

2021UBiCOMP  
2021SWC

# SquiggleMilli: Approximating SAR Imaging on Mobile Millimeter-Wave Devices

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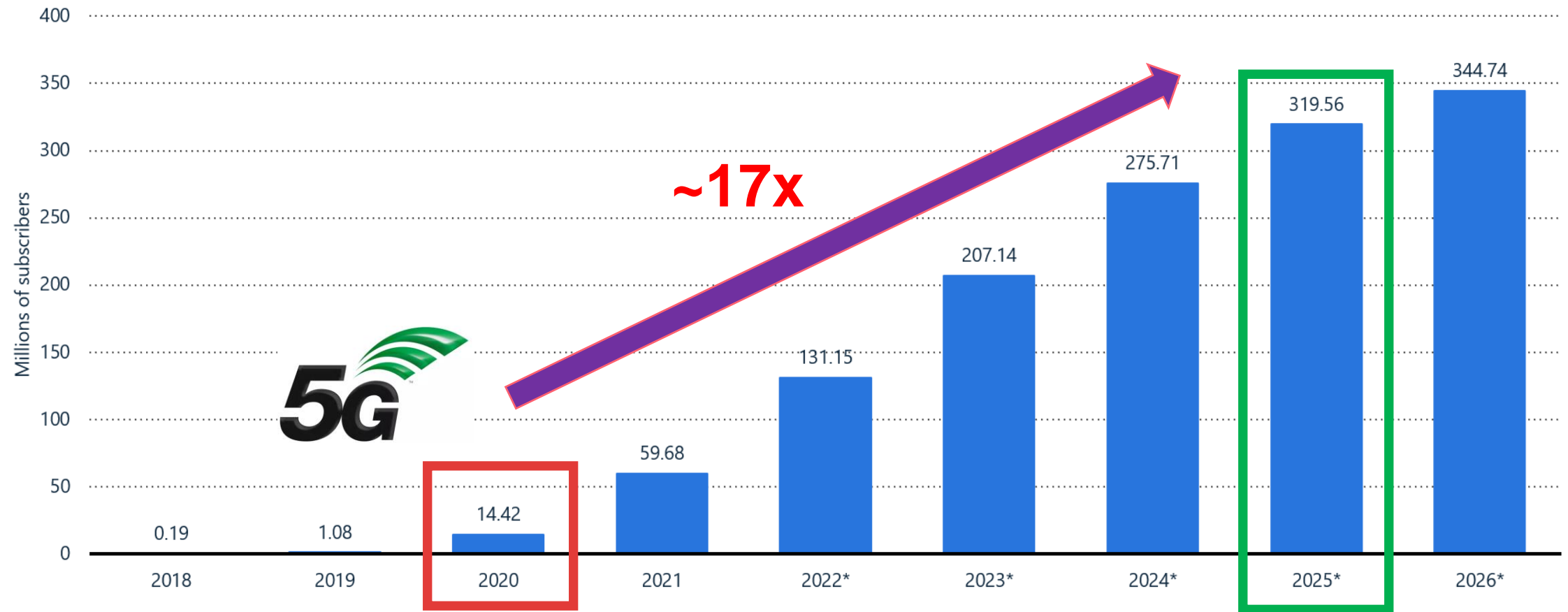
<https://github.com/hregmi77/SquiggleMilli>

Contact: [hregmi@email.sc.edu](mailto:hregmi@email.sc.edu)



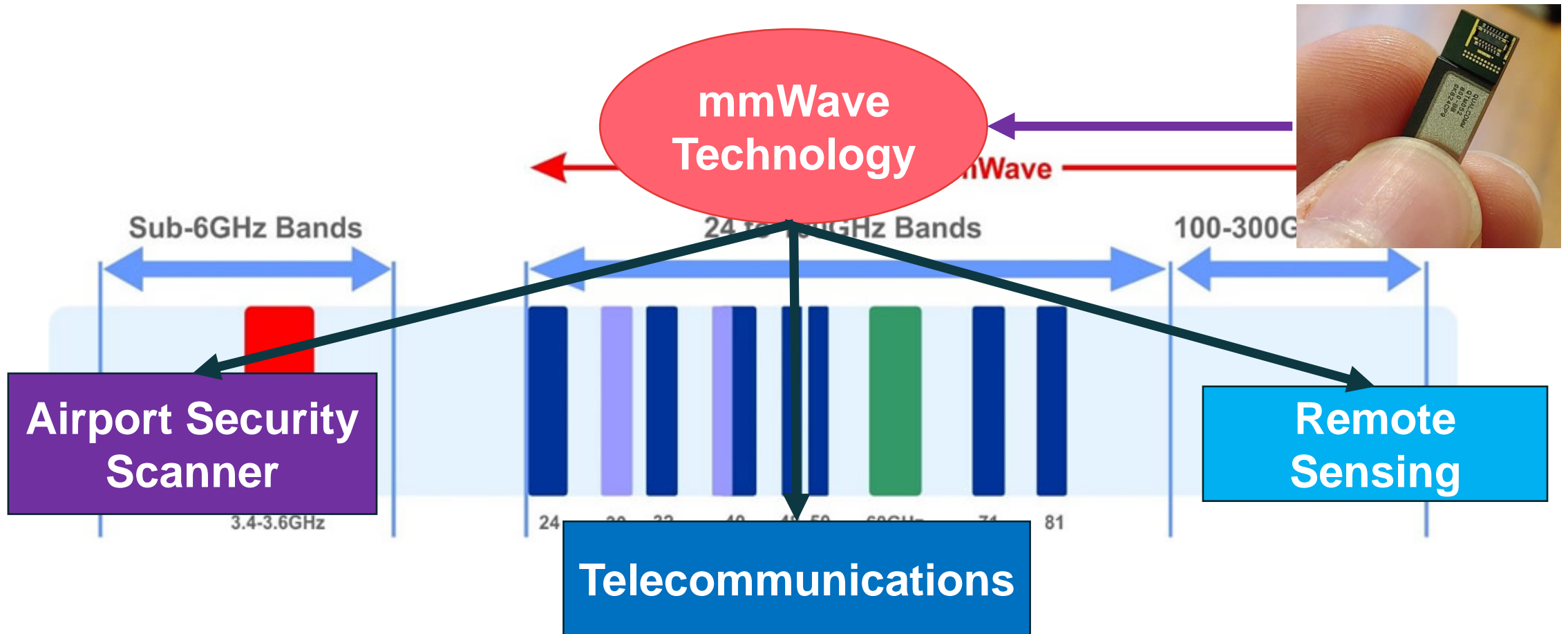
# Number of 5G subscriptions in North America from 2018 to 2026 (in millions)

5G subscriptions in North America 2018-2026



Source: Statista

# What Is 5G And Mmwave?

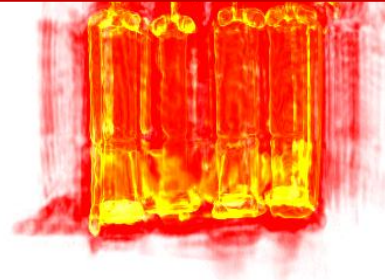


# Imaging Concealed Objects



Can we bring these functionalities to commodity 5G smartphones?

