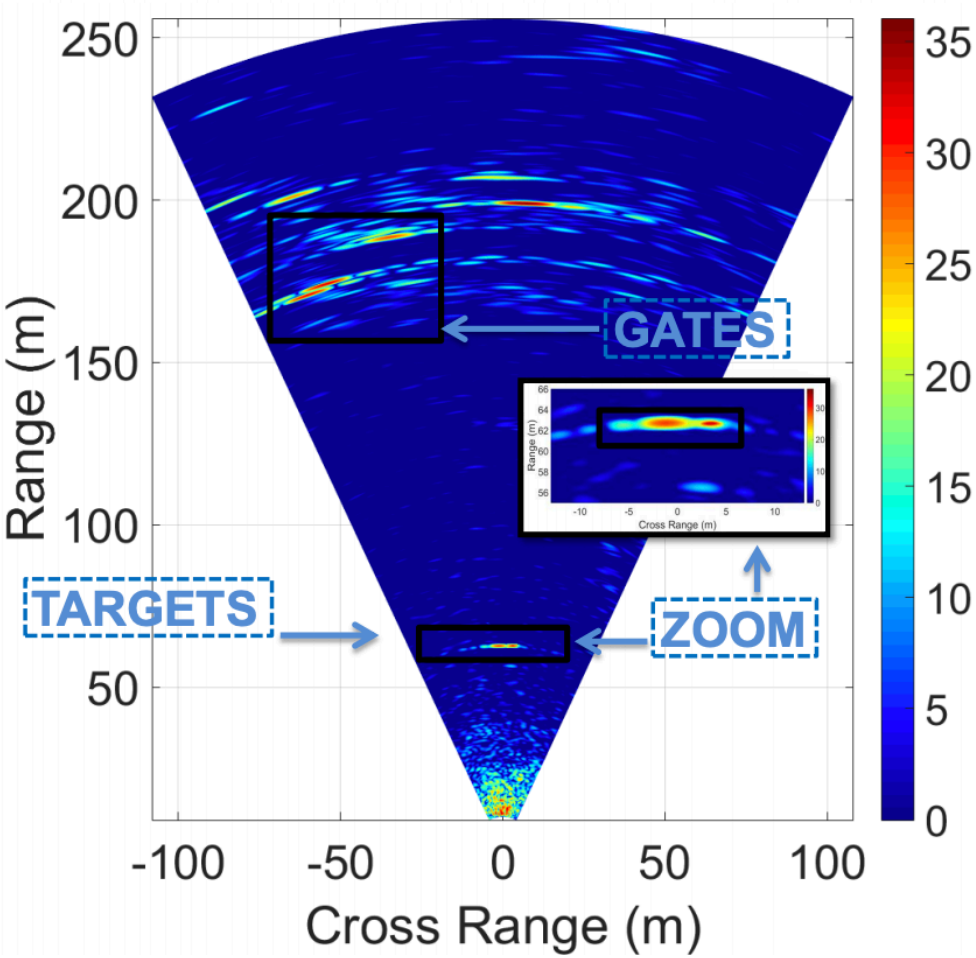




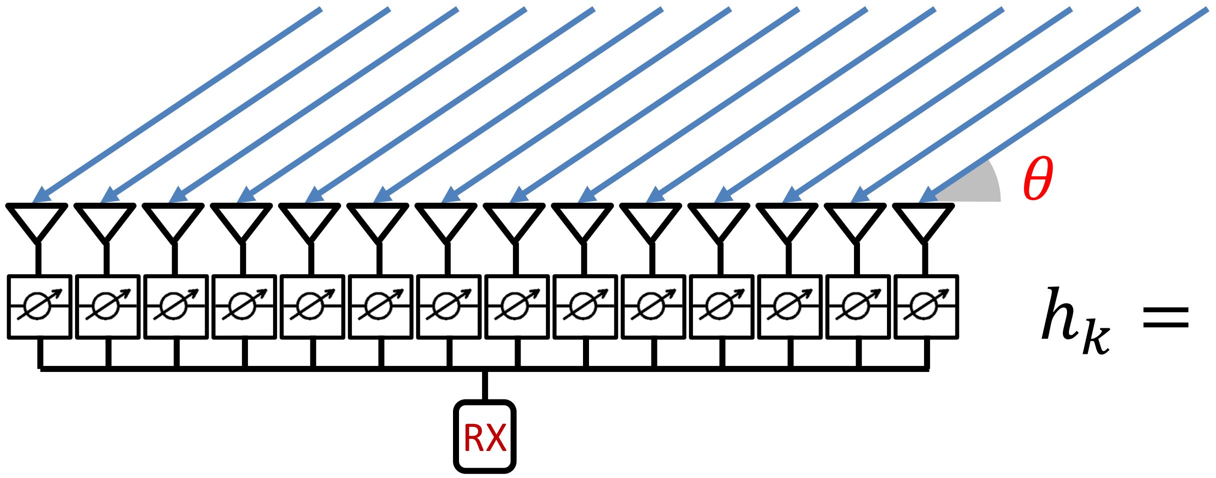
Analog Phased Arrays



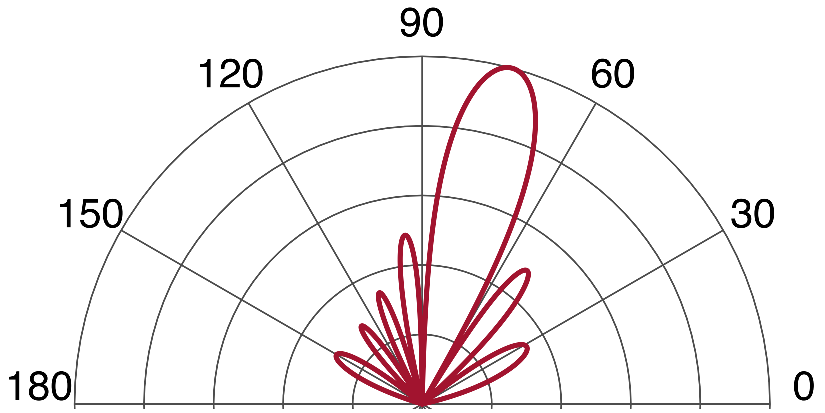


Ganis, A.; Miralles-Navarro, E.; Schoenlinner, B.; Prechtel, U.; Meusling, A.; Heller, C.; Spreng, T.... (2018). A portable 3D Imaging FMCW MIMO Radar Demonstrator with a 24x24 Antenna Array for Medium Range Applications. IEEE Transactions on Geoscience and Remote Sensing. 56(1):298-312. https://doi.org/10.1109/TGRS.2017.2746739

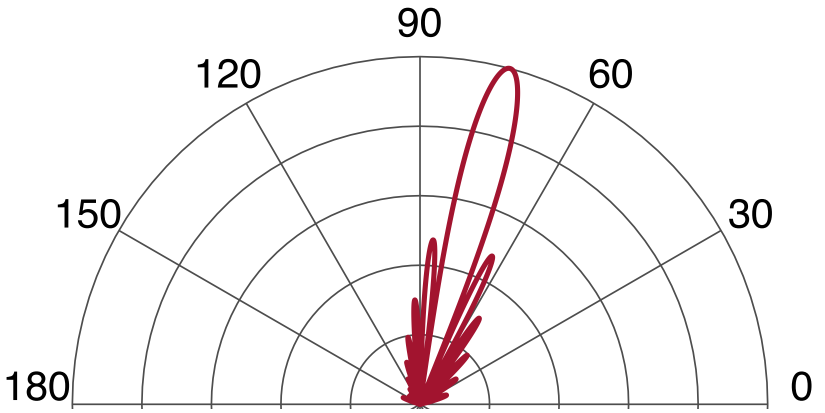
Analog Phased Arrays



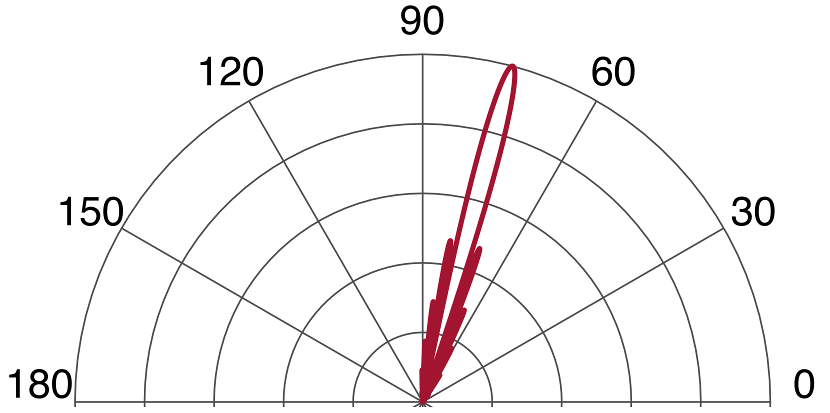
$$h_k = \alpha e^{-j2\pi\frac{d-k\,s\cos\theta}{\lambda}}$$



8 Antenna



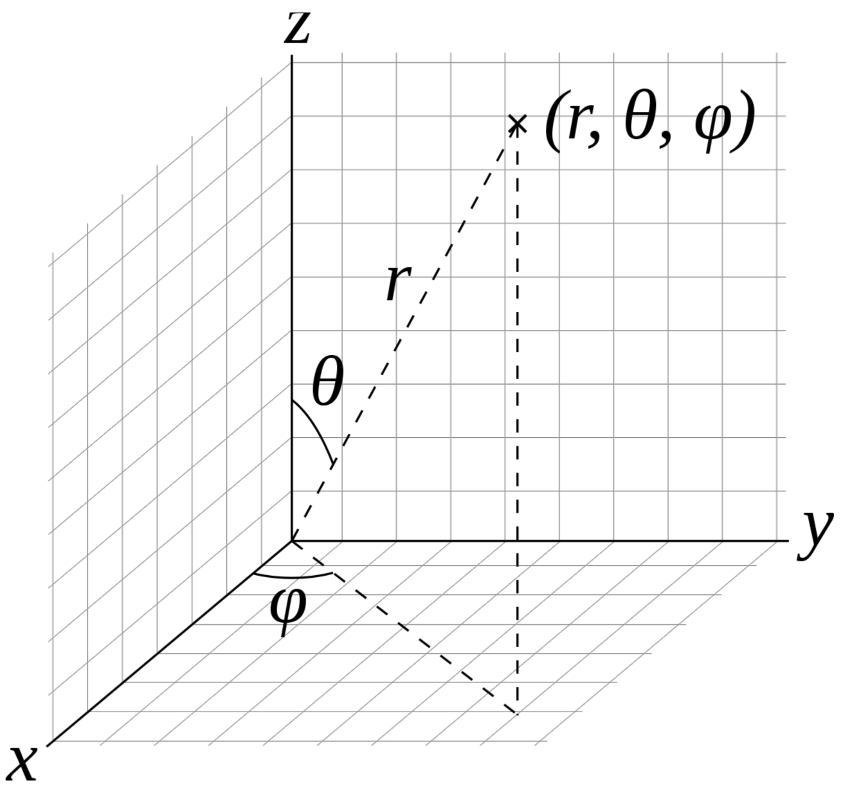
16 Antenna

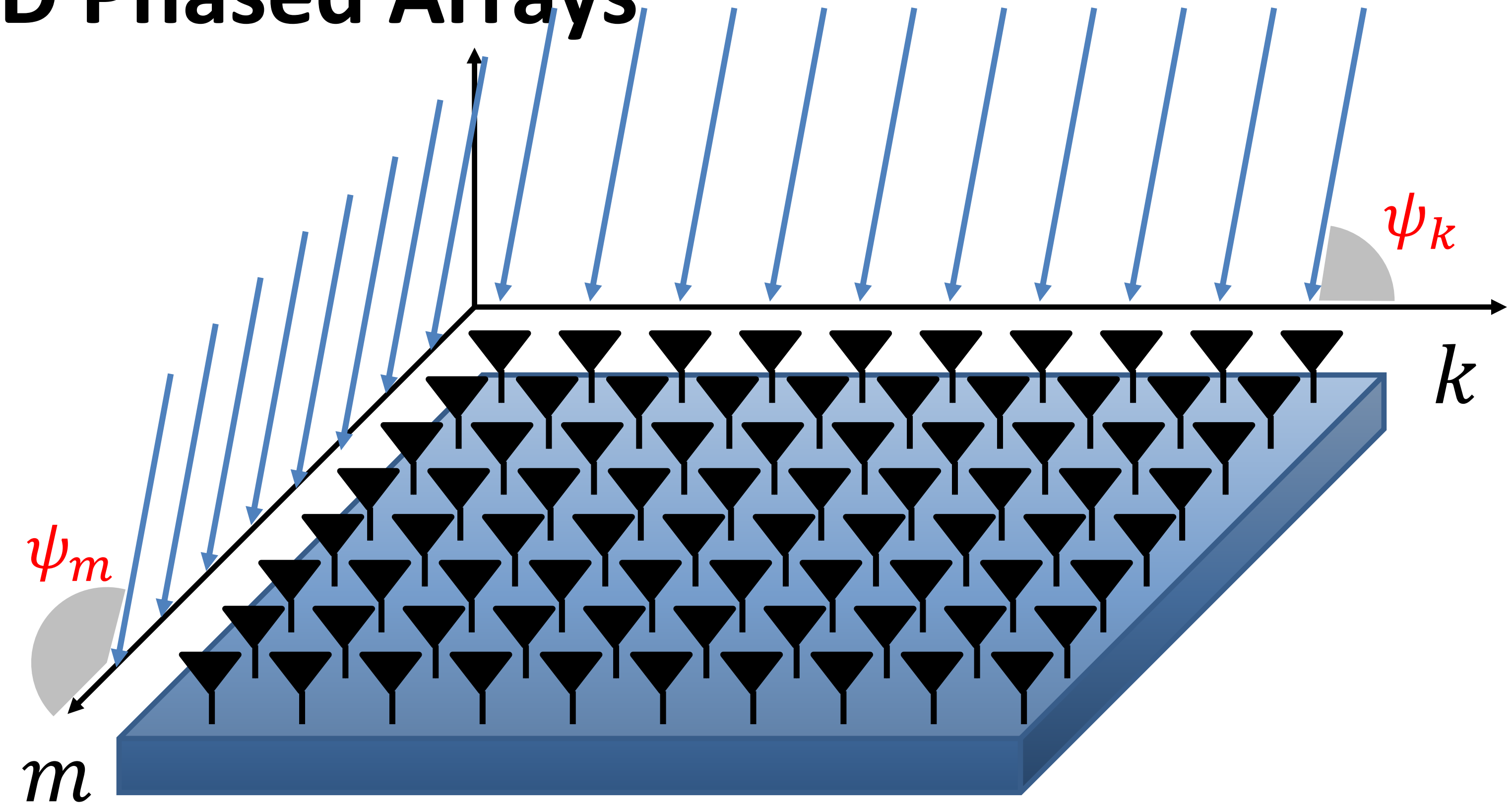


32 Antenna

Larger Array → Narrower Beams → Higher Resolution

2D Phased Arrays





Can recover:

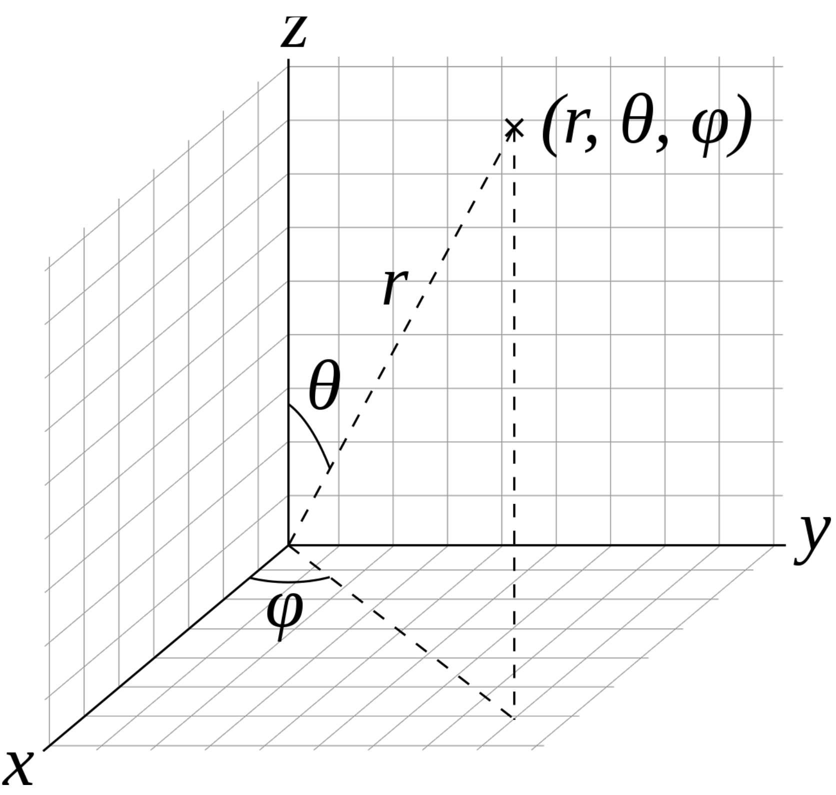
- Range: r
- Azimuth AoA: φ
- Elevation AoA: θ

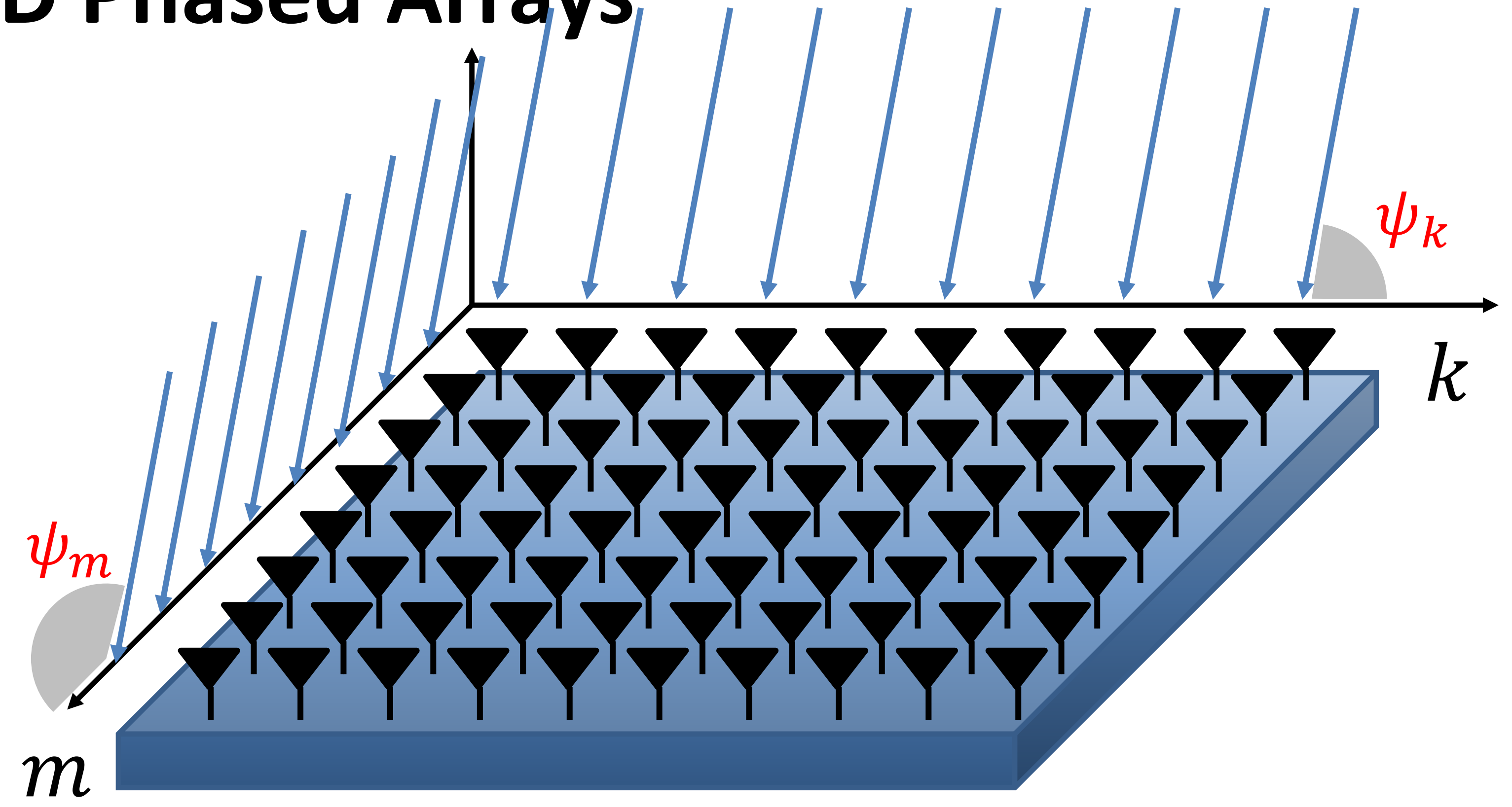
$$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r+f(m)+f(k))}$$

Fix m: $$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r+f(m)+ks\cos\psi_k)}$$

Fix k: $$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r+ms\cos\psi_m+ks\cos\psi_k)}$$

2D Phased Arrays





$$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r+ms\cos\psi_m+ks\cos\psi_k)}$$

$$\cos\psi_m = \sin\theta\cos\varphi$$

$$\cos\psi_k = \sin\theta\sin\varphi$$

Can recover:

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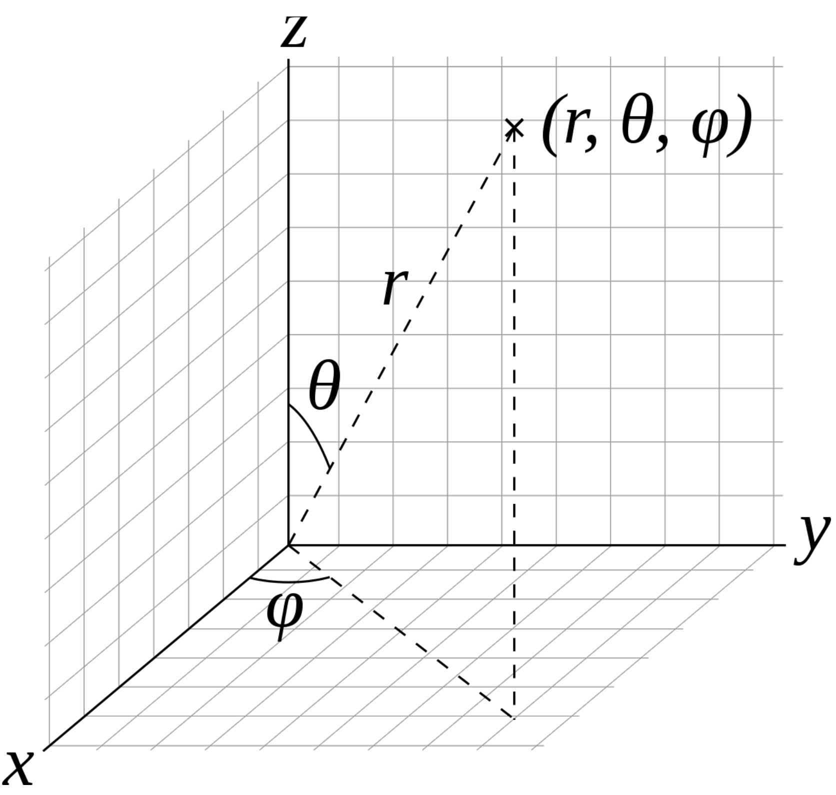
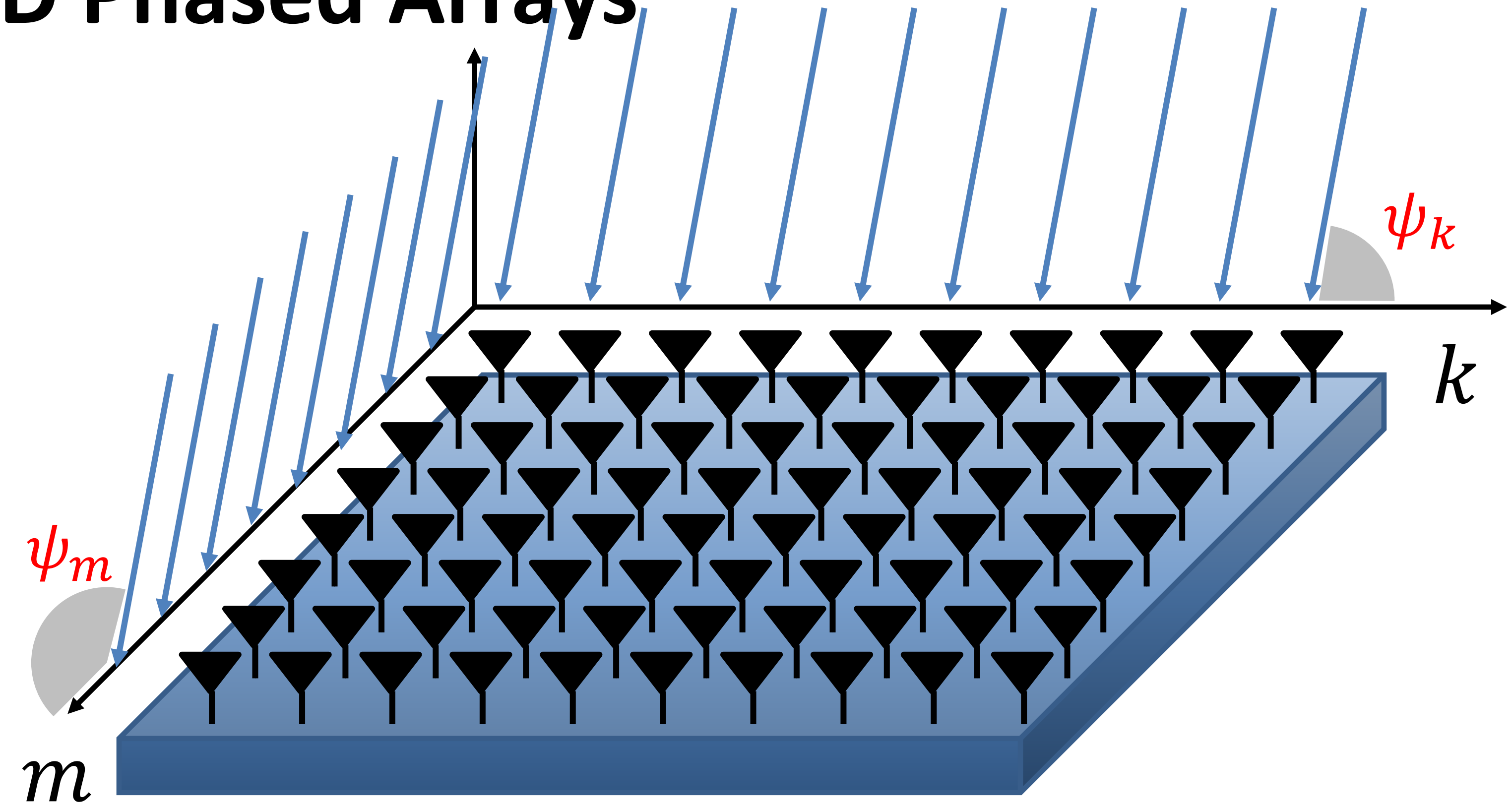
2D Phased Arrays





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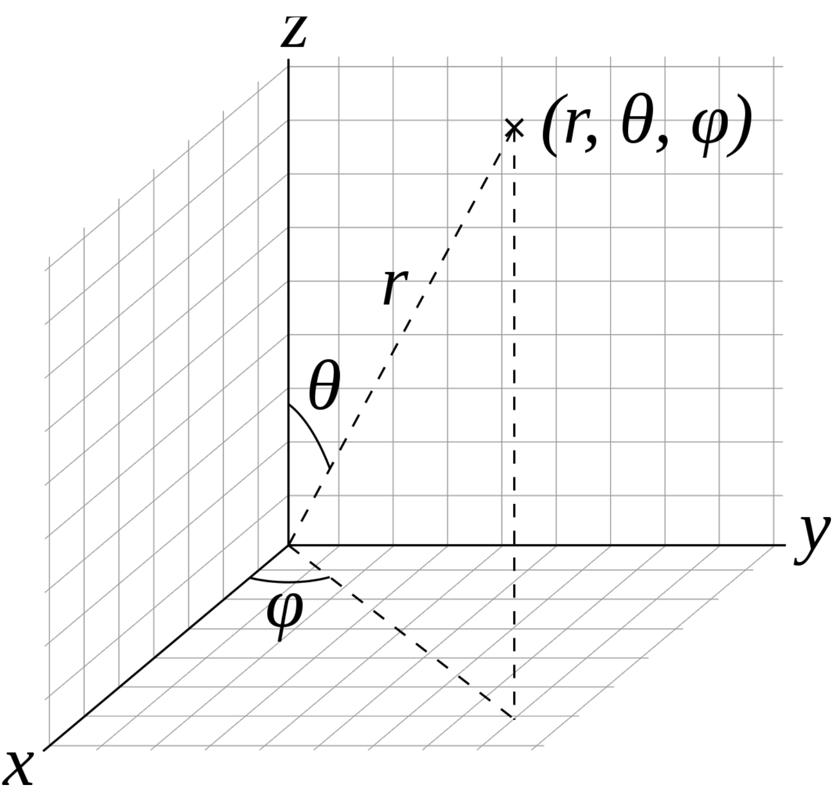
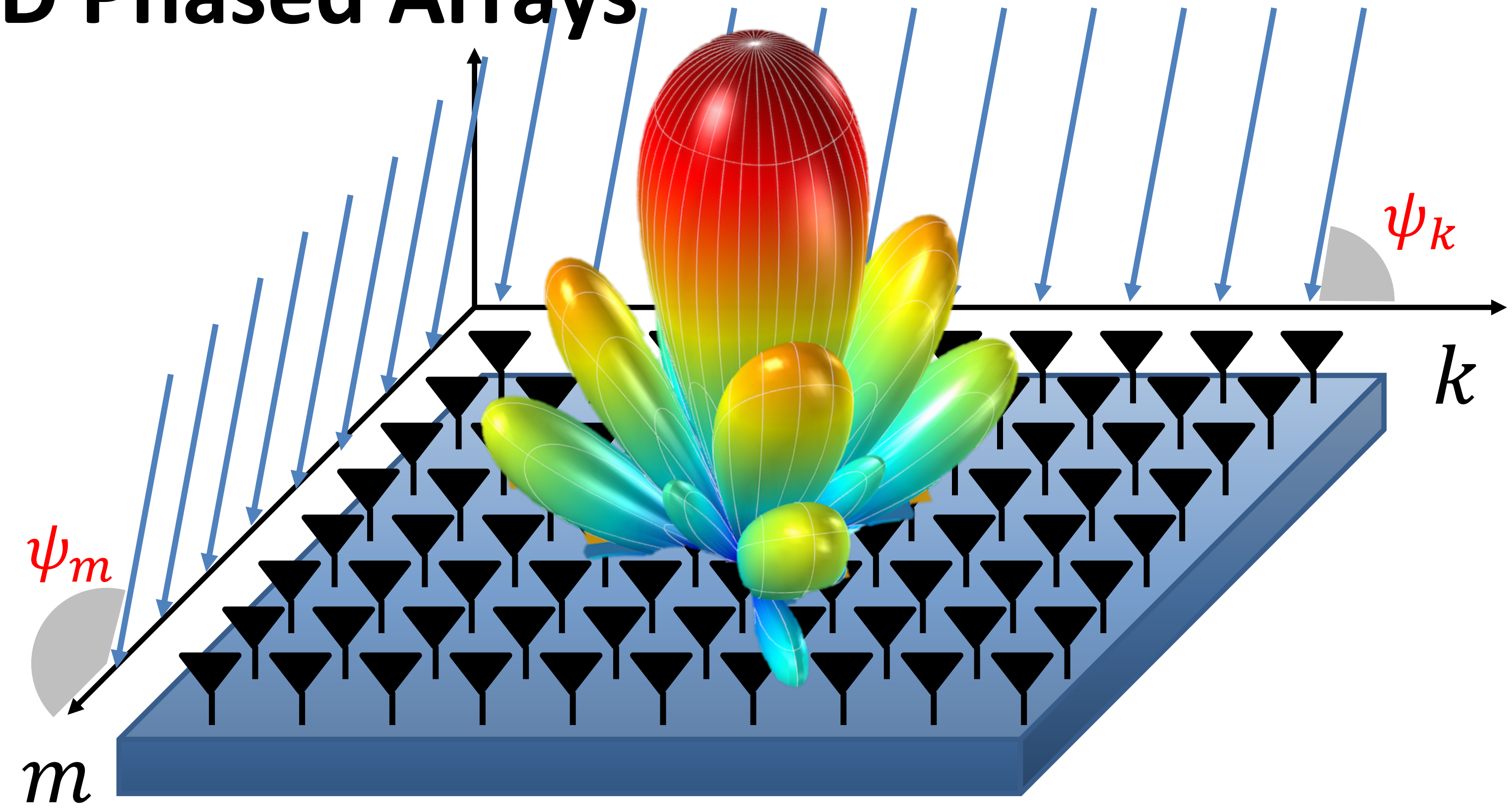
$$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r+ms\sin\theta\cos\varphi+ks\sin\theta\sin\varphi)}$$

2D Phased Arrays





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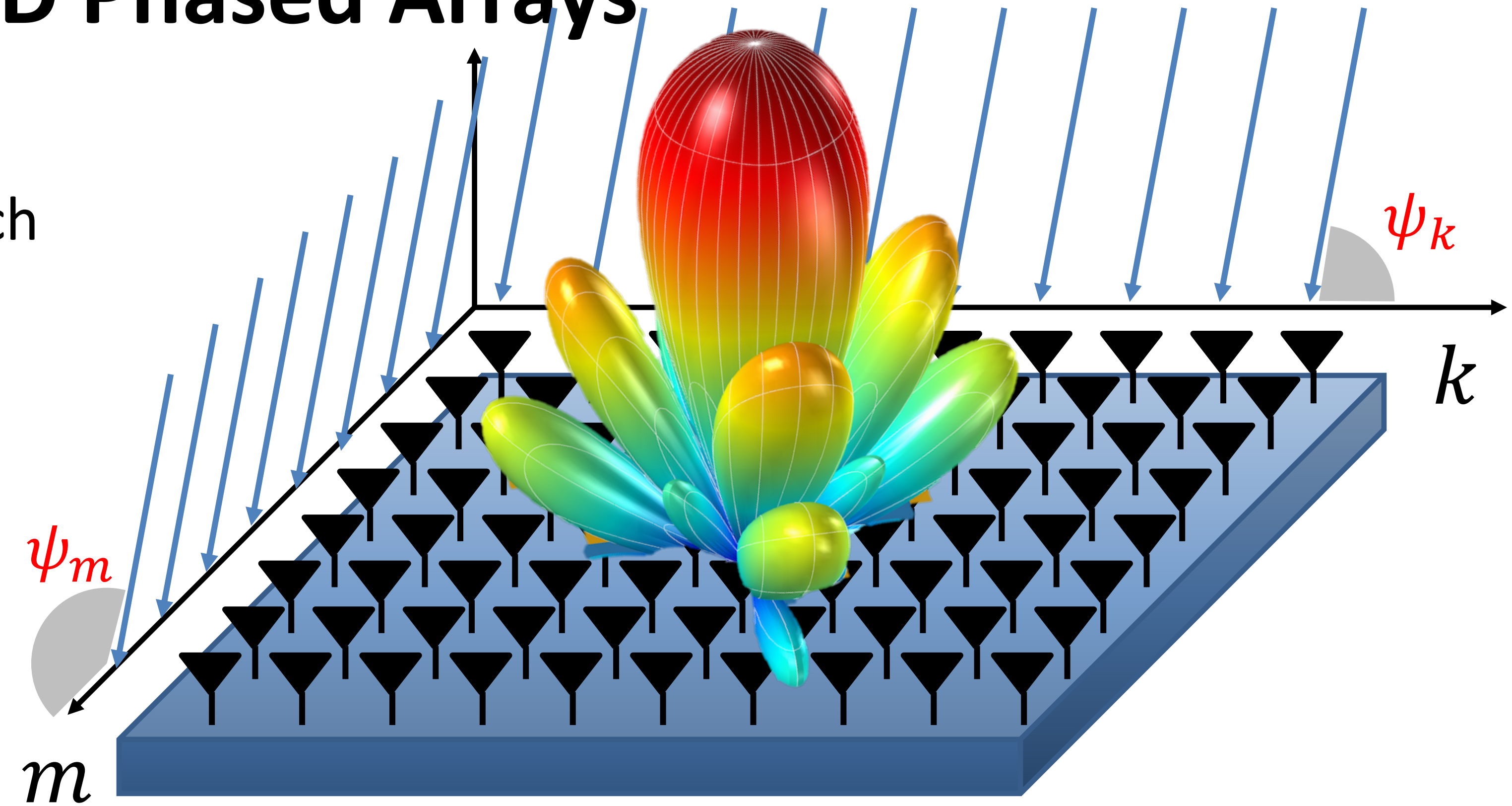
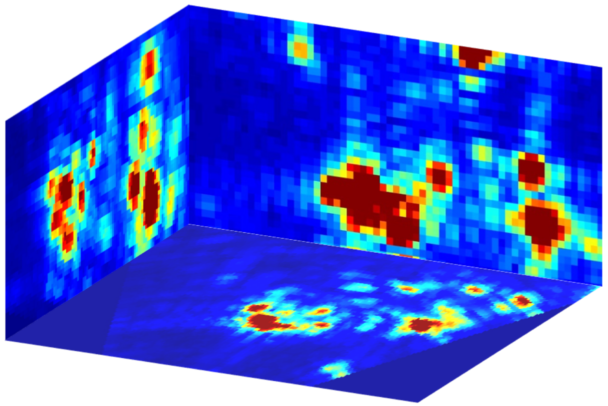
$$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r+ms\sin\theta\cos\varphi+ks\sin\theta\sin\varphi)}$$