**Behind Wall Detection**

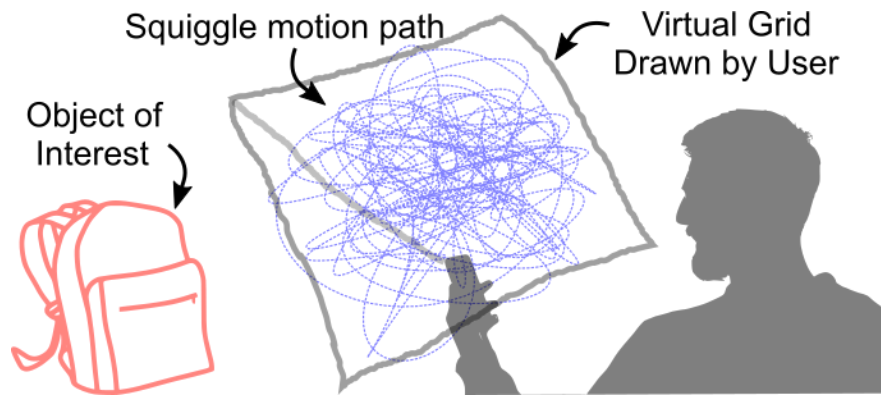


**Packaging and Inventory**



**Airport Contra-band Scanner**

# SquiggleMilli



Pistol inside bag



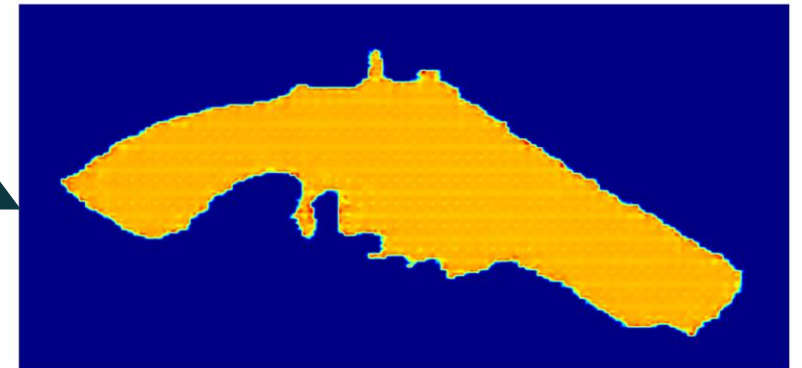
# SquiggleMilli

What vision camera produces

Actual Object



What SquiggleMilli produces





# SquiggleMilli

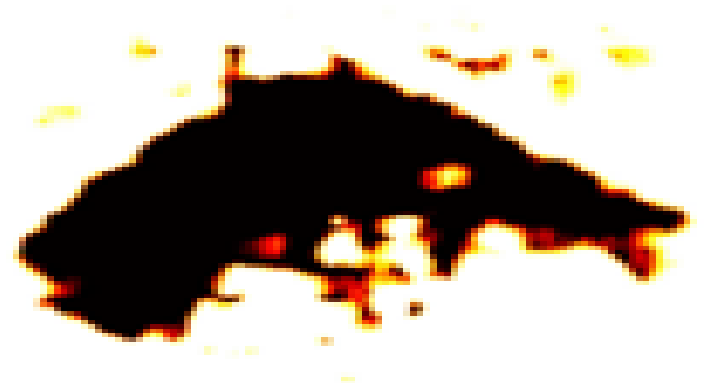
**Actual Object**



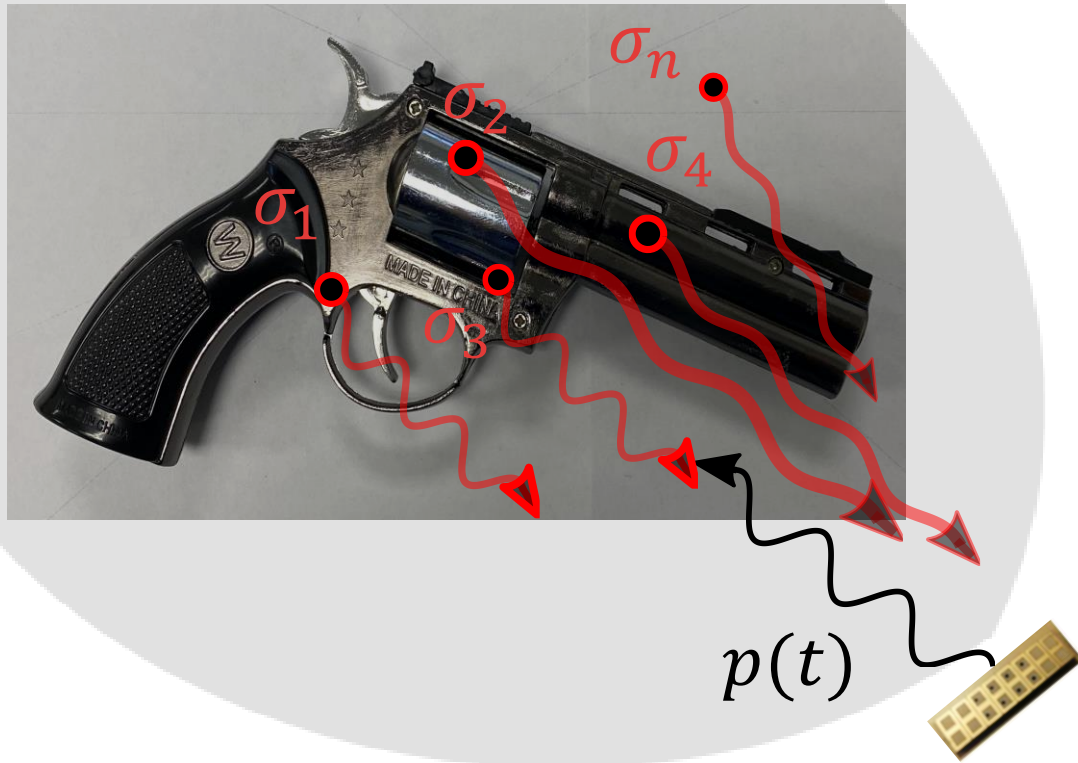
**What vision camera produces**



**What SquiggleMilli produces**



# Constructing Millimeter-Wave Image



mmWave antenna

$\sigma_1$

$\sigma_n$

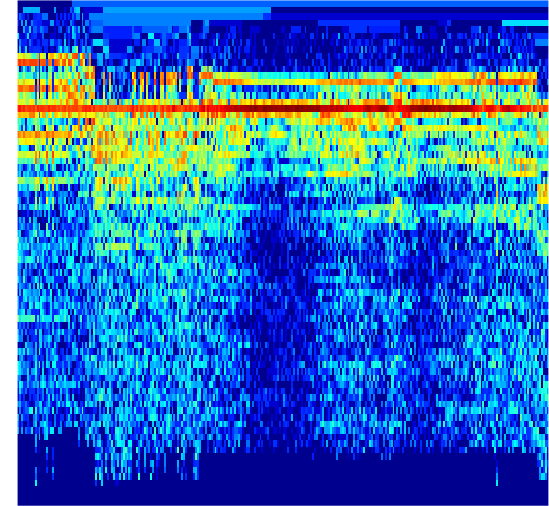
Reflected signals



# Constructing Millimeter-Wave Image



Time (t)



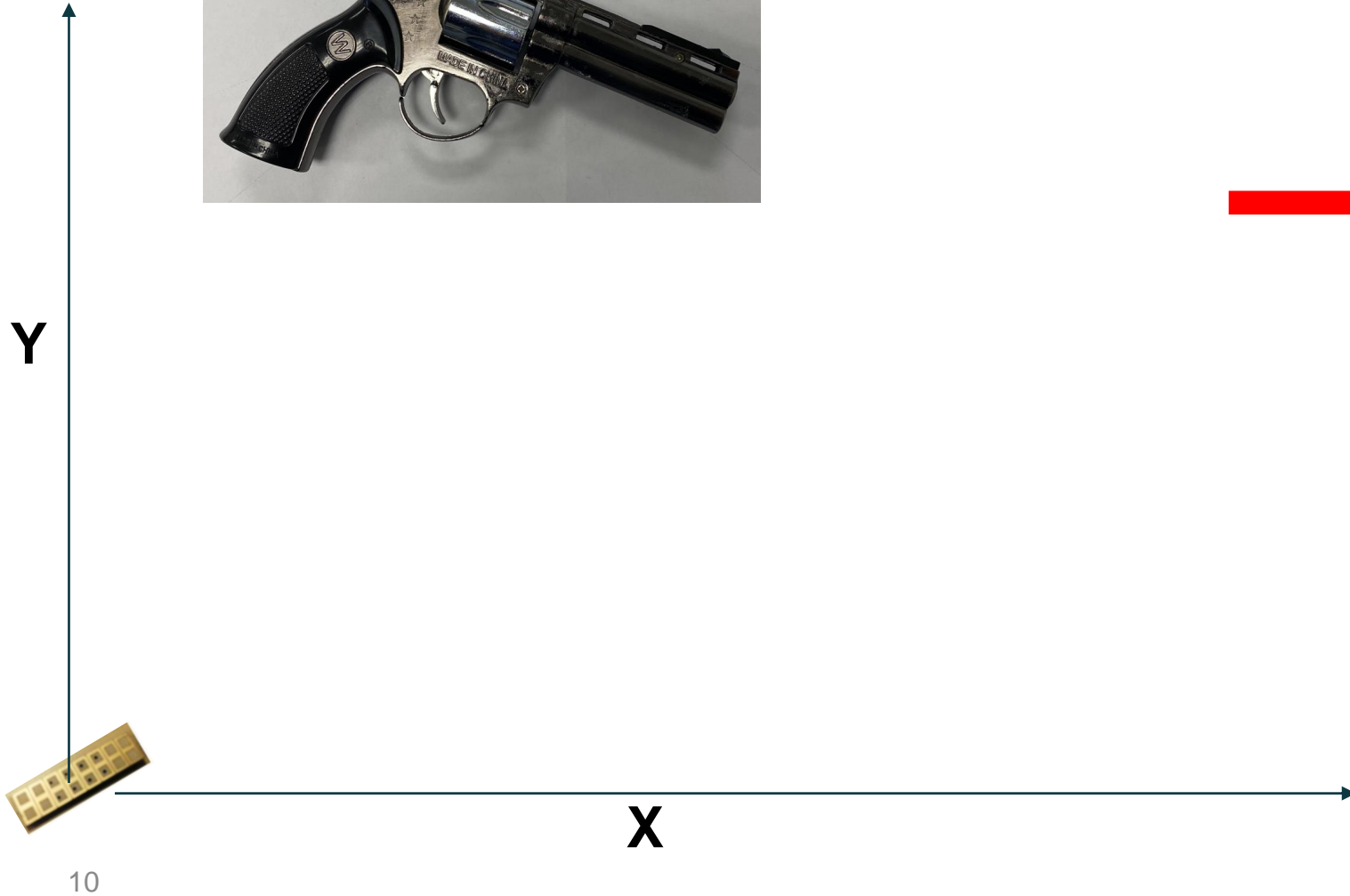
Space (u)