2D Phased Arrays

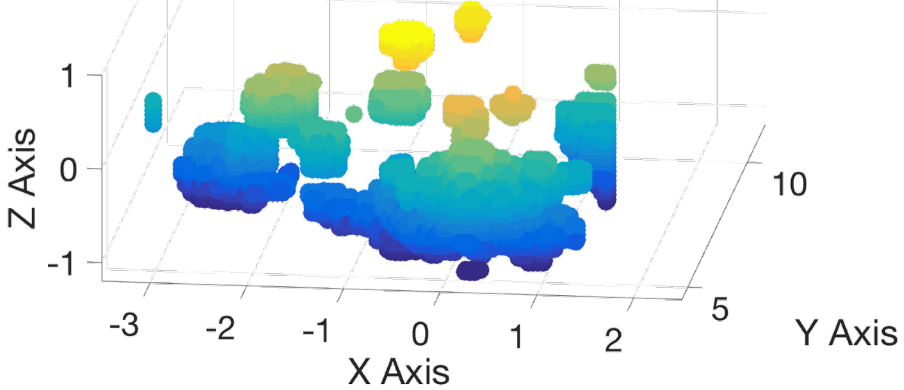
1) Pick the phase shift on each antenna to create a beam in each 3D direction.
2) Transmit FMCW signals and receive reflections.
3) Mix RX signal with TX and take range FFT .
4) Repeat in every direction.



3D Heatmap Image

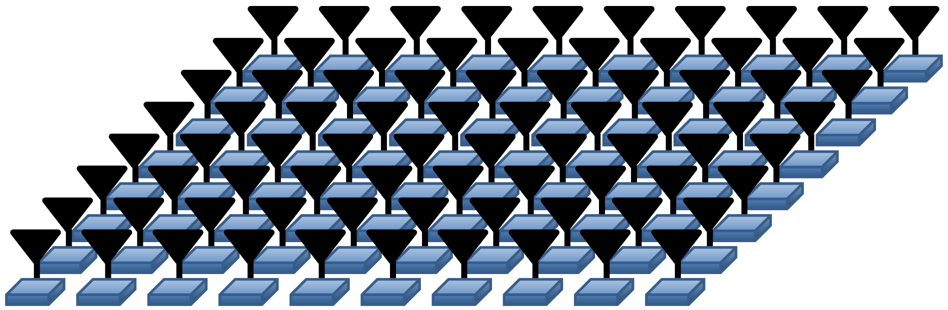


3D Point Cloud



Phased Arrays Primer

Digital Phased Arrays



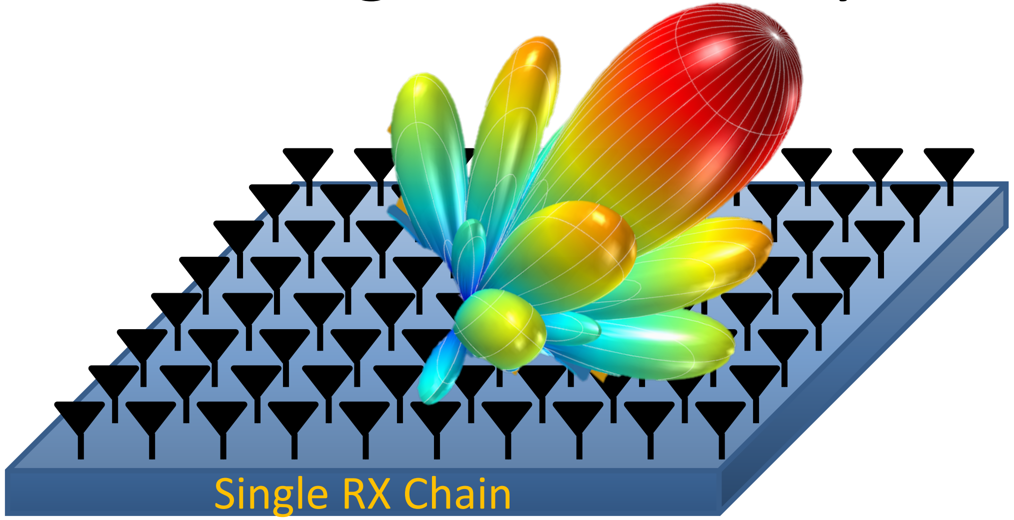
$N \times N$ RX Chains

Could Potentially Do the Same thing:

1) Mix the RX signal with TX.
2) Multiply the resulting signal on each antenna with $e^{j\phi_{m,k}}$ and sum the signals.
3) Compute Range FFT.
4) Repeat in every direction.

$$(N \times N \times T + T \log T) \times N \times N = O(N^4 T + N^2 T \log T)$$

Analog Phased Arrays



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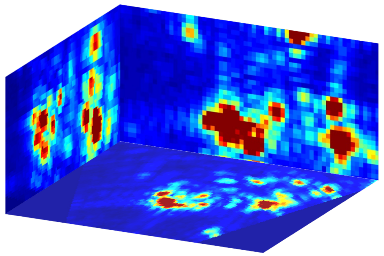
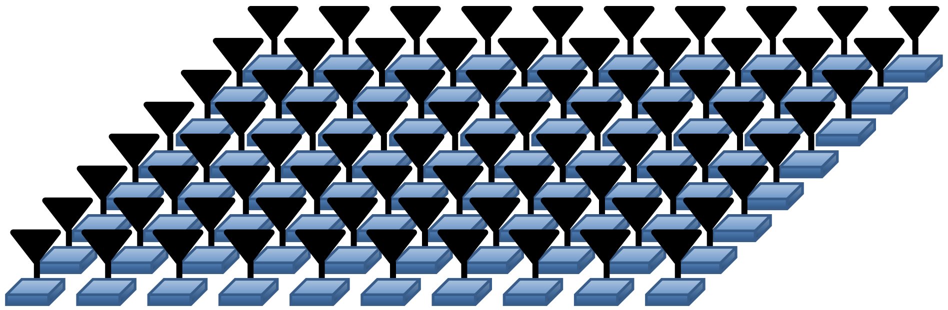
3D Heatmap Image



Phased Arrays Primer

Digital Phased Arrays



$N\times N$ **RX Chains**

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3) Compute Range FFT.

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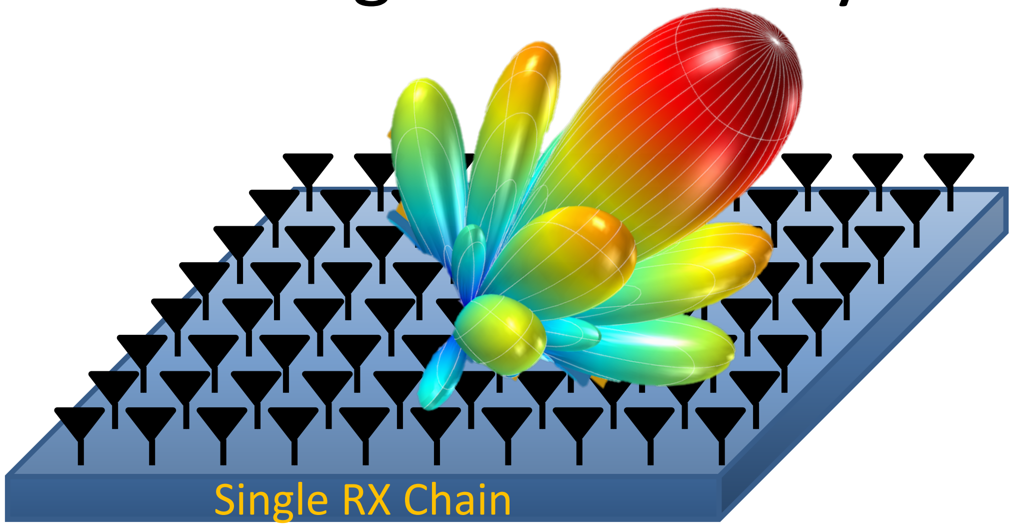
4) Repeat in every direction.

$$N\times N\times T\log T + N\times N\times T\times N\times N = O(N^4T + N^2T\log T)$$

Analog Phased Arrays



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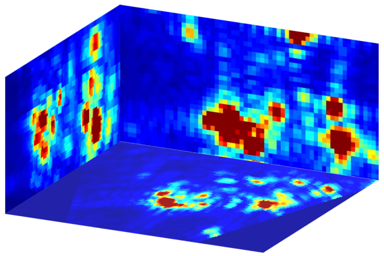
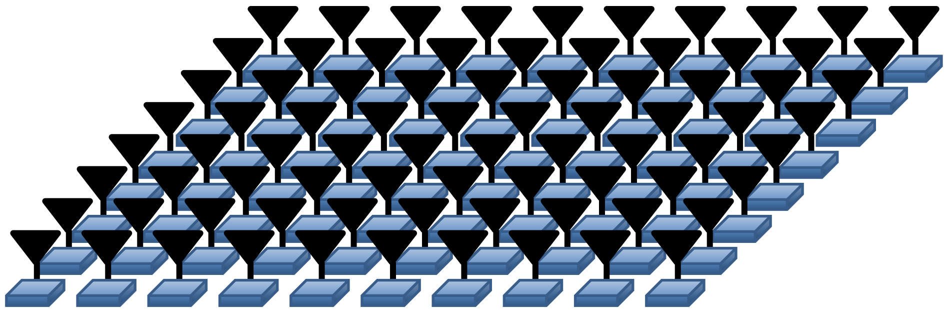
4) Repeat in every direction.

3D Heatmap Image



Phased Arrays Primer

Digital Phased Arrays



$N \times N$ **RX Chains**

Algorithm 1: $O(N^4 T + N^2 T \log T)$

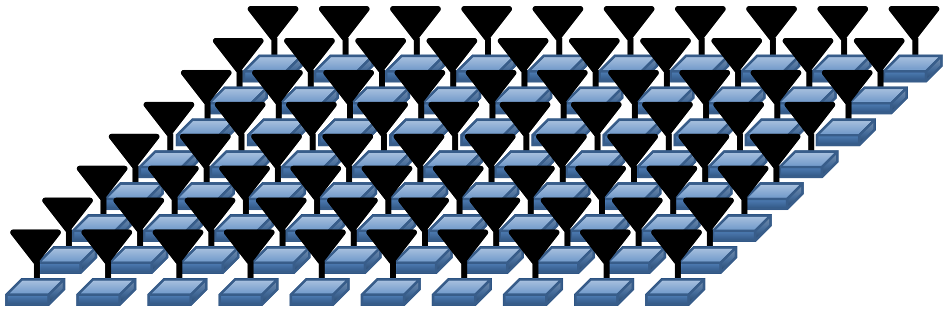
1) Mix the RX signal with TX.
3) Compute Range FFT.
2) Multiply the resulting signal on each antenna with $e^{j\phi_{m,k}}$ and sum the signals.
4) Repeat in every direction.

Algorithm 2: (Faster) **IDEA: antenna arrays are Fourier Transforms**

$$h_{m,k} = \alpha e^{-j\frac{2\pi}{\lambda}(r + ms \sin\theta \cos\varphi + ks \sin\theta \sin\varphi)}$$

Phased Arrays Primer

Digital Phased Arrays



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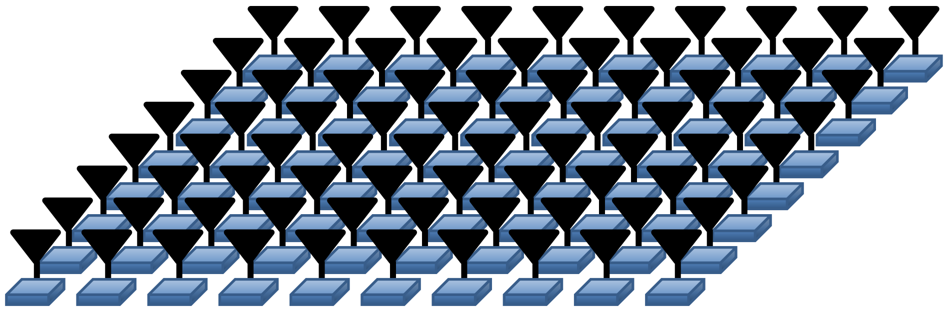
$$h(x,y) = \sum_{f_x} \sum_{f_y} P(f_x, f_y) e^{-j2\pi(xf_x + yf_y)}$$

Use 2D FFT

$$\boxed{\begin{aligned} f_x &= sin(\theta_l)cos(\phi_l), \\ f_y &= sin(\theta_l)sin(\phi_l), \\ x &= ms/\lambda, \\ y &= ks/\lambda \\ P(f_x, f_y) &= \alpha_l e^{-j\frac{2\pi r_l}{\lambda}} \end{aligned}}$$

Phased Arrays Primer

Digital Phased Arrays



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Algorithm 2: (Faster) **IDEA: antenna arrays are Fourier Transforms**

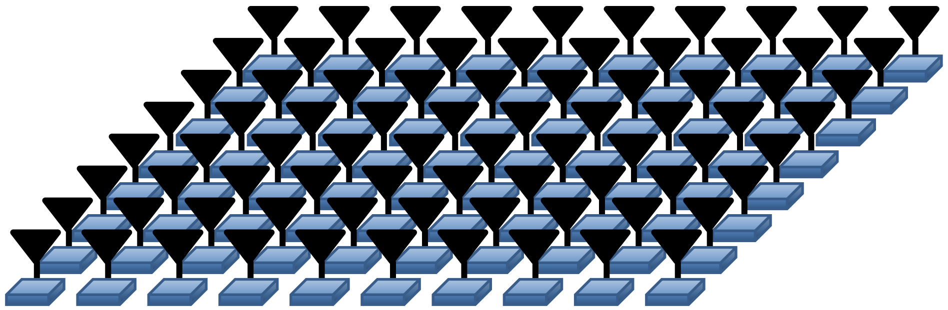
1) Mix the RX signal with TX.

$$\left.\begin{array}{l}\text{2) Compute 2D FFT across antennas}\\ \text{3) Compute Range FFT.}\end{array}\right\}\ \textbf{3D FFT}$$

$$N^2 \log N^2 \times T + N \times N \times T \log T = O(N^2 T \log NT)$$

Phased Arrays Primer

Digital Phased Arrays



$N \times N$ **RX Chains**

Algorithm 3: (More Accurate)

Algorithm 1: $O(N^4 T + N^2 T \log T)$

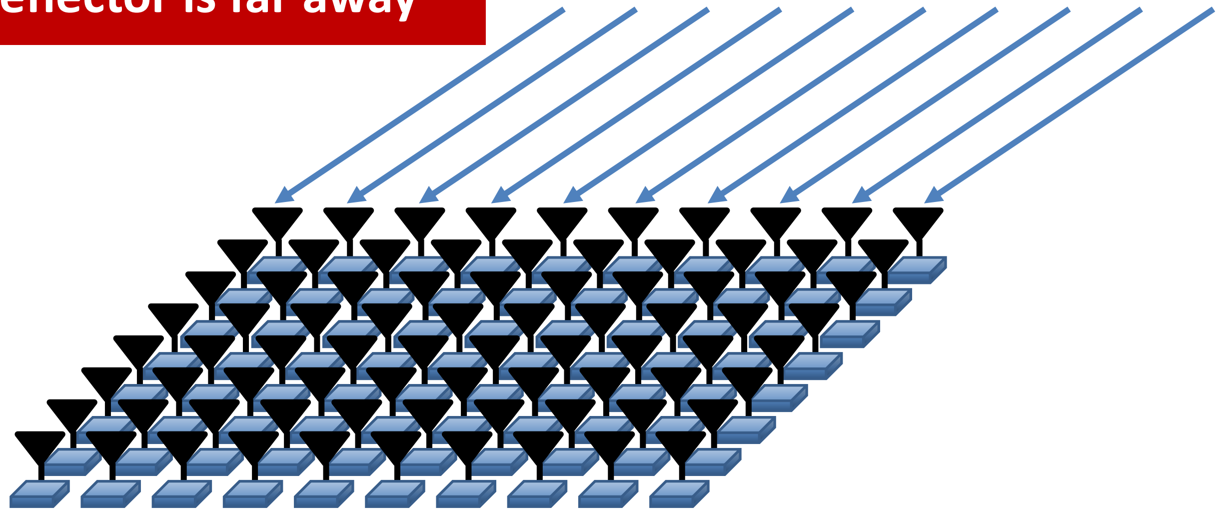
1) Mix the RX signal with TX.
3) Compute Range FFT.
2) Multiply the resulting signal on each antenna with $e^{j\phi_{m,k}}$ and sum the signals.
4) Repeat in every direction.