Time (t)

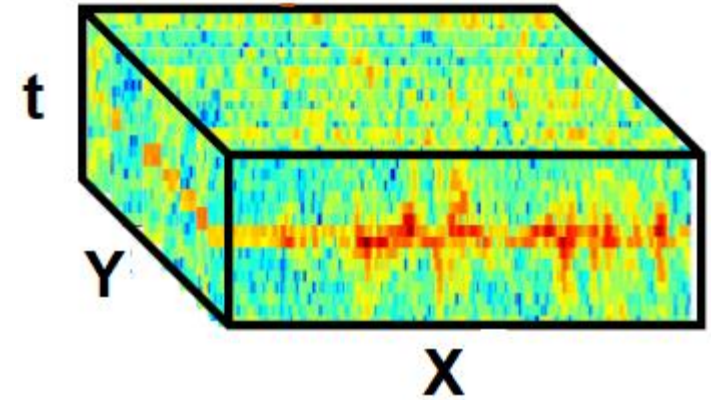
Space (u)



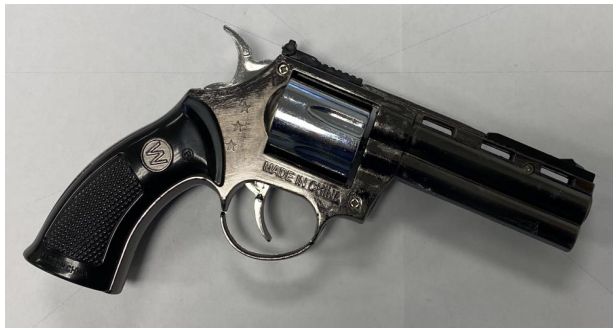
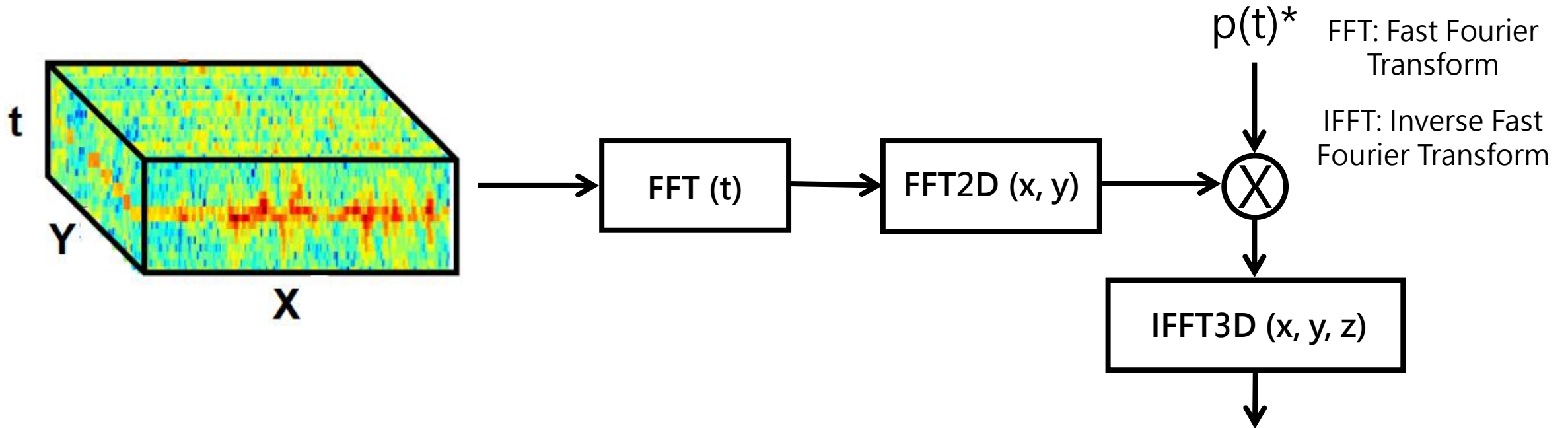
# Constructing Millimeter-Wave Image



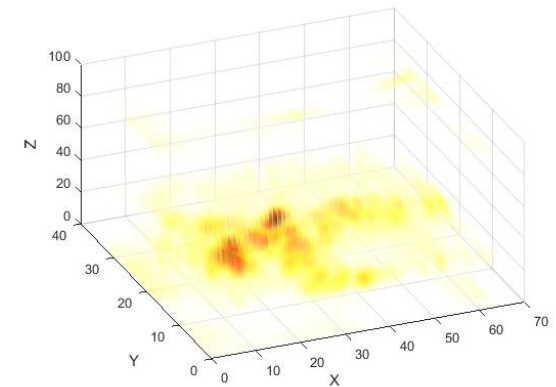
3D Spectrogram



# From Measured Signal to Image



Camera image



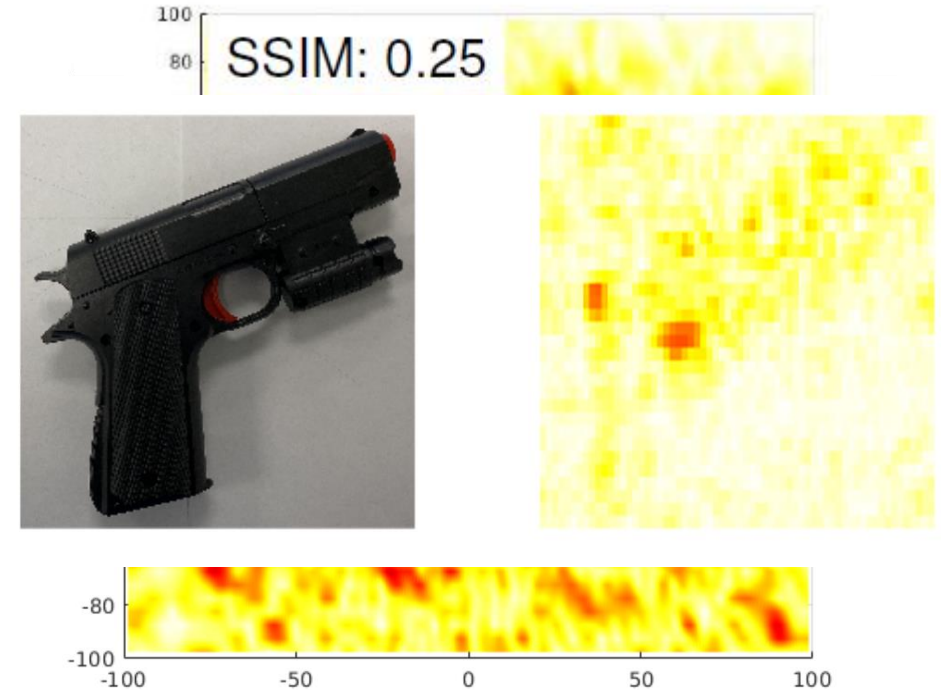
3D mmWave image

# Challenges

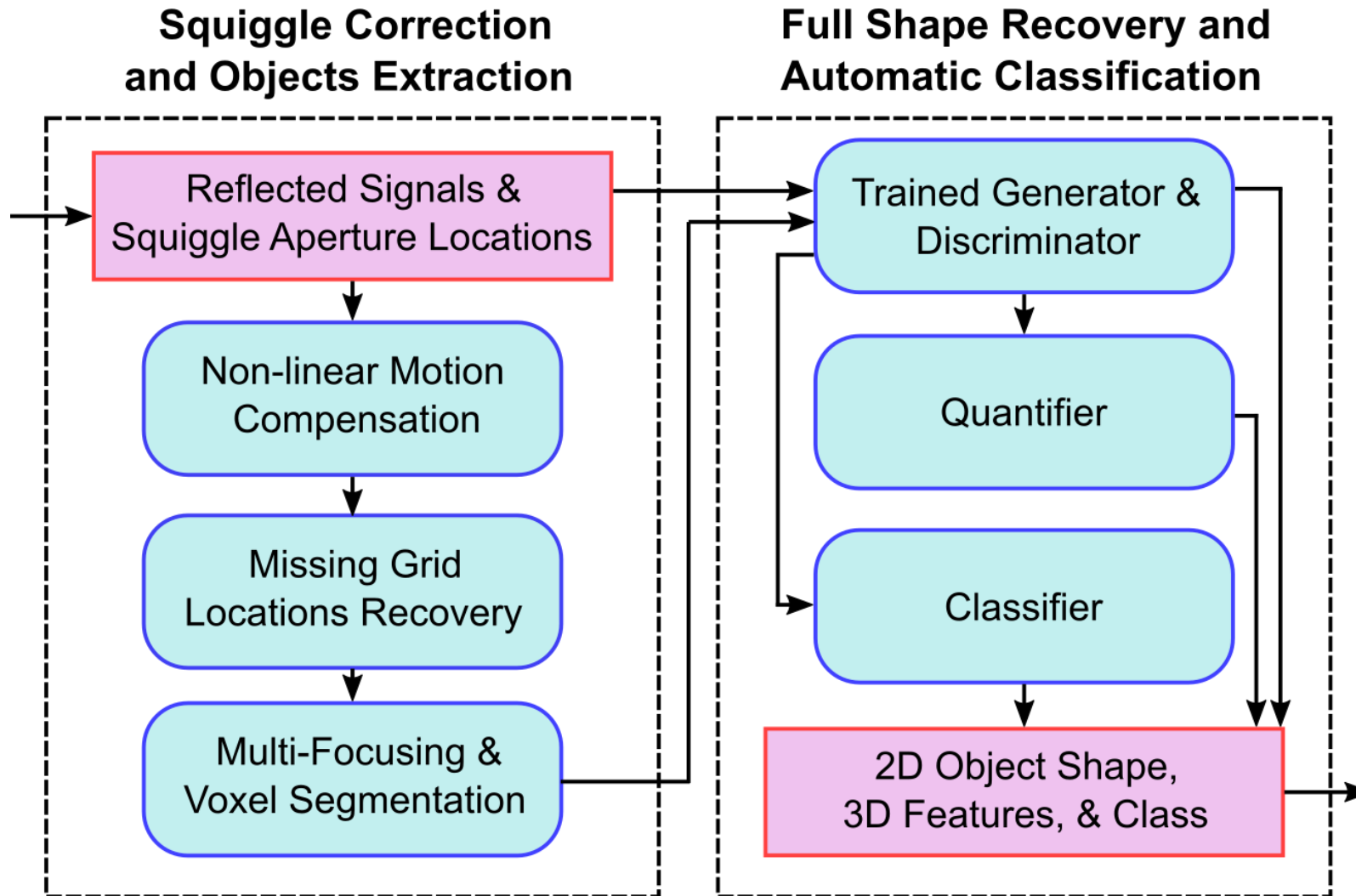
## Hand-held imaging

- ☐ Non-linear motion
- ☐ Non-Uniform Sampling
- ☐ Multiple Objects