Algorithm 2: (Faster) $O(N^2 T \log NT)$ **3D FFT**

1) Mix the RX signal with TX.
2) Compute 2D FFT across antennas
3) Compute Range FFT.

Phased Arrays Primer

Assumes parallel waves
Reflector is far away



$N \times N$ RX Chains

Algorithm 3: (More Accurate)

Phased Arrays Primer

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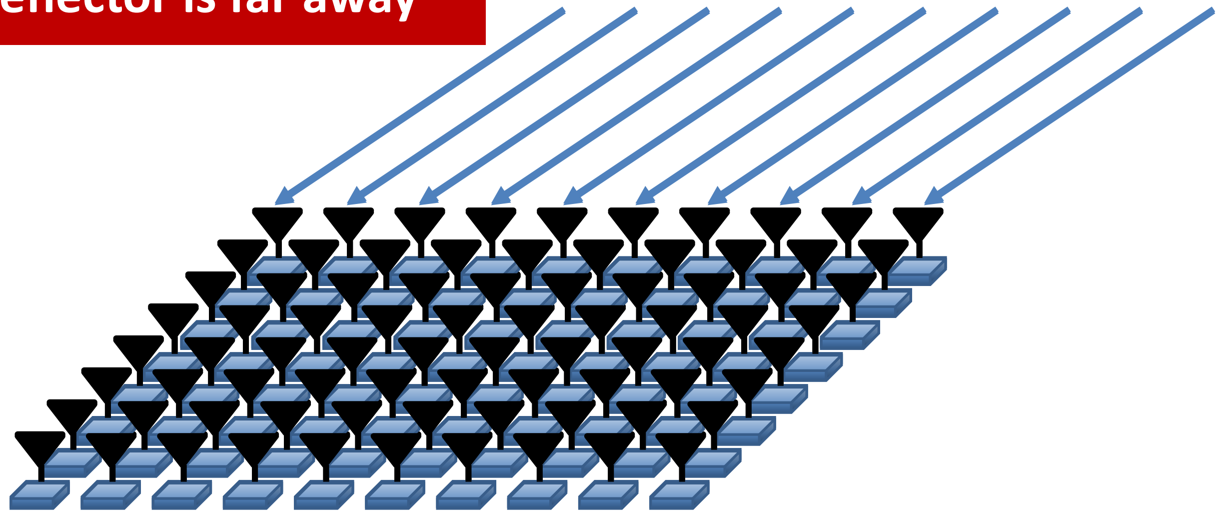
Reflector is far away



$N \times N$ RX Chains

Algorithm 3: (More Accurate)

Phased Arrays Primer

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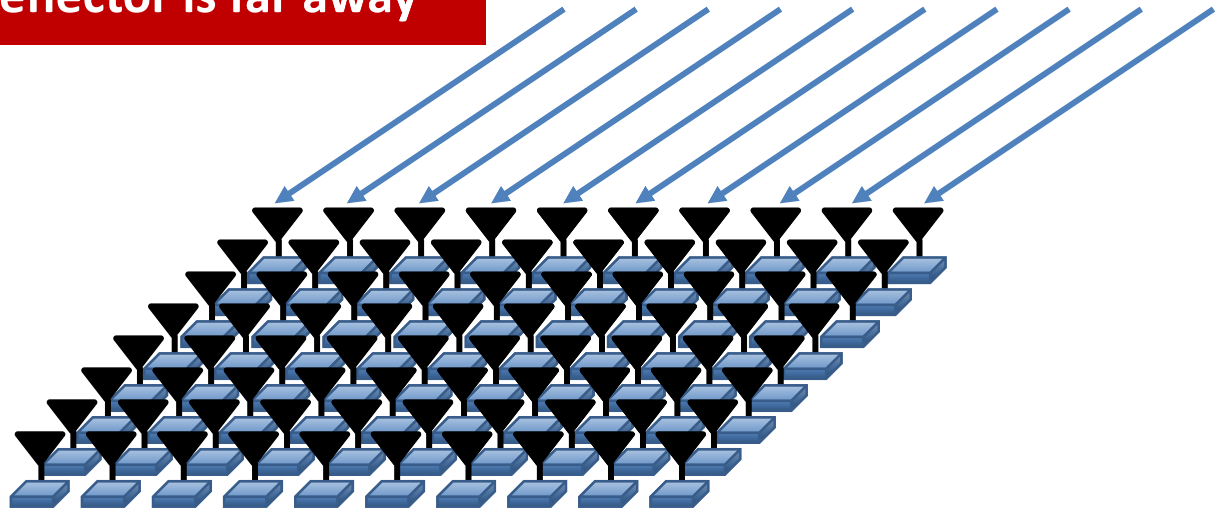
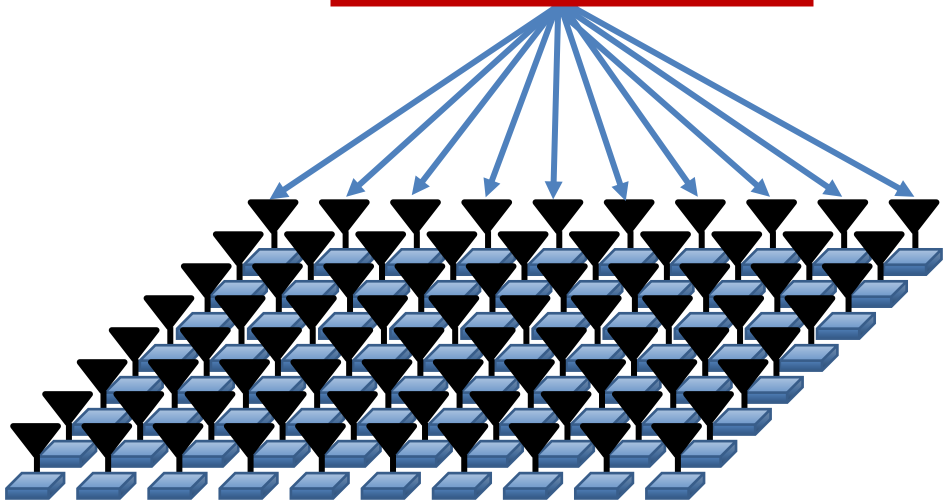


$N\times N$ **RX Chains**

Reflector is not far



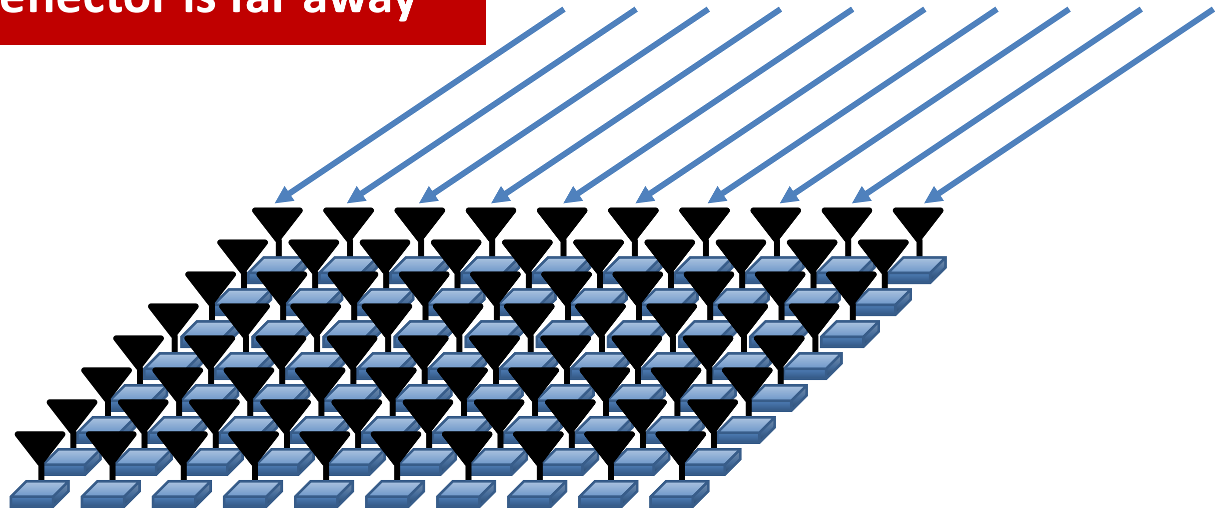
$N\times N$ **RX Chains**

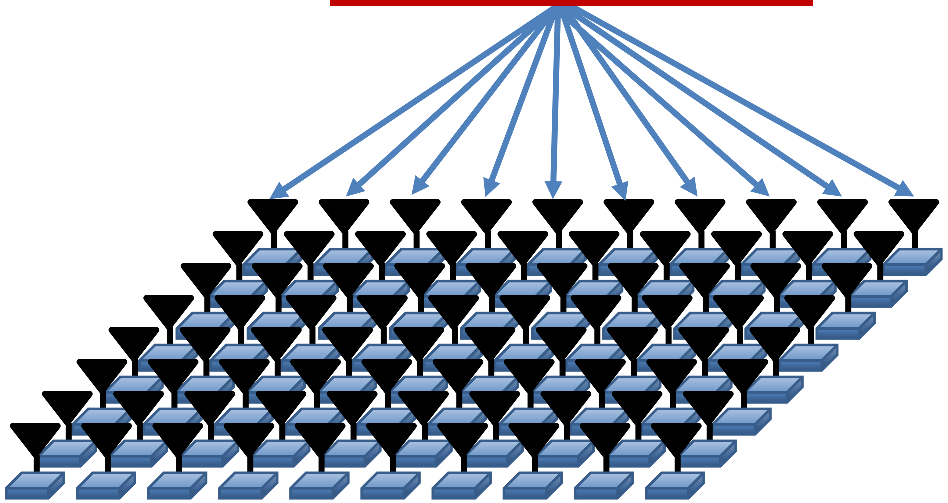
Algorithm 3: (More Accurate) **IDEA: use the exact equation**

$$s_{m,k}(t) = \alpha_l e^{-j2\pi(k\tau_l t + f_0\tau_l)} = \alpha_l e^{-j2\pi(k2d_l t/c + 2d_l/\lambda)}$$

Received FMCW signal from reflector l after mixing with TX

Phased Arrays Primer





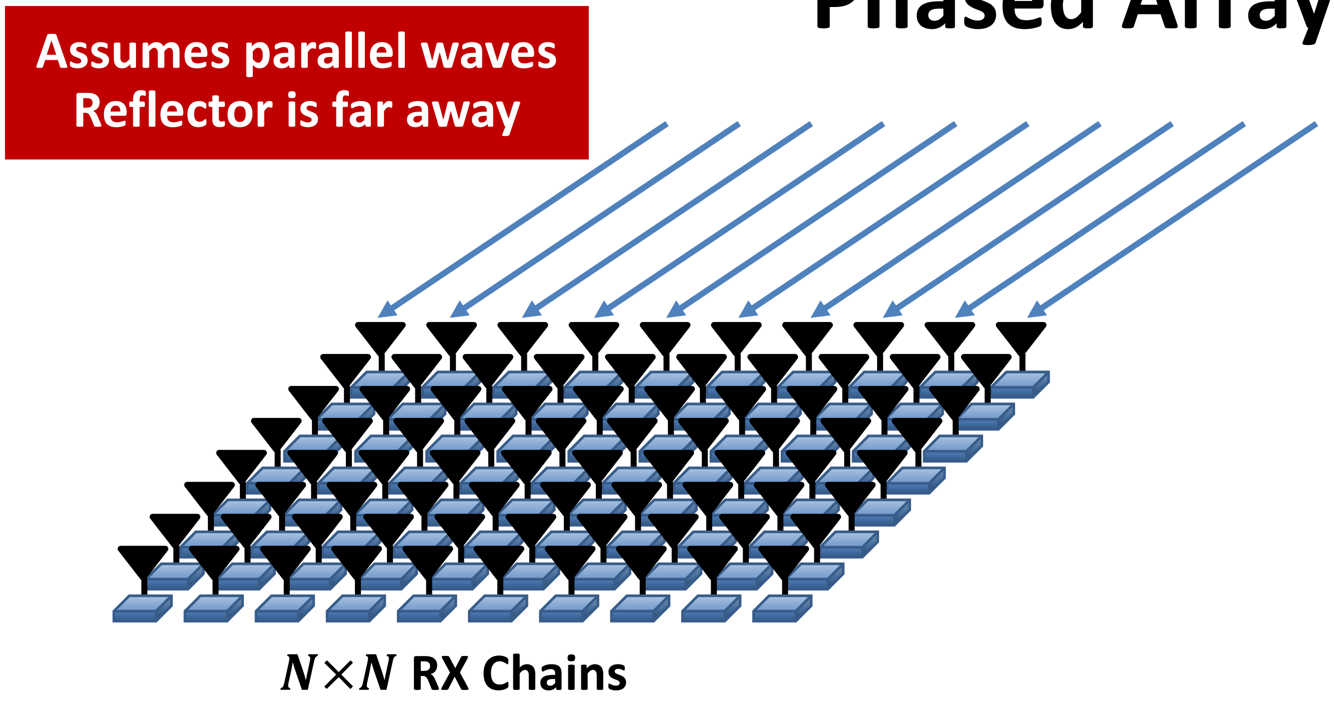
Assume antenna 0,0 at origin
$x_{m,k} = ms, y_{m,k} = ks, z_{m,k} = z_c$

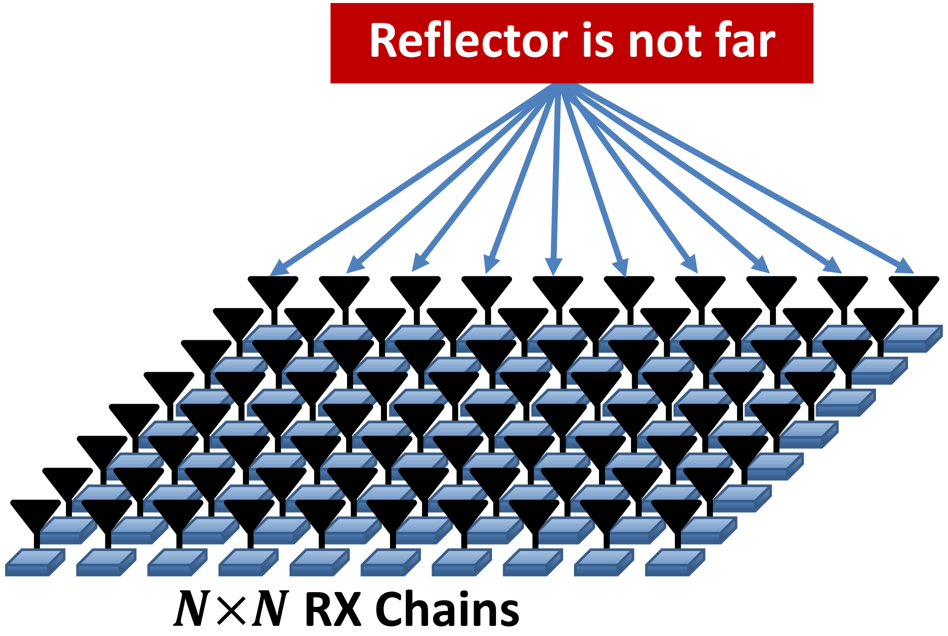
Algorithm 3: (More Accurate) **IDEA: use the exact equation**

$$s_{m,k}(t) = \alpha_l e^{-j2\pi(k\tau_l t + f_0\tau_l)} = \alpha_l e^{-j2\pi(k2d_l t/c + 2d_l/\lambda)}$$

$$d_l = \sqrt{(x_l - x_{m,k})^2 + (y_l - y_{m,k})^2 + (z_l - z_{m,k})^2} = \sqrt{(x_l - ms)^2 + (y_l - ks)^2 + (z_l - z_c)^2}$$

Phased Arrays Primer





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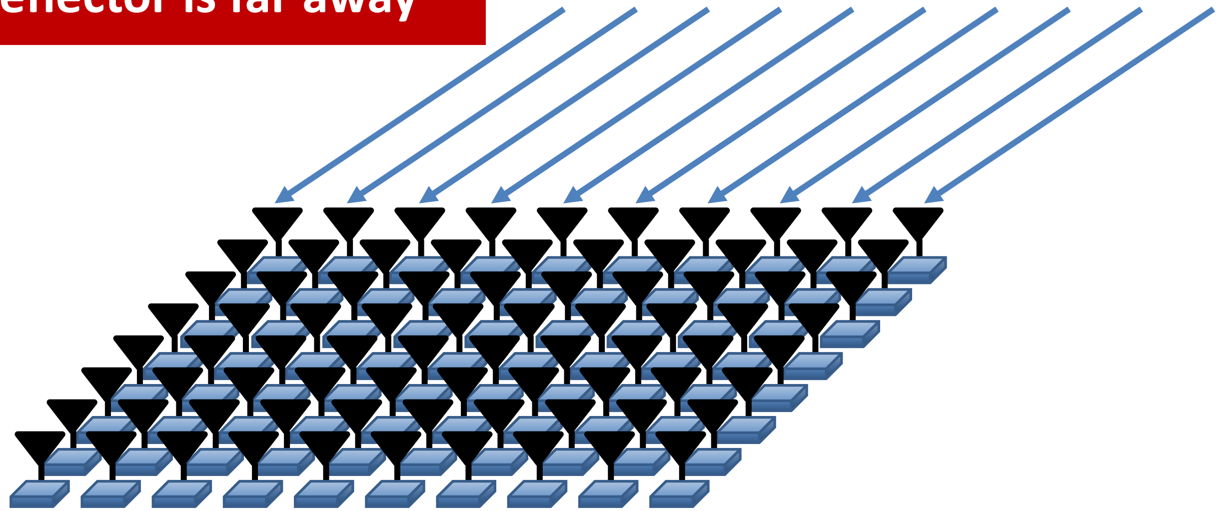
$$= \alpha_l e^{-j4\pi(kt/c + 1/\lambda)\sqrt{(x_l - ms)^2 + (y_l - ks)^2 + (z_l - z_c)^2}}$$