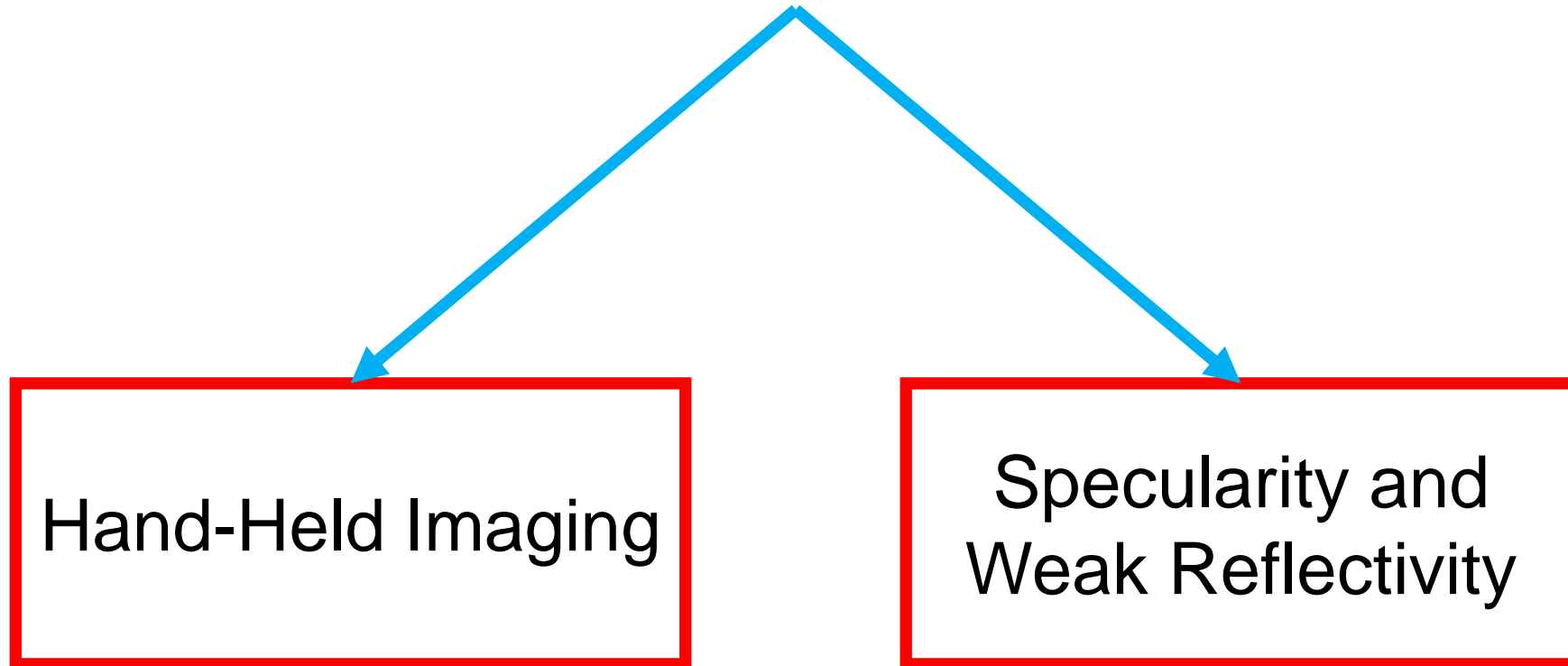
## Specularity and weak reflectivity



# SquiggleMilli Overview

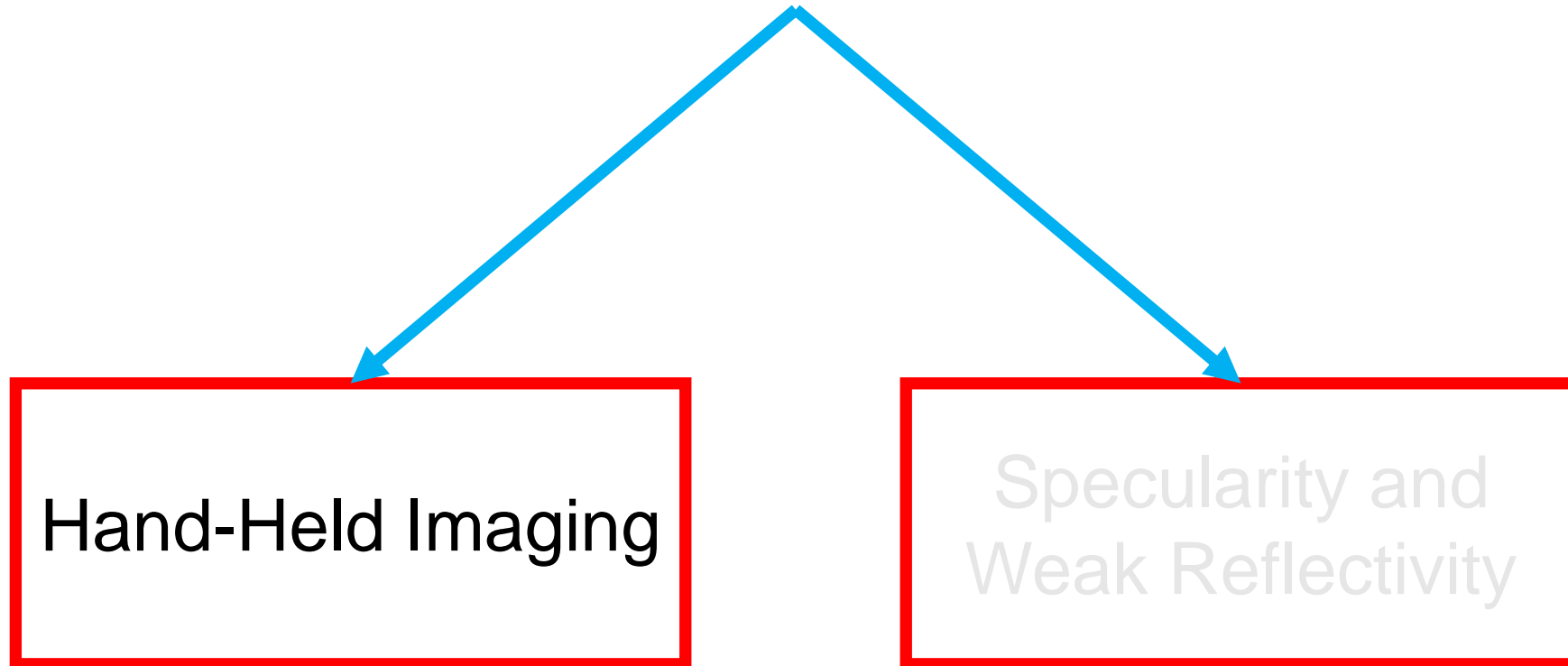


# Challenges



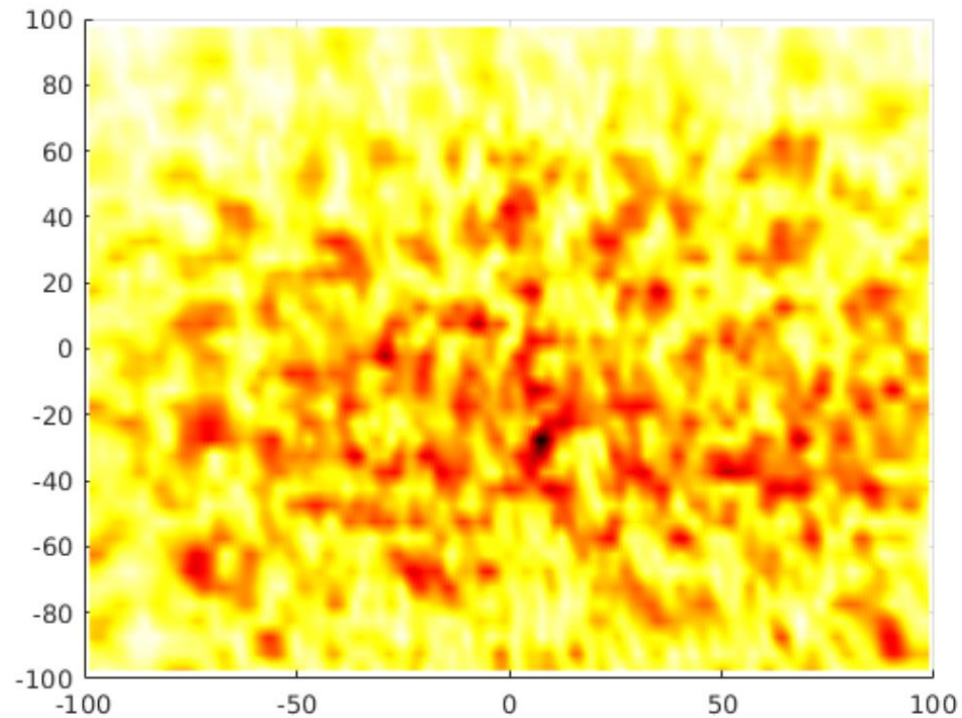


# Challenges

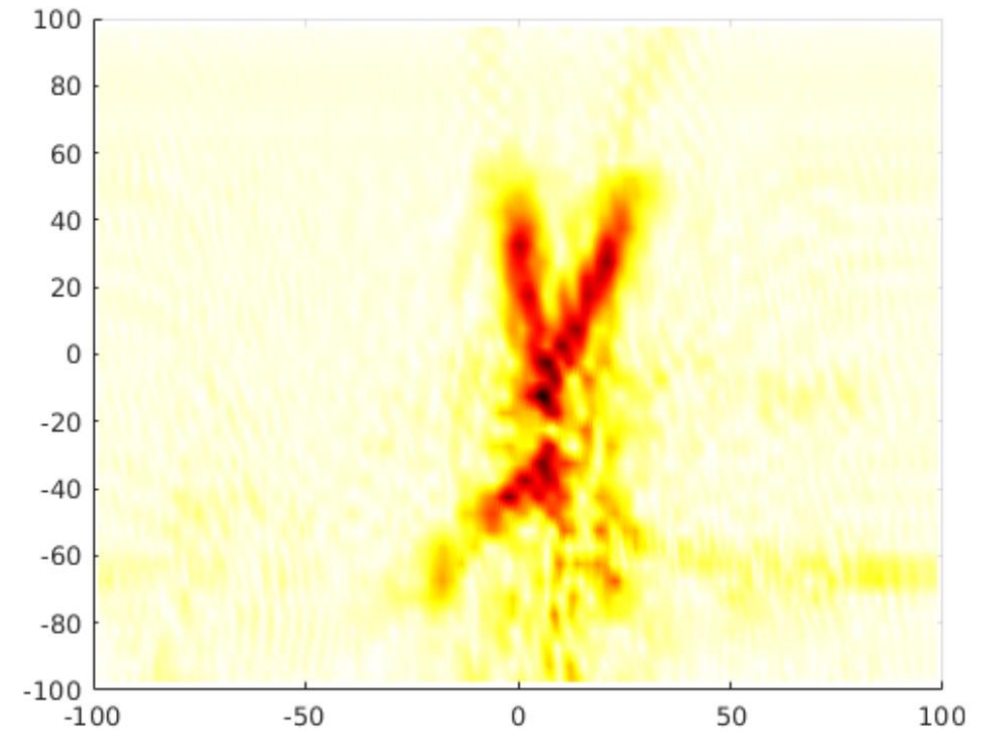


# Non-linear Motion

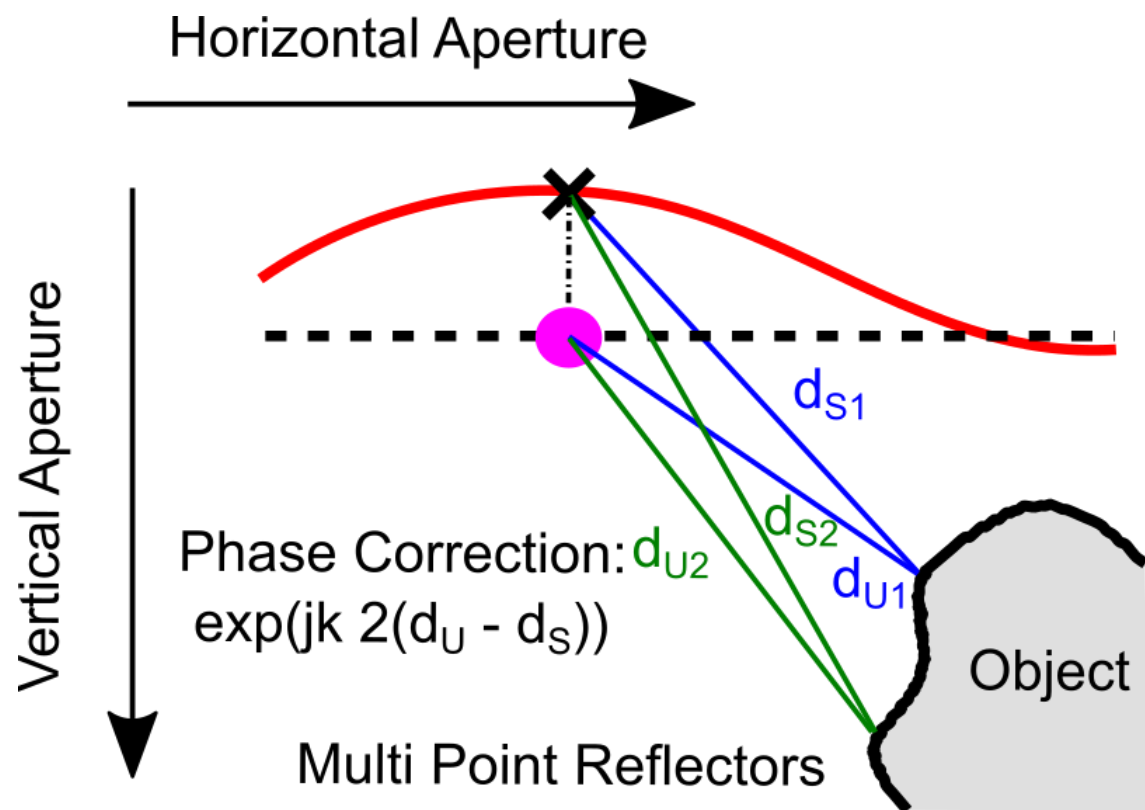