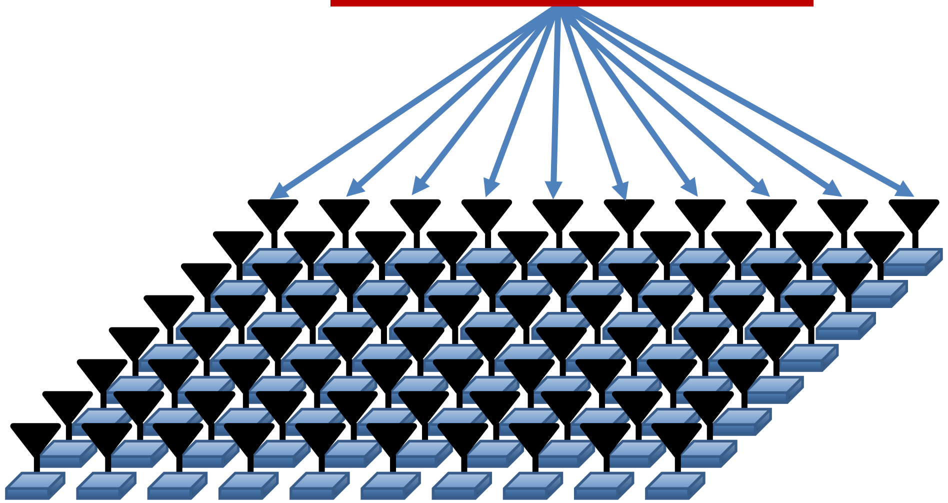
Phased Arrays Primer

Assumes parallel waves
Reflector is far away



$N\times N$ **RX Chains**

Reflector is not far



$N\times N$ **RX Chains**

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$$= \sum_l \alpha_l e^{-j4\pi(kt/c+1/\lambda)\sqrt{(x_l - ms)^2 + (y_l - ks)^2 + (z_l - z_c)^2}}$$

Phased Arrays Primer

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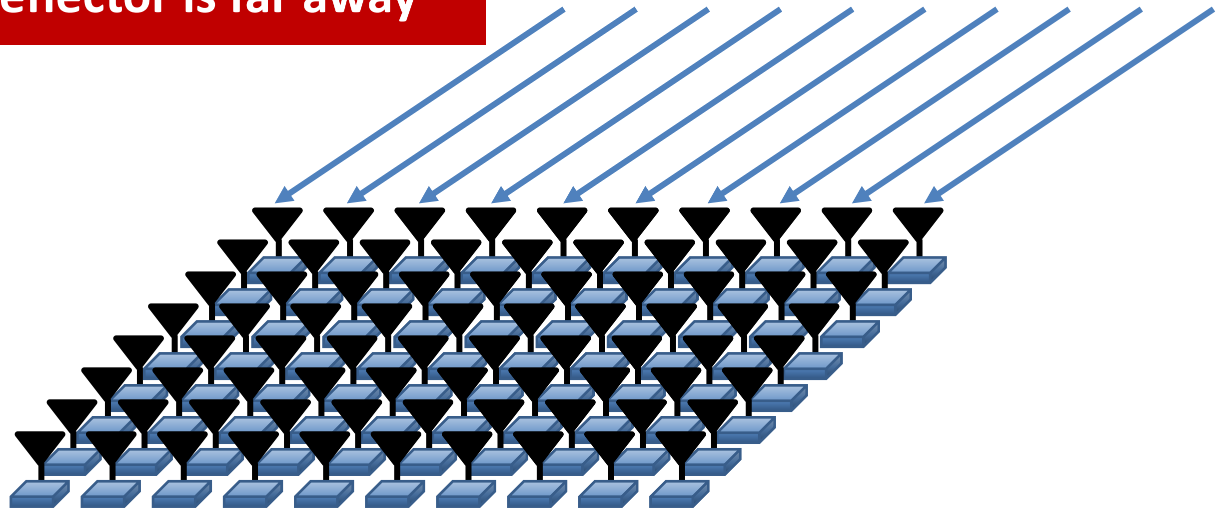
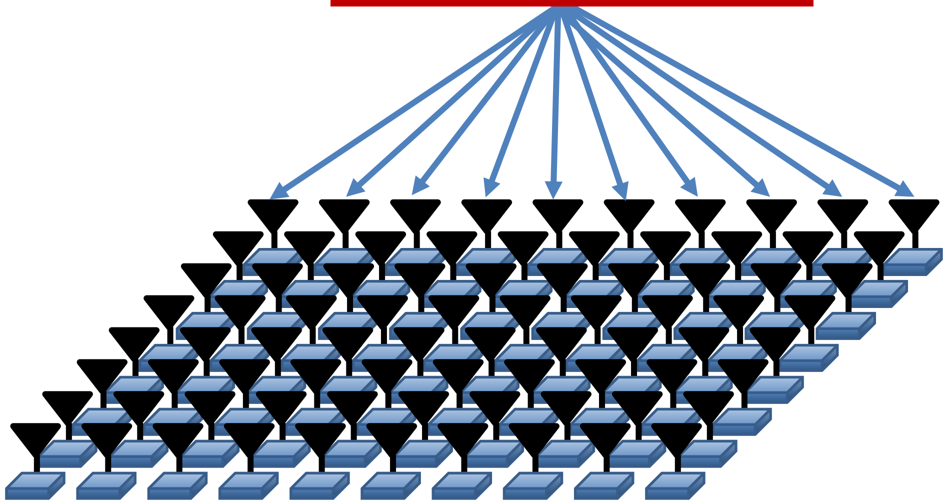


$N \times N$ **RX Chains**

Reflector is not far



$N \times N$ **RX Chains**

Assume antenna 0,0 at origin

$x_{m,k} = ms, y_{m,k} = ks, z_{m,k} = z_c$

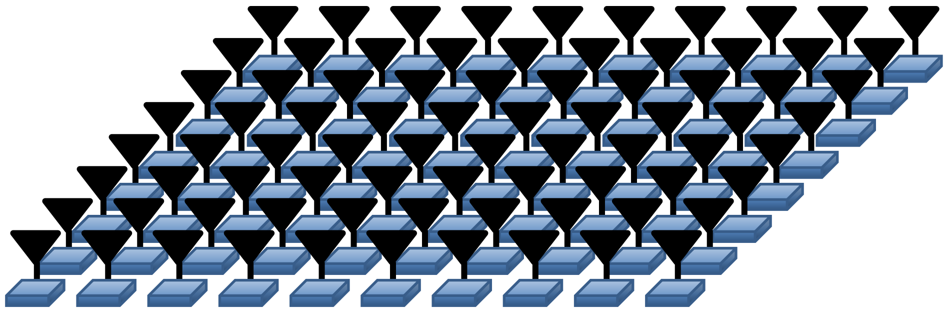
Algorithm 3: (More Accurate) **IDEA: use the exact equation**

$$s_{m,k}(t) = \sum_{l} \alpha_l e^{-j4\pi(kt/c+1/\lambda)\sqrt{(x_l - ms)^2 + (y_l - ks)^2 + (z_l - z)^2}}$$

$$P(x,y,z) = \sum_{m}\sum_{k}\sum_{t} s_{m,k}(t) \times e^{j4\pi(kt/c+1/\lambda)\sqrt{(x - ms)^2 + (y - ks)^2 + (z - z_c)^2}} = N^2 T \alpha_l$$

Phased Arrays Primer

Digital Phased Arrays



$N{\times}N$ **RX Chains**

Algorithm 3: (More Accurate) $O(L^3N^2T) = o(N^5T)$

1) Descritize space into $L{\times}L{\times}L$ grid.
2) For each point in space compute the received signal using the below equation.

$$P(x,y,z) = \sum_m \sum_k \sum_t s_{m,k}(t) \times e^{j4\pi(kt/c+1/\lambda)\sqrt{(x-ms)^2+(y-ks)^2+(z-z_c)^2}}$$

Algorithm 1: $O(N^4T + N^2T\log T)$

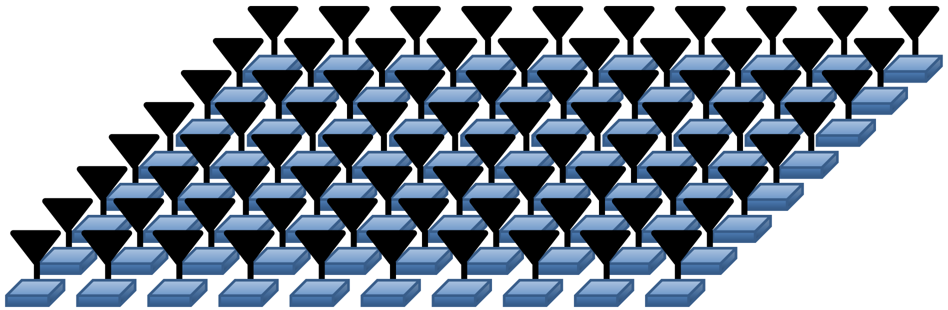
1) Mix the RX signal with TX.
3) Compute Range FFT.
2) Multiply the resulting signal on each antenna with $e^{j\phi_{m,k}}$ and sum the signals.
4) Repeat in every direction.

Algorithm 2: (Faster) $O(N^2T\log NT)$ **3D FFT**

1) Mix the RX signal with TX.
2) Compute 2D FFT across antennas
3) Compute Range FFT.

Phased Arrays Primer

Digital Phased Arrays



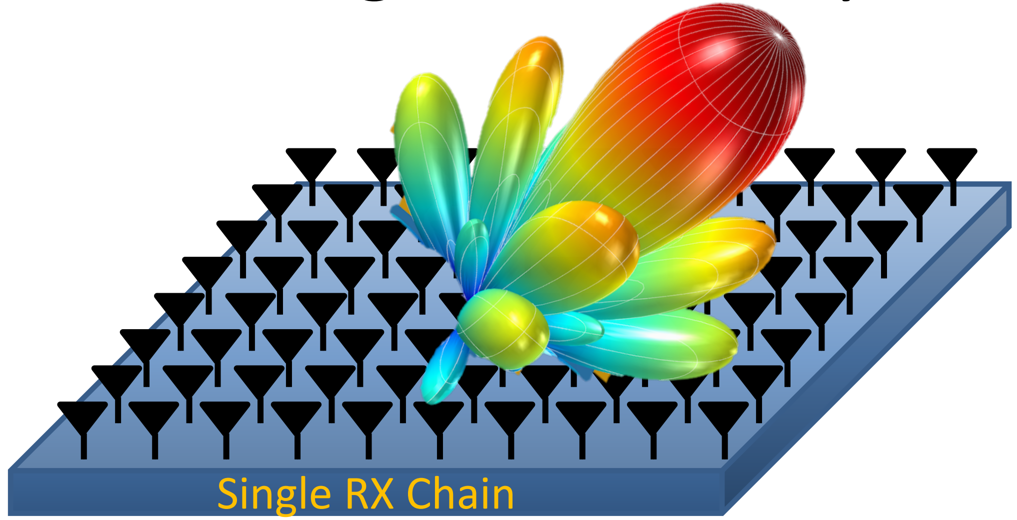
$N \times N$ **RX Chains**

Algorithm 1: $O(N^4 T + N^2 T \log T)$ **Similar to Analog**

Algorithm 2: (Faster) $O(N^2 T \log NT)$ **3D FFT**

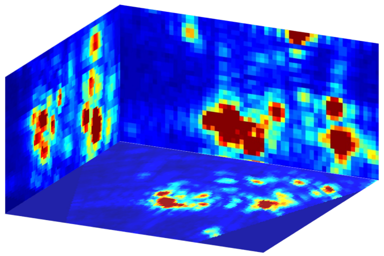
Algorithm 3: (More Accurate) $O(L^3 N^2 T) = o(N^5 T)$

Analog Phased Arrays



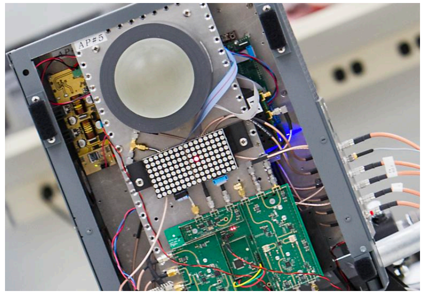
1) Pick the phase shift on each antenna to create a beam in each 3D direction.
2) Transmit FMCW signals and receive reflections.
3) Mix RX signal with TX and take range FFT .
4) Repeat in every direction.

3D Heatmap Image

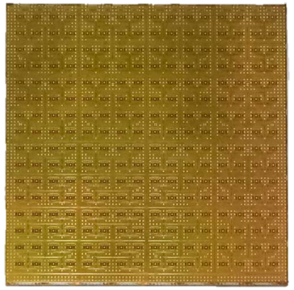


Can we use millimeter wave radars for 3D imaging and not just ranging?

5G pushing research into delivering large 2D millimeter wave phased arrays

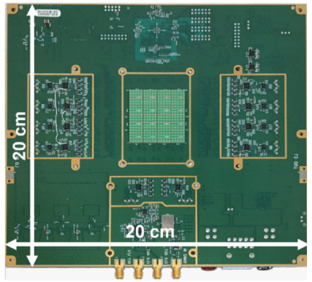


Nokia & National Instruments

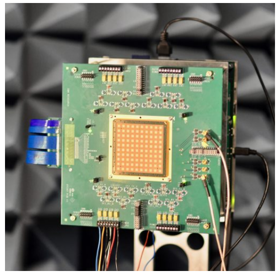


UCSD
256 elements

UCSD
64 elements

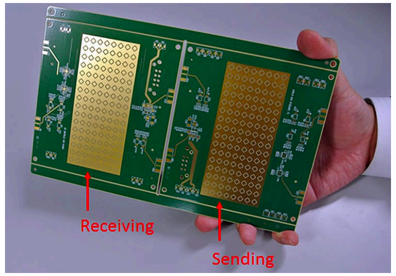


Bell Labs
384 elements



Anokiwave
256 elements

IBM
64 elements



Fujitsu
64 elements

Small wavelength enables thousands of antennas to be packed into small space

→ Extremely narrow beams

Challenges in mmWave Imaging

1. Extremely Low Resolution
- Blobs of radar reflections
- No Sharp Boundaries/Shapes

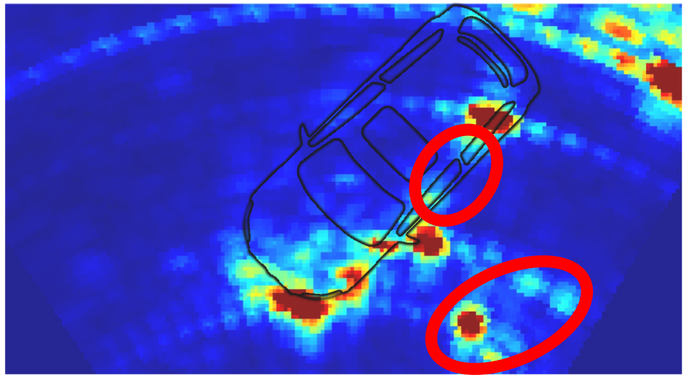
2. Specularity
- Major parts of Car are Missing

3. Multipath and artifacts
- Spurious Reflections

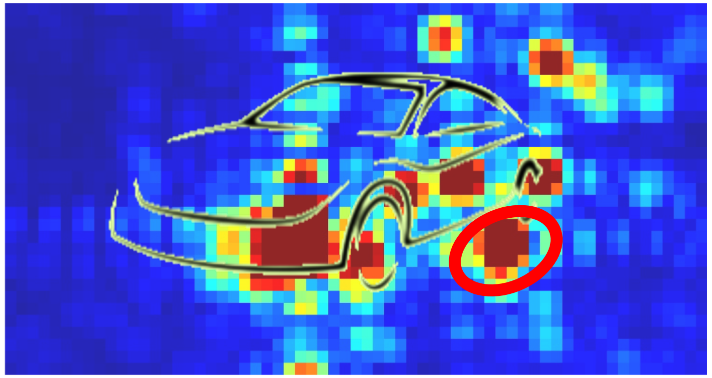
(a) Camera Image

(b) Radar Point Cloud

(c) Top-View of Radar Heatmap



(d) Front-View of Radar Heatmap

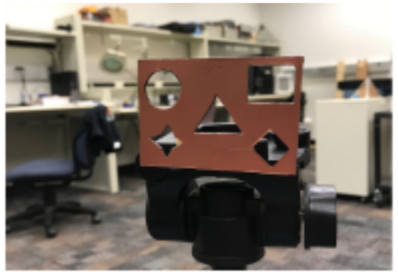


Radar images lack perceptual and contextual information about the scene

State of the Art Millimeter Wave Imaging

Limited to Near Field

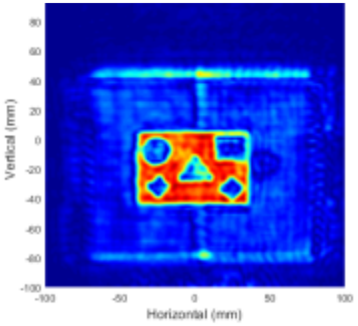
Target Object



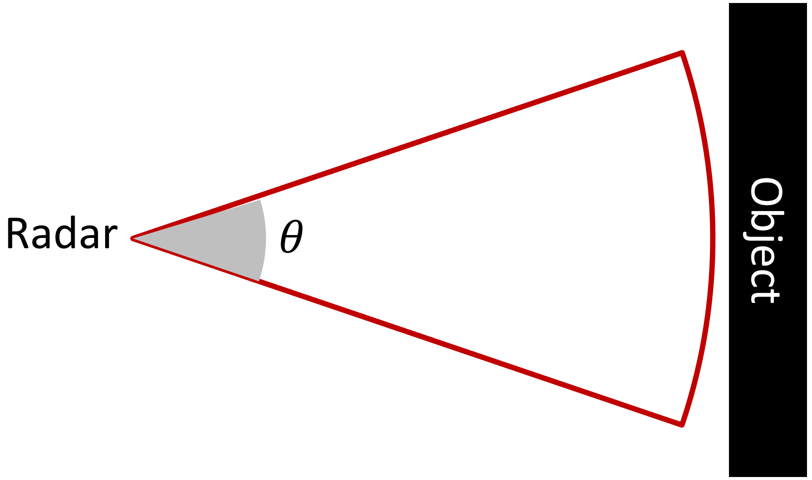
Setup

Yanik et al.,

Near Field Image



Imaged object is only few cm away from radar



State of the Art Millimeter Wave Imaging

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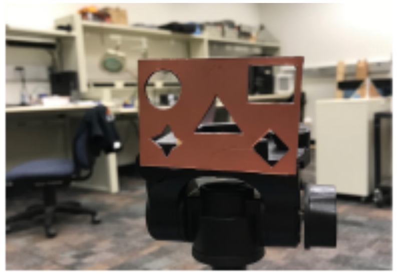
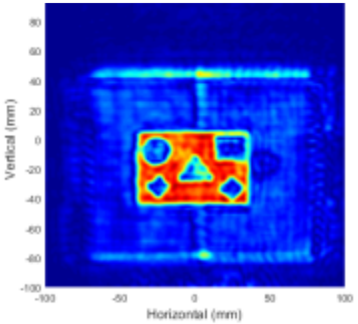