## Squiggle Grid



## Ideal Grid



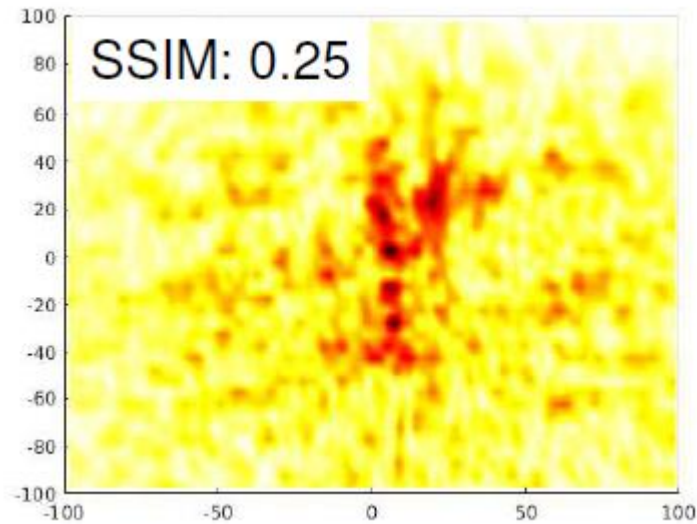
# Motion Error Compensation



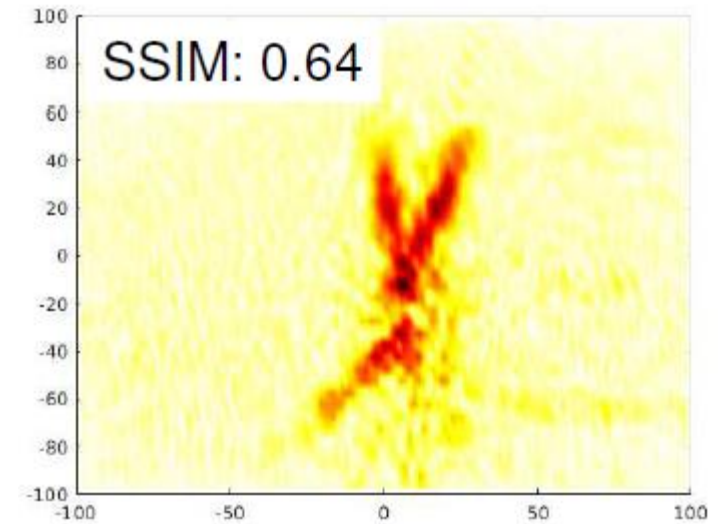
$$\min \sum_{i \in N, j \in N, i \neq j} \left| s_u^i(x_u, y_u, \omega) - s_u^j(x_u, y_u, \omega) \right|_{k=\omega/c} \quad s. t. \quad |d_u - d_s| < \lambda/2$$