Setup

Near Field Image

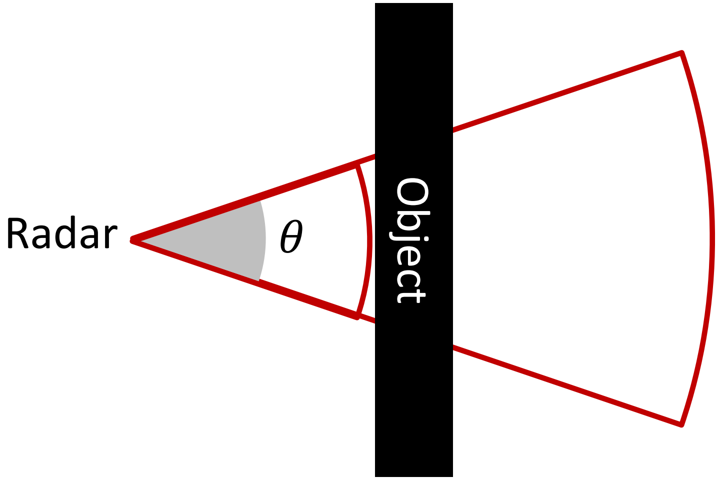


Yanik et al.,

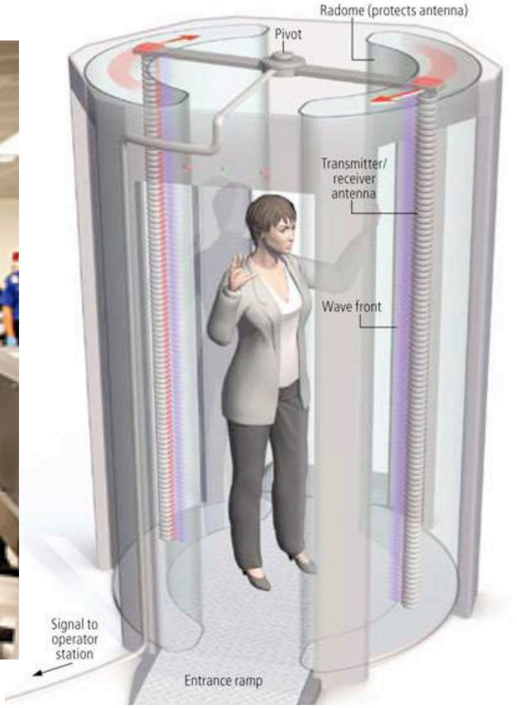
Airport Security Scanners

- Human-sized Arrays
- 360° Scanning with Rotation
- Isolation in Near Field

Imaged object is only few cm away from radar



For res. 12° (0.209 rad)
At range 5cm, res. = 1cm
At range 5m, res. = 1m

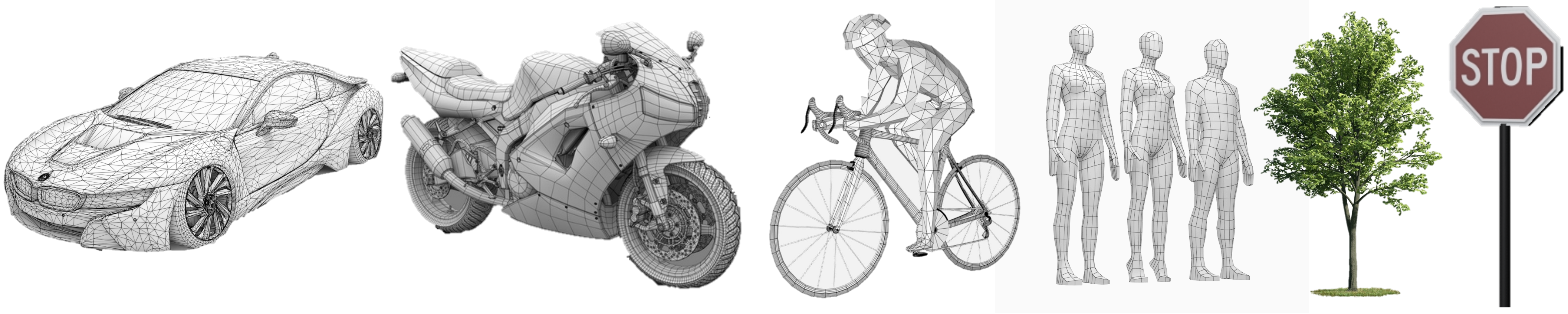


Resolution= AoA resolution × Range = $r\,\theta$

HawkEye Paper

Cast mmWave Imaging as learning problem:

- Taking a data driven approach to recover high frequency shapes and details
- Leveraging geometric priors on structures of commonly found streetside objects
- Providing robustness to hard-to-model radar reflections and sources of noise



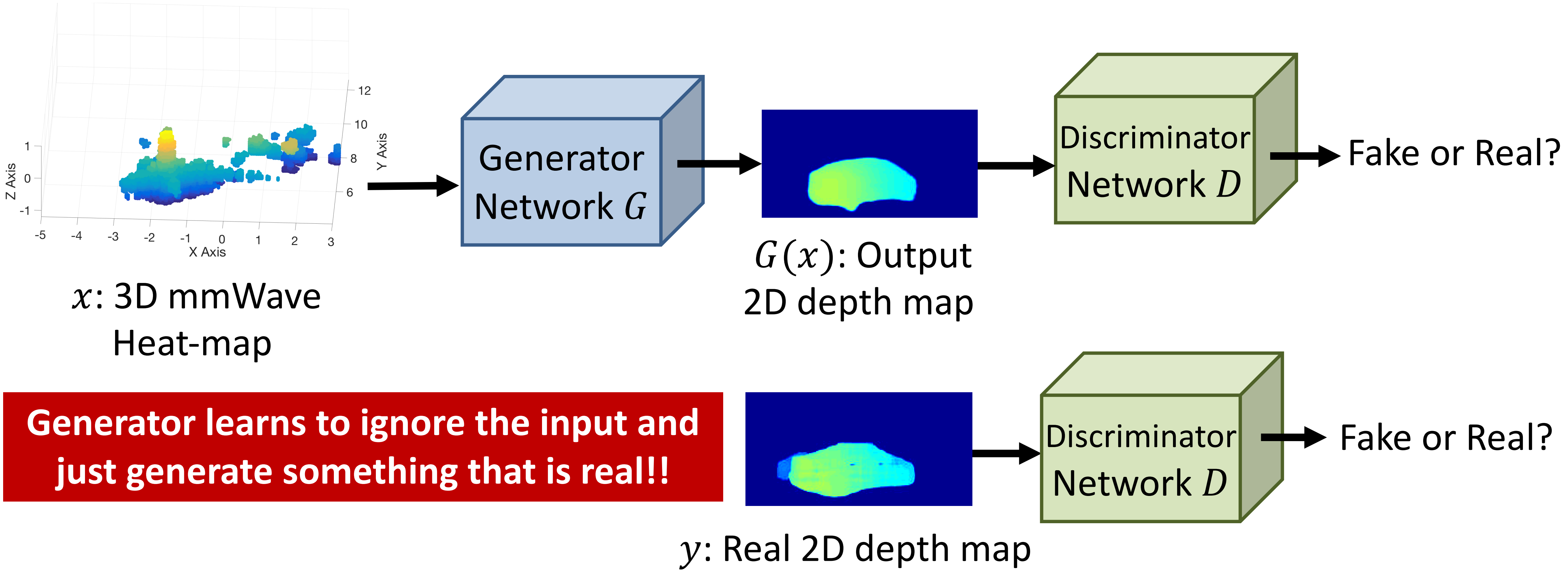
Leverage Conditional Generative Adversarial Network (GAN) Framework with Deep ConvNets

Generative Adversarial Network (GAN)

- Machine Learning Framework
- Extensively used for:
  - Super resolution
  - Learning image priors
  - Image transformation
  - Deep fakes

Generative Adversarial Network (GAN)

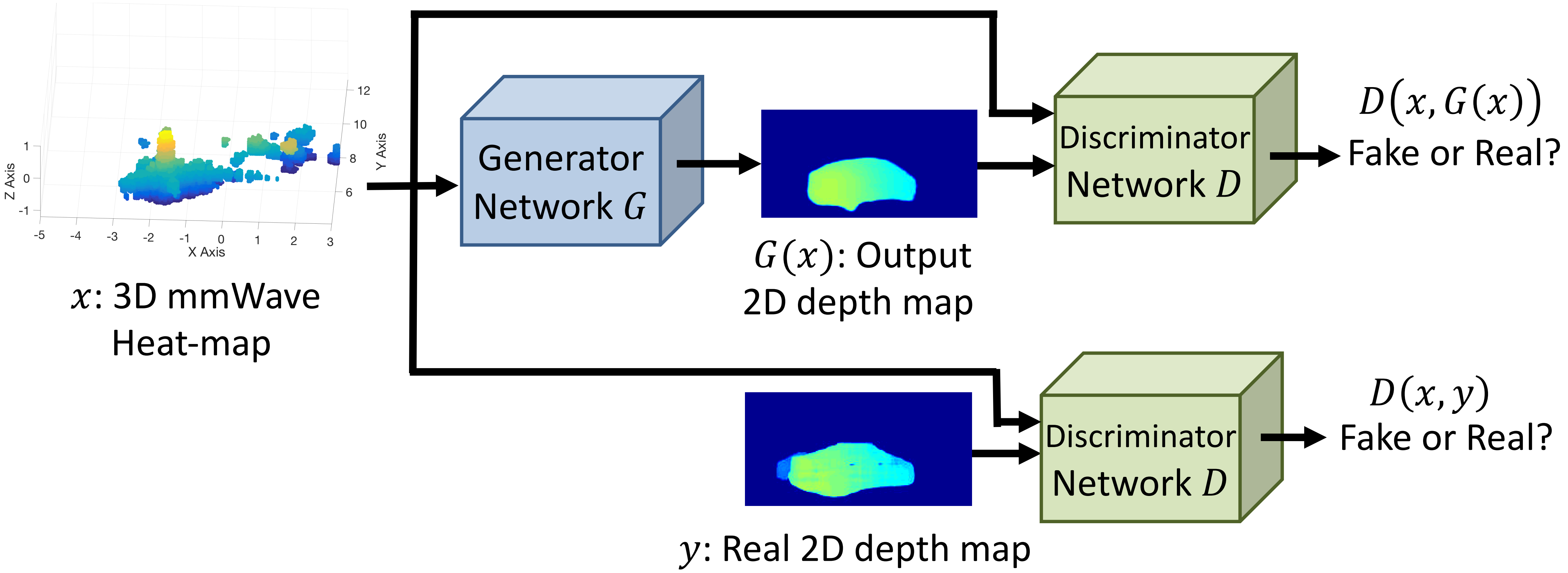
- Generator takes 3D radar heatmap as input and outputs high resolution depth map.
- Discriminator tries to guess is the high resolution depth map is real of fake.
- Generator's goal is to fool the discriminator into thinking this is real



Generator learns to ignore the input and just generate something that is real!!

Conditional Generative Adversarial Network (cGAN)

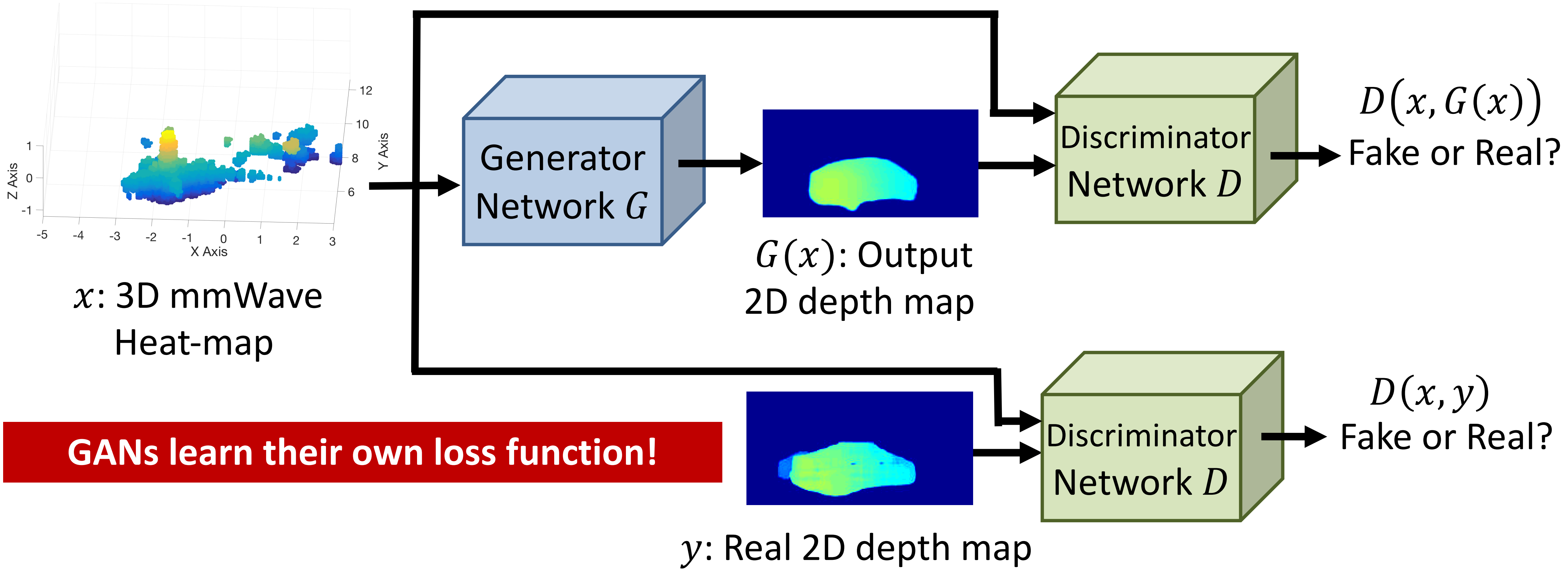
- Generator takes 3D radar heatmap as input and outputs high resolution depth map.
- Discriminator tries to guess is the high resolution depth map is real of fake.
- Generator’s goal is to fool the discriminator into thinking this is real



Conditional Generative Adversarial Network (cGAN)

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

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

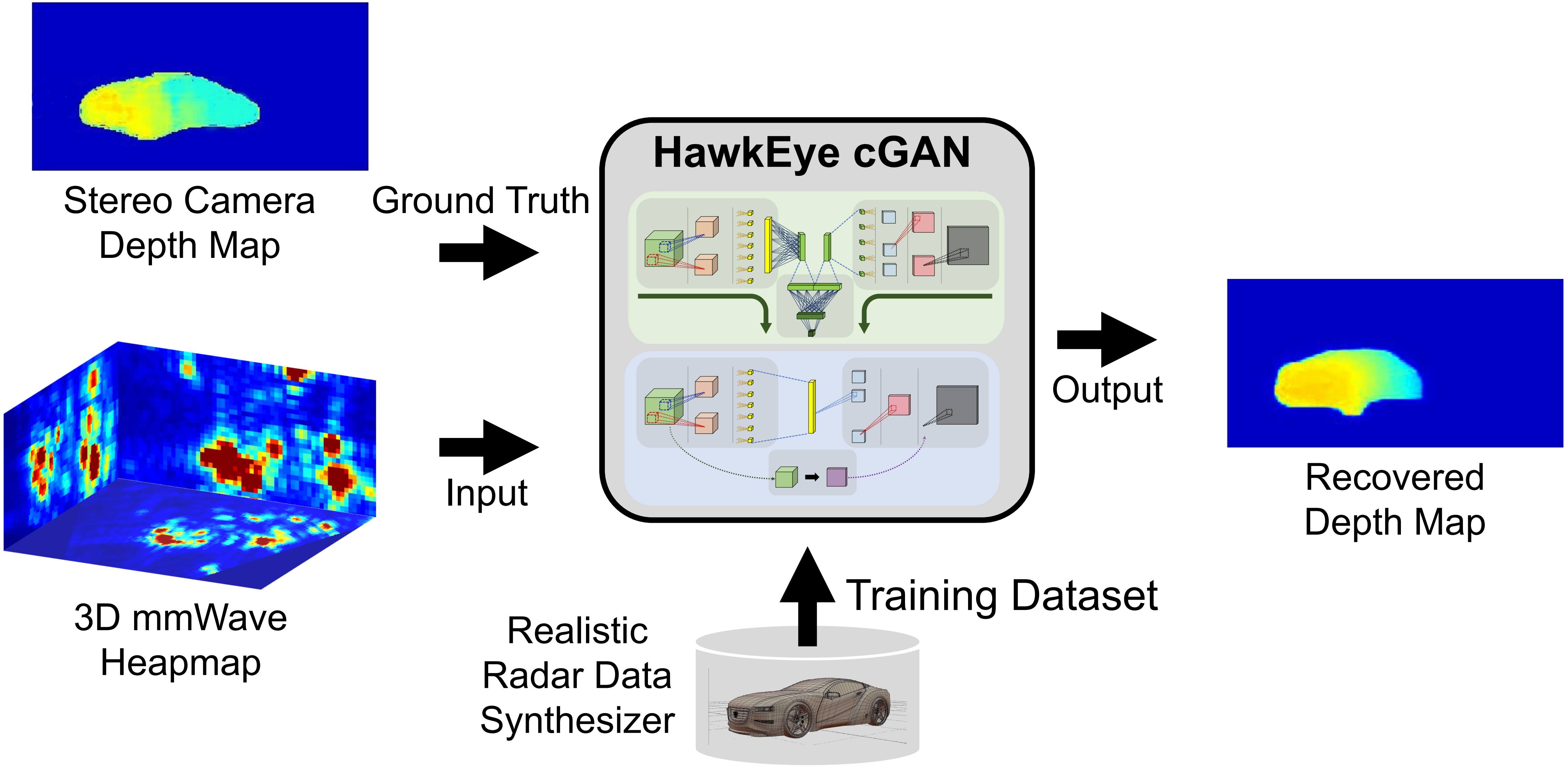


GANs learn their own loss function!