# Missing Samples

## Missing Samples

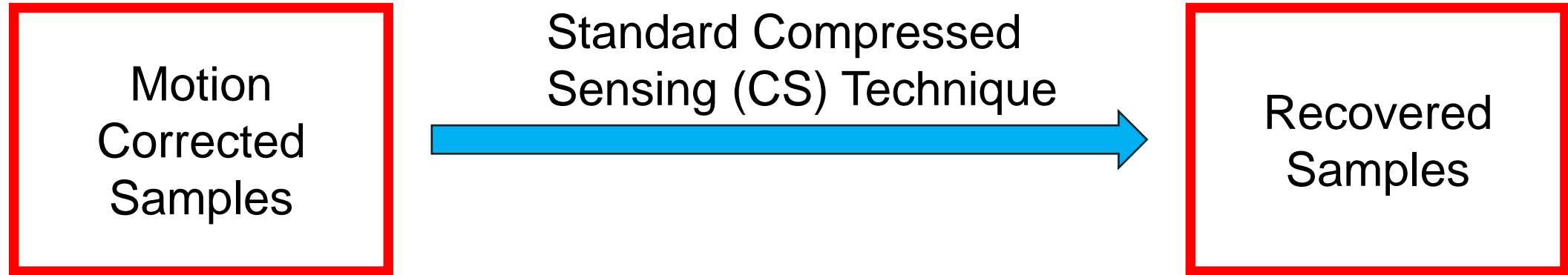


## Missing Samples Recovered



More than 50% samples are missing

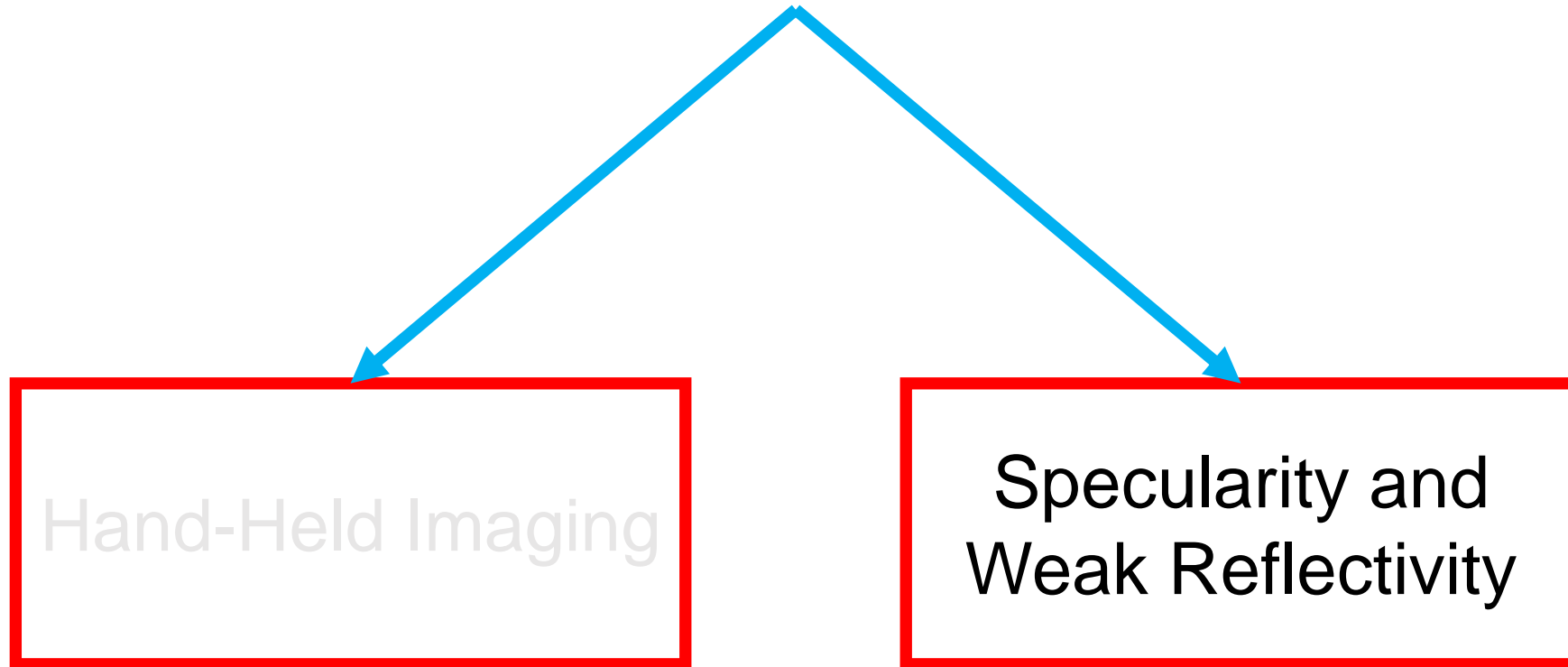
# Missing Samples Recovery



## CS Customization

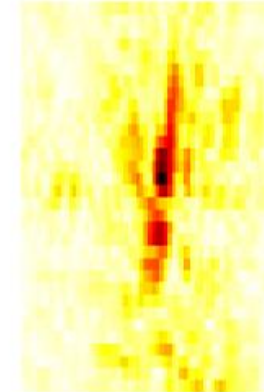
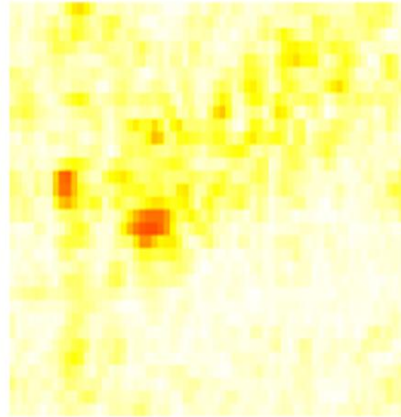
- ☐ Compressed Sensing fails if data are **correlated** and **wide**
- ☐ Visual-aid ensures **randomness** in data points collected
- ☐ we also **limit the range to 4 m** to avoid wide problem as our application is targeted for short range
- ☐ Additionally, **we use Density based clustering algorithm (DBSCAN) to separate objects in the scene**

# Challenges

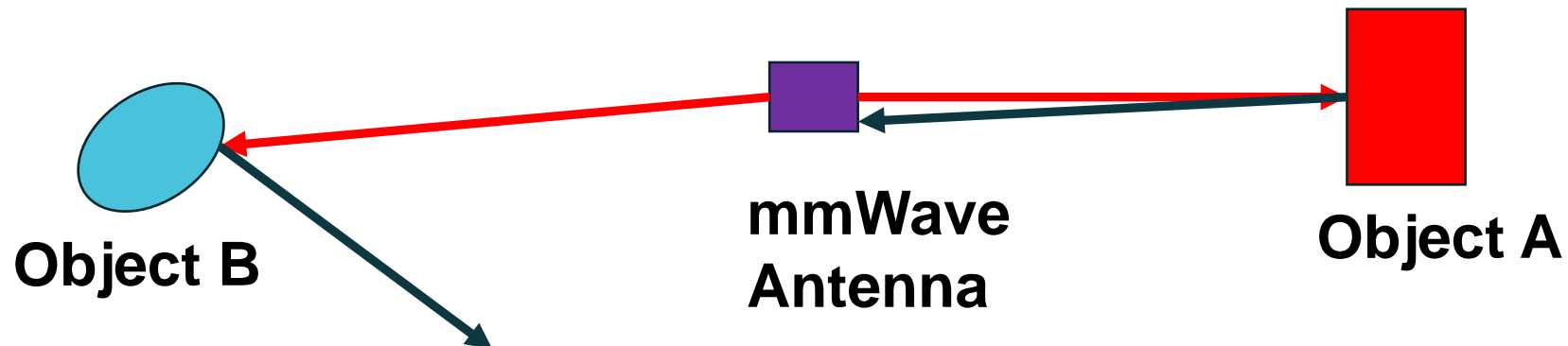




# Specularity And Weak Reflectivity

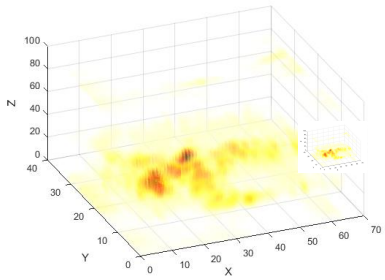


Object surface acts like mirror and transmitted signal bounces off an angle it will not come back to the receiver