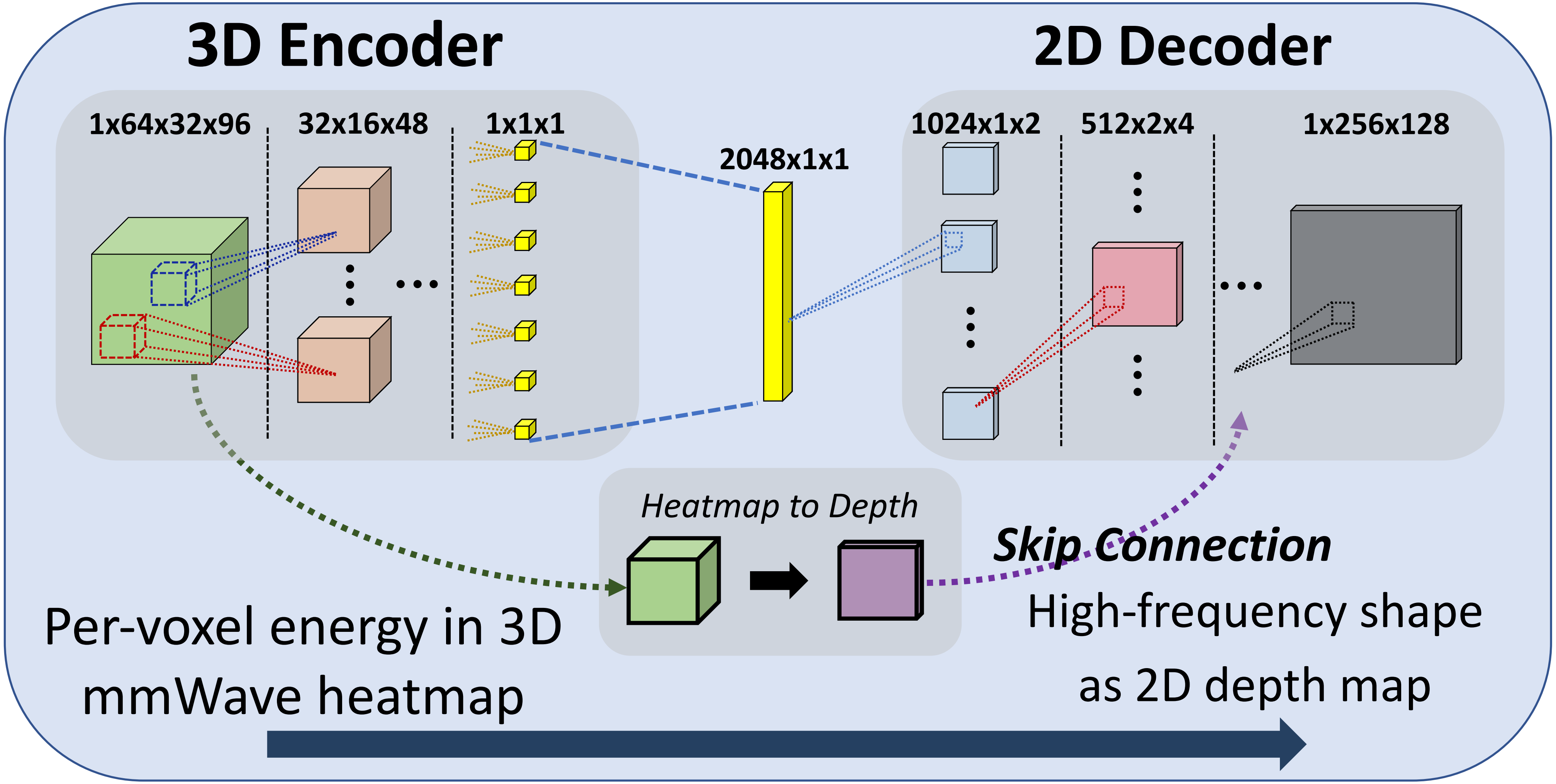
Challenges in Using cGANs & Deep Learning for Radar Imaging

- Deep learning requires a lot of data to train!
  - Unlike vision and images, not much mmWave radar imaging data is available.
  - Collecting radar data is hard and time consuming.
- 3D Radar image has bad resolution along the azimuth and elevation but good resolution along range due of FMCW
  - Must preserve range information.
- Ground truth: LiDAR point clouds? Visions? …
  - Perceptual and dimension mismatch.

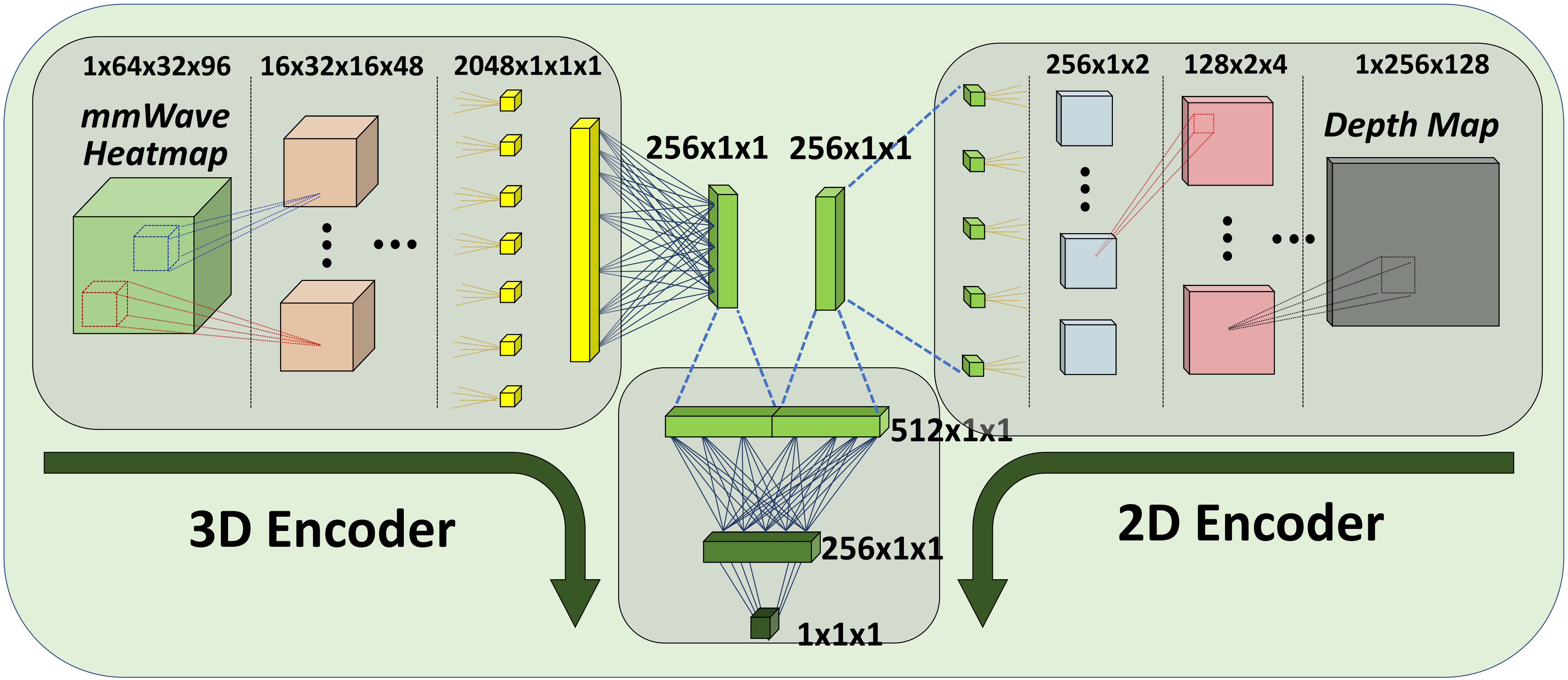
Hawkeye Overview



Generator Architecture



Discriminator Architecture



Preserving Range Information

Skip Connection

- Provide higher layers in the decoder with high-frequency ranging information from the 3D mmWave input.

Loss Function

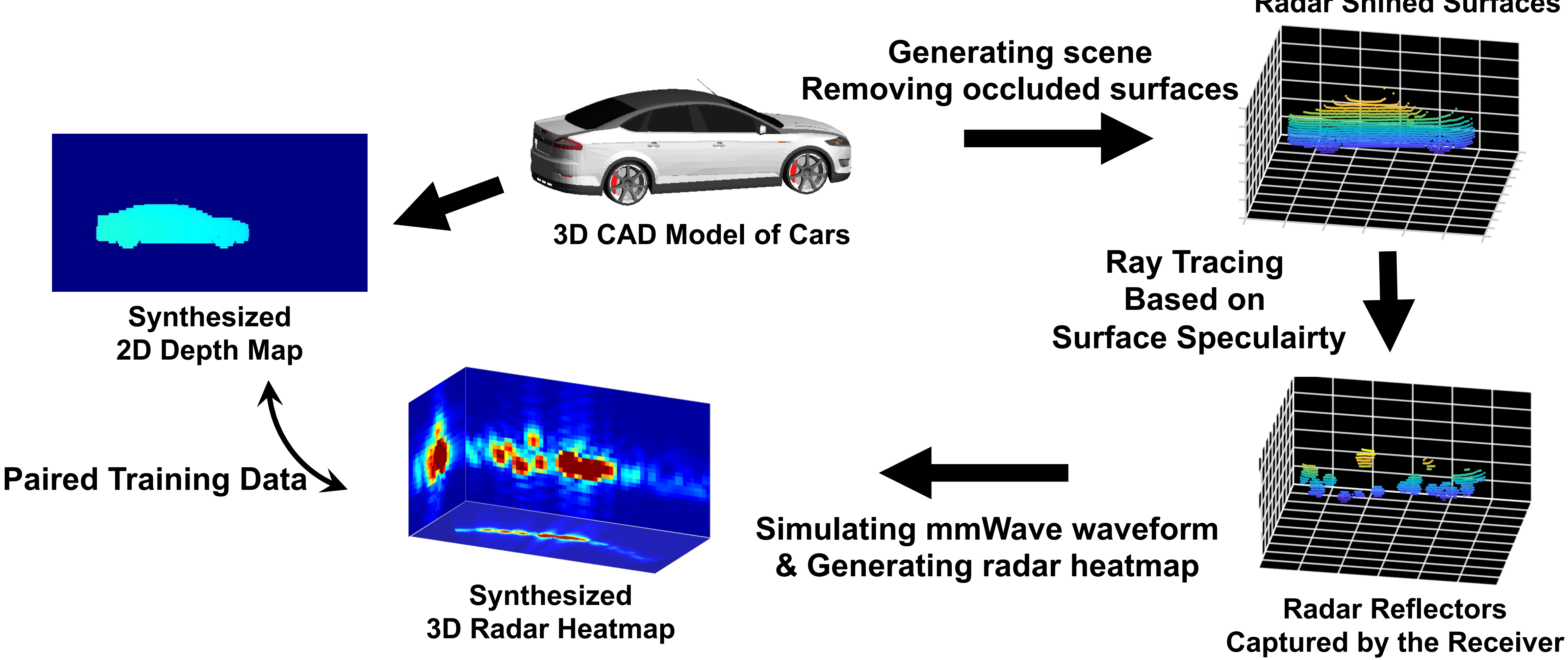
HawkEye employs a combination of three losses:

$$\mathcal{L}_H(G) = \mathcal{L}(G) + \lambda_1 \mathcal{L}_1 + \lambda_p \mathcal{L}_p$$

- $\mathcal{L}_1$ loss enforce depth values in output depth map.
- Perceptual loss from pre-trained VGG network provides perceptually interpretable images.

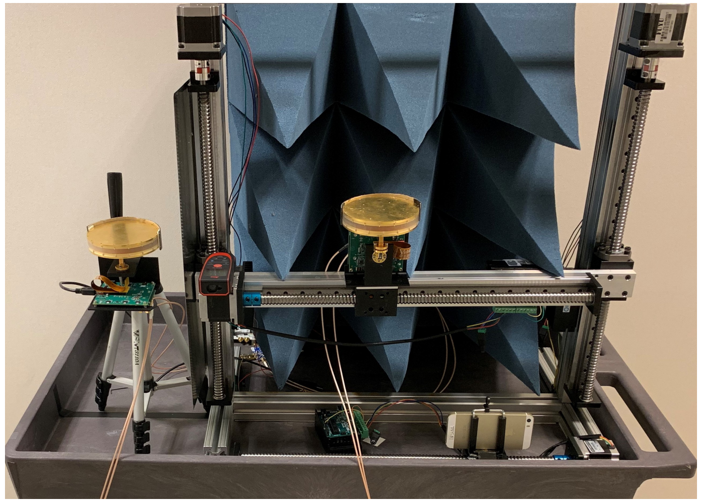
Synthesizing Large Scale mmWave Dataset

Synthesizer generates paired 3D mmWave heatmaps and 2D depth maps of cars from 3D CAD models.

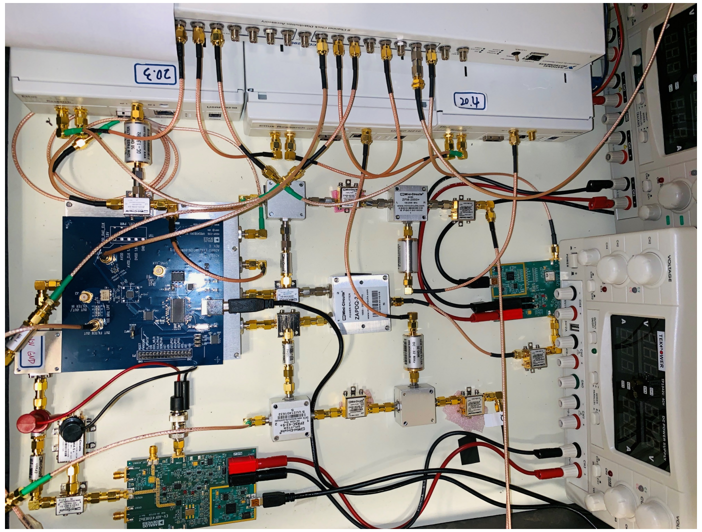


Real-World mmWave Data Collection

Millimeter Wave SAR Platform



FMCW Baseband Circuit



Custom-built mmWave Imaging Module:

- Emulating 2D antenna array with 60 GHz radio.
- Transmitting FMCW radar waveform.

Controlled Experiments in Fog and Rain:

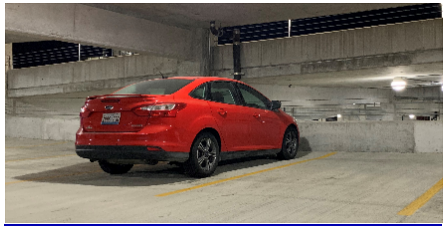
- Emulating fog and rain with fog machine and water hose.

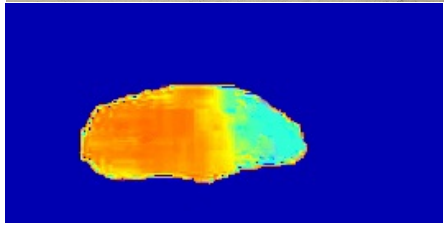
Collected Real-World Dataset:

- Paired 3D mmWave Heatmaps, RGB Camera images, and stereo camera depth maps
- 327 Scenes of Cars (including 101 experiments in fog and rain)

Results

Original Scene in clear visibility



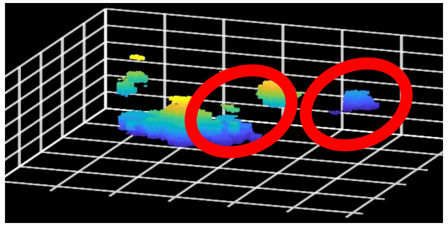


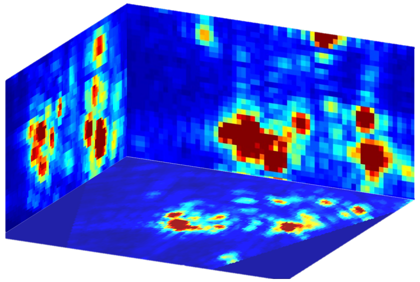
Ground Truth

Cameras in Dense Fog

Cameras fail in fog!