# Motivation To Use Machine Learning

**3D mmWave  
Image**

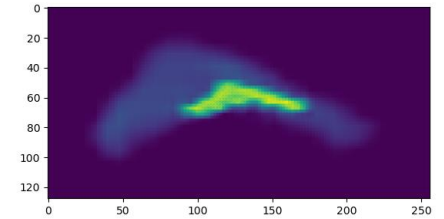


**Ground-Truth  
Image**



**Conditional  
Generative  
Adversarial  
Networks (cGAN)**

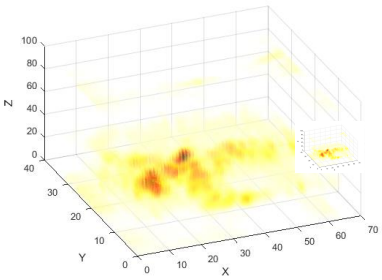
**Epoch: 1**



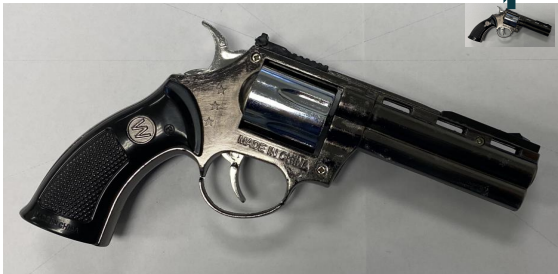
**Difficult to  
Recognize  
Shape**

# Motivation To Use Machine Learning

**3D mmWave  
Image**

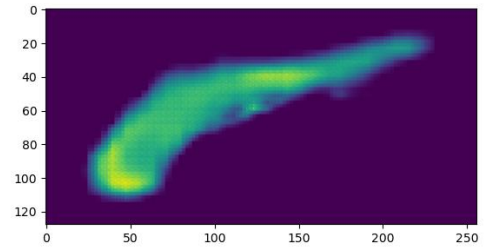


**Ground-Truth  
Image**



**Conditional  
Generative  
Adversarial  
Networks (cGAN)**

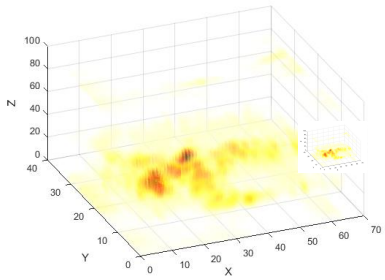
**Epoch: 10**



**Learning  
real image  
distribution**

# Motivation To Use Machine Learning

**3D mmWave  
Image**

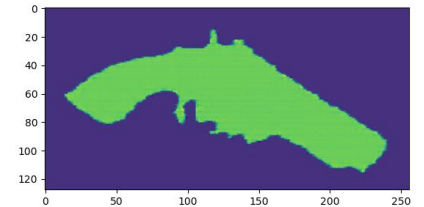


**Ground-Truth  
Image**



**Conditional  
Generative  
Adversarial  
Networks (cGAN)**

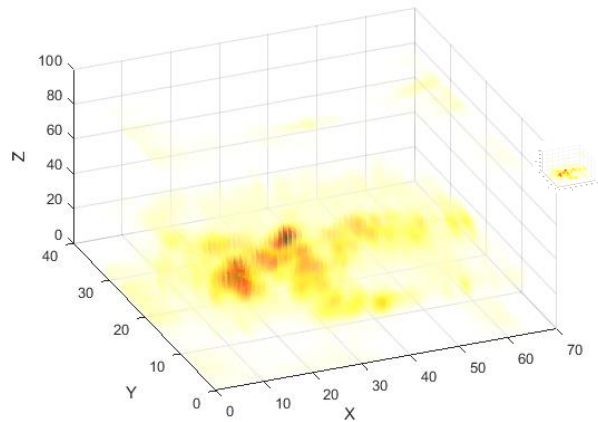
**Epoch: 1000**



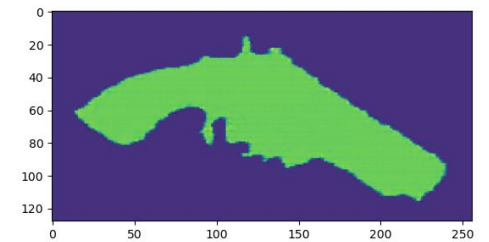
**Shape  
Fully  
Recovered**

# Motivation To Use Machine Learning

**3D mmWave  
Image**



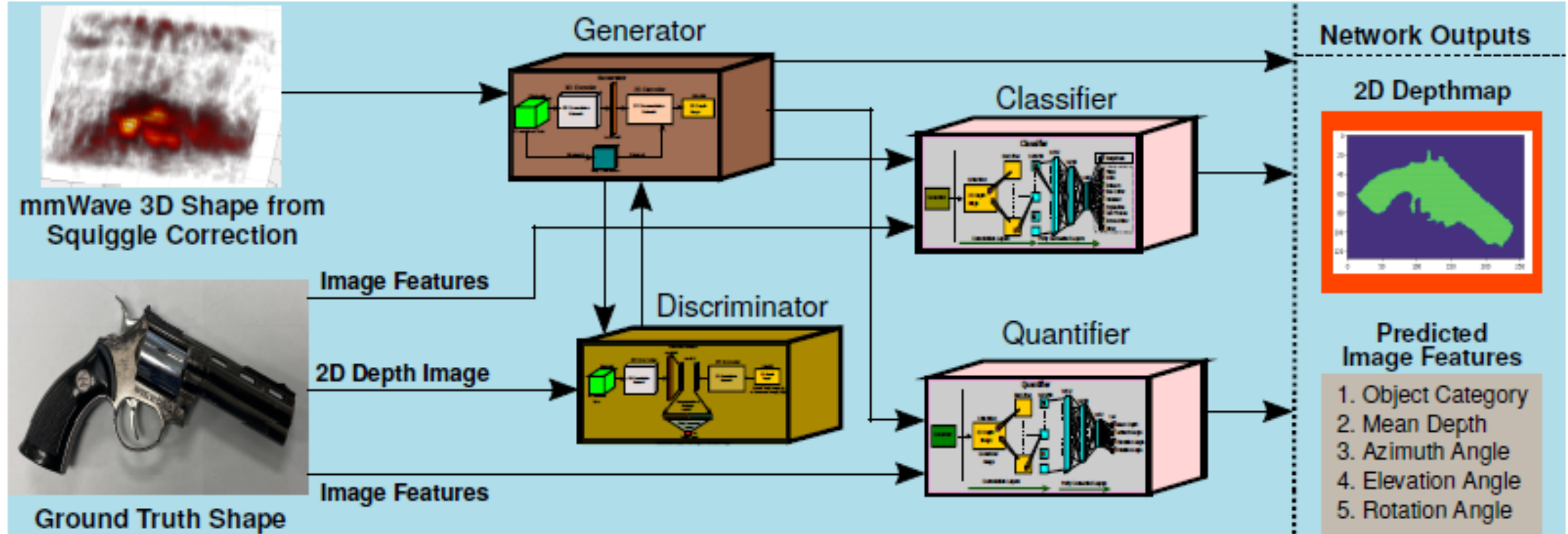
**Generator**



**Post Training**

**Object is human perceptible**

# Shape Recovery With SquiggleMilli

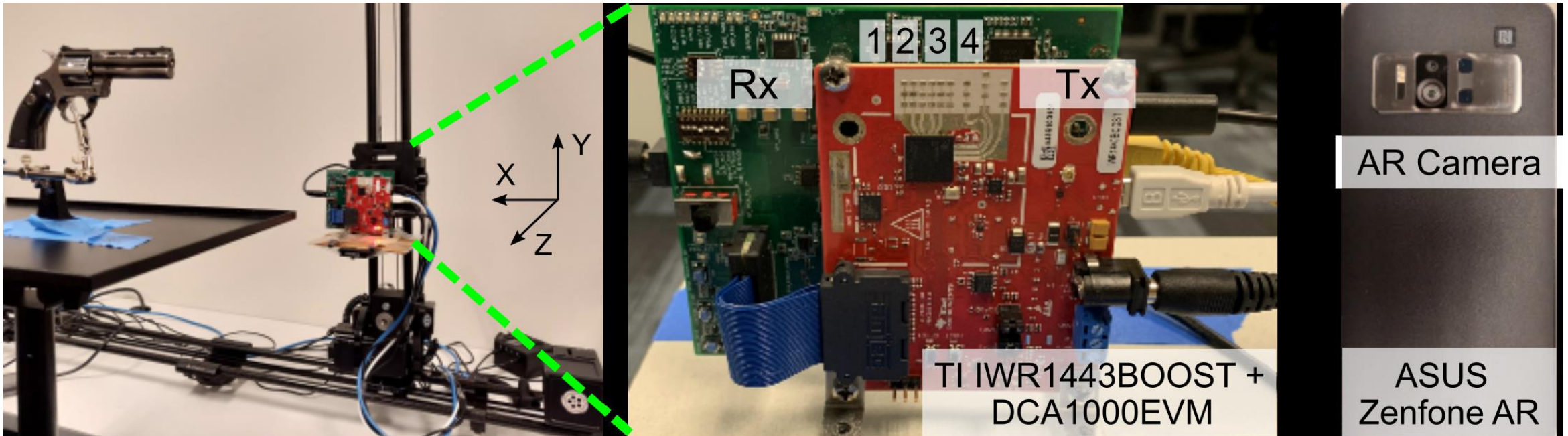




# Implementation

## mmWave Hardware

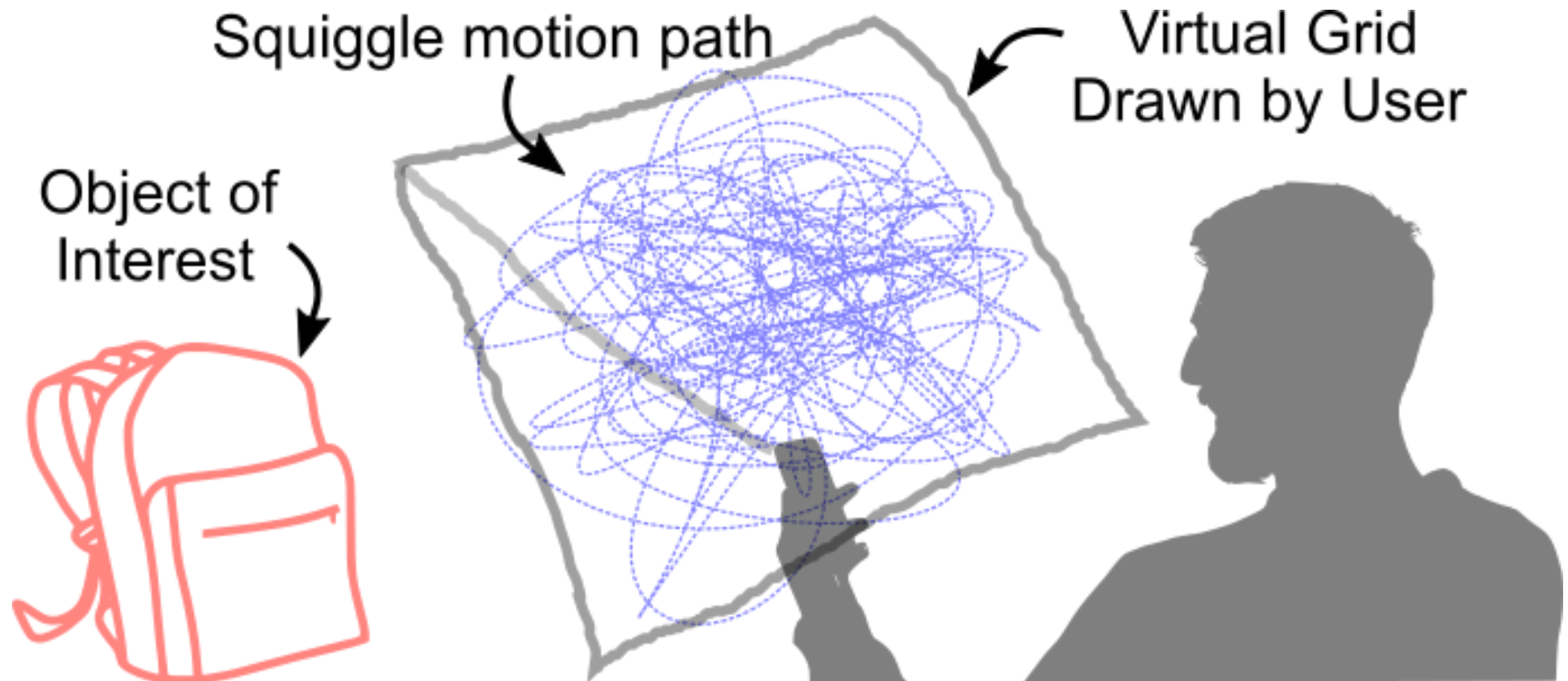
- ❑ Start Frequency: 77.33 GHz
- ❑ Effective BW: 3.22 GHz



Co-located mmWave