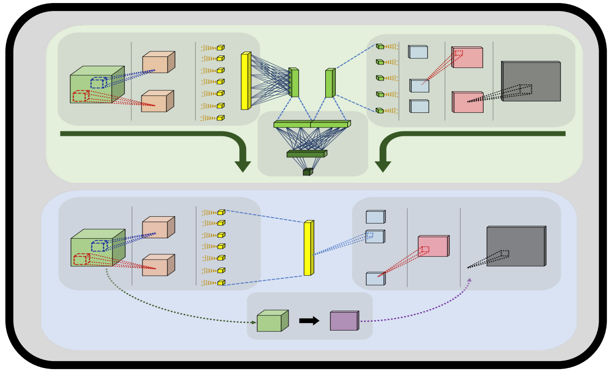
Radar Heatmap Captured in Fog

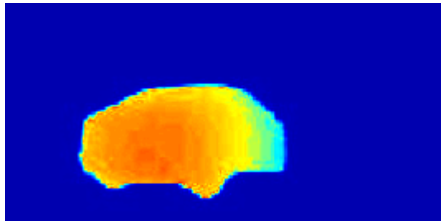




mmWave Data Collection

Conditional GAN

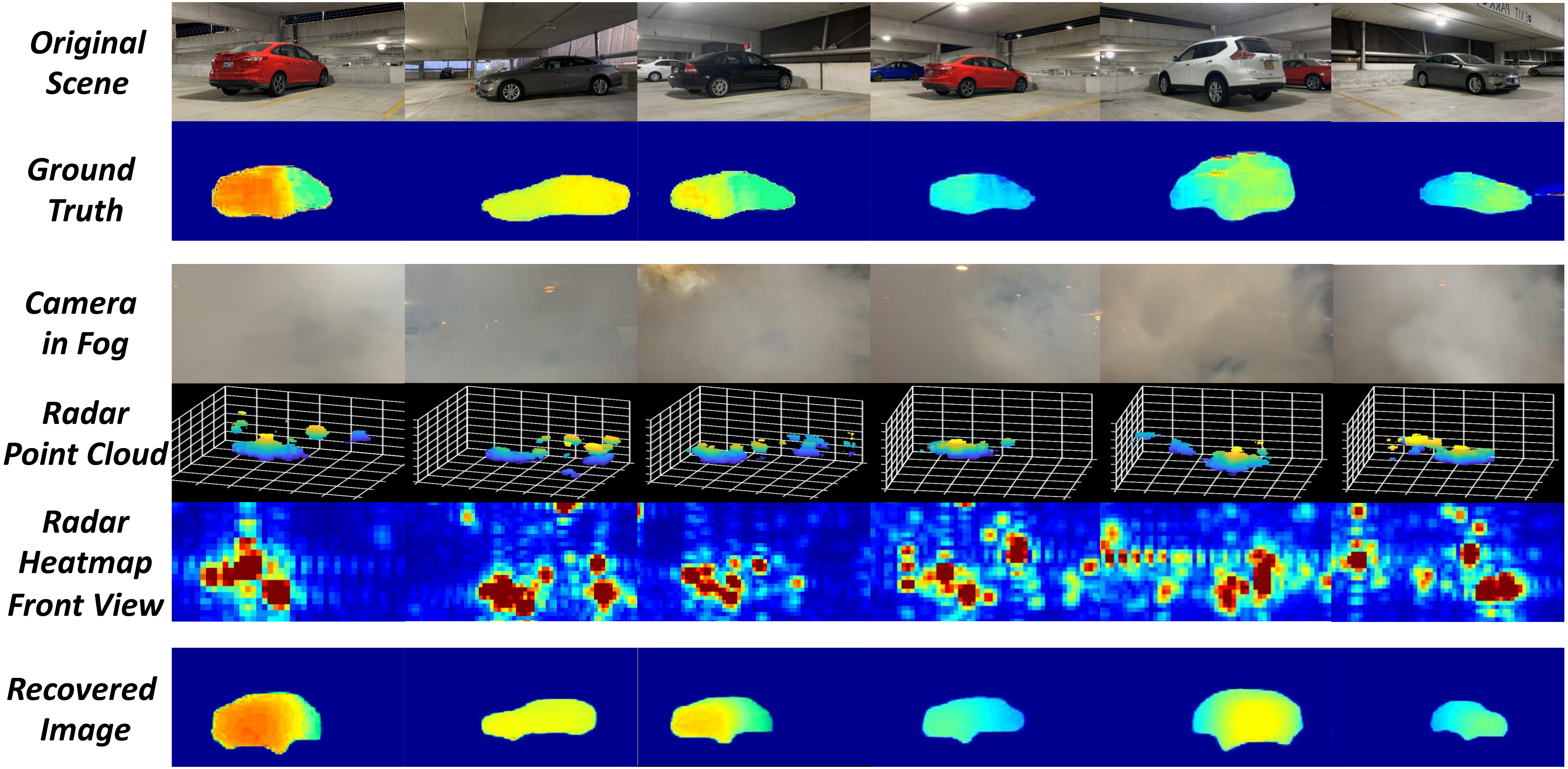




Recovered Image

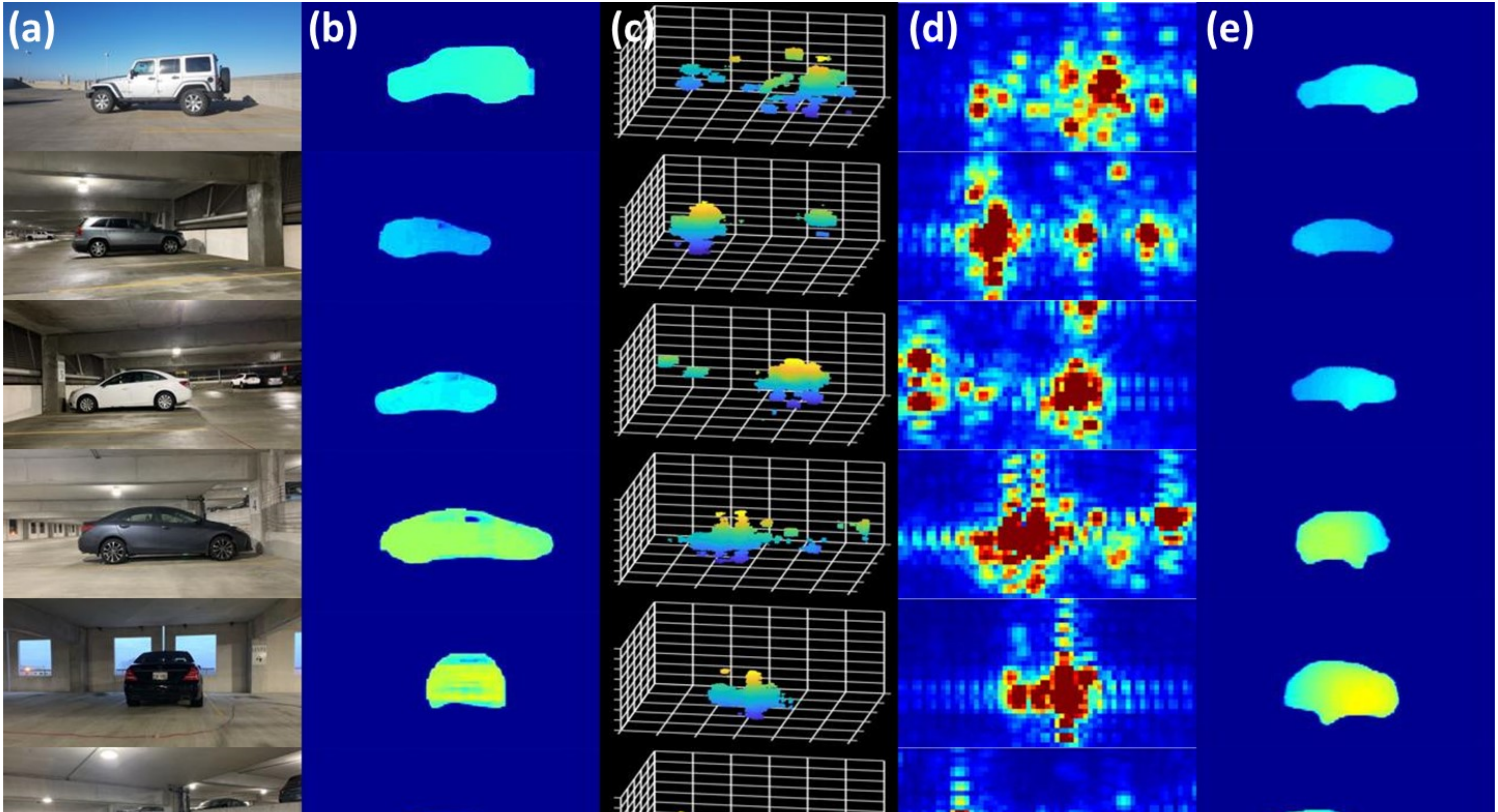
- Enhanced resolution
- Missing parts from Specularity filled
- Artifacts rejected

Results

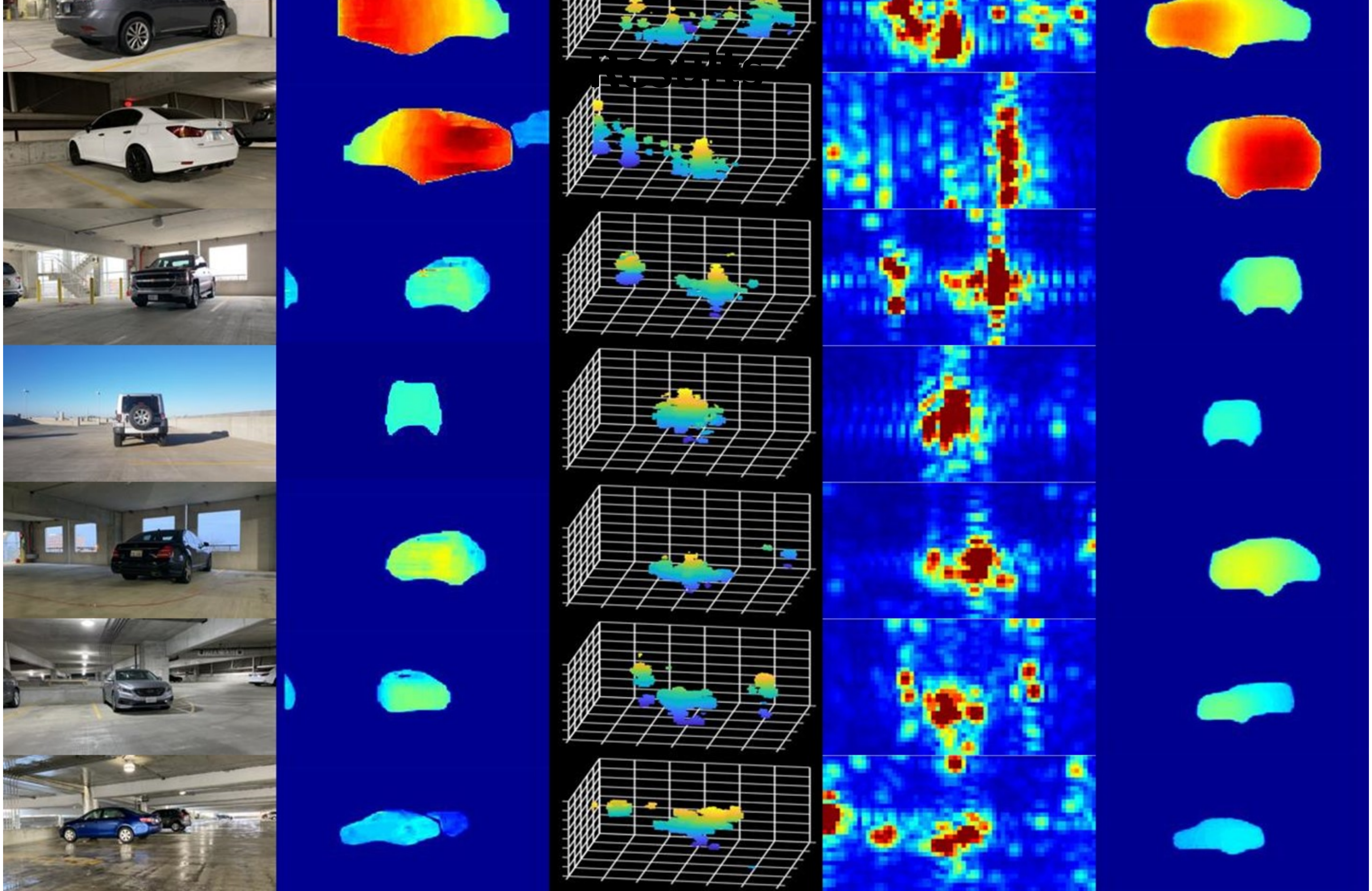


Trained using simulated data and tested using real data.

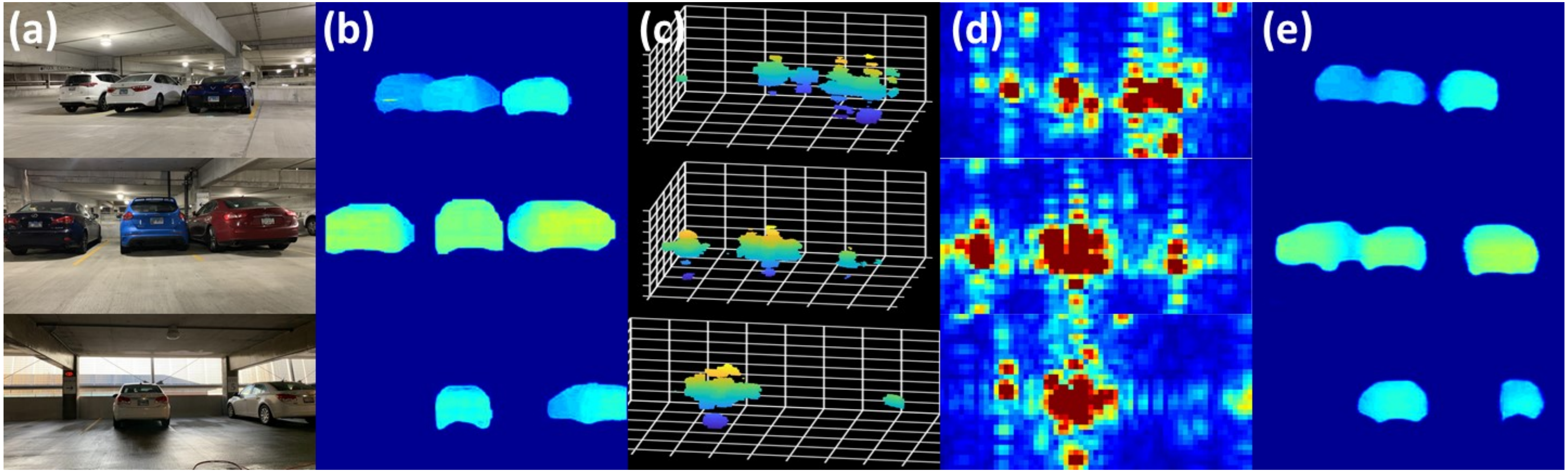
Results



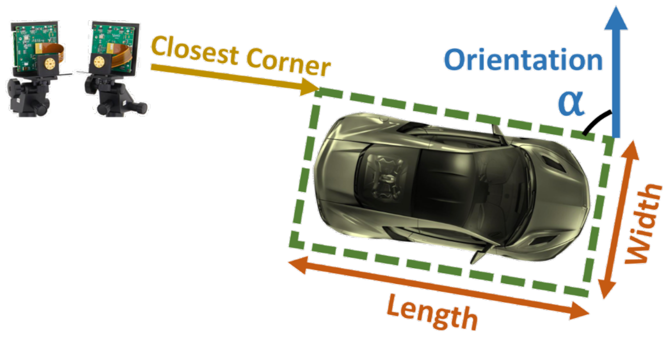
Results



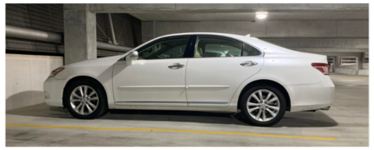
Results



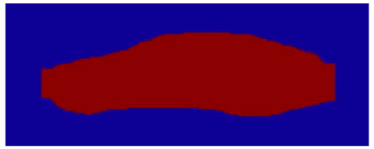
Results



(i) Top View of Scene



(ii) Front View of Scene



(iii) Front View Object Mask

Experiment	System	Error in Ranging	Error in Length	Error in Width	Error in Height	Error in Orientation	% Fictitious Reflections	% Car Surface Missed
Clean Air	HawkEye	**30 cm**	**47 cm**	**29 cm**	**9 cm**	**27°**	**1.5%**	**12.9%**
	mmWave	53 cm	179 cm	89 cm	45 cm	64°	15.6%	30.5%
	L_1 Based Loss	40 cm	97 cm	76 cm	13 cm	37°	2.5%	13.1%
	Nearest Neighbor	90 cm	114 cm	70 cm	17 cm	68°	3.5%	16.0%
Fog	HawkEye	**50 cm**	**83 cm**	**44 cm**	**11 cm**	**29°**	**2.5%**	15.4%
	mmWave	67 cm	222 cm	99 cm	53 cm	72°	20.9%	31.9%
	L_1 Based Loss	60 cm	108 cm	80 cm	12 cm	38°	3.5%	**13.8%**
	Nearest Neighbor	121 cm	117 cm	76 cm	18 cm	45°	3.6%	22.3%
Synthesized Data	HawkEye	23 cm	**64 cm**	**37 cm**	**8 cm**	**30°**	**1.3%**	10.2%
	mmWave	29 cm	182 cm	77 cm	31 cm	62°	10.8%	19.2%
	L_1 Based Loss	**20 cm**	113 cm	73 cm	14 cm	47°	3.4%	**9.3%**
	Nearest Neighbor	81 cm	81 cm	57 cm	13 cm	64°	5.2%	17.5%

Limitations

- Works for single cars.
- Only cars and nothing other than cars.
- Radar is uses SAR and is not real time.
- Mobile experiments not possible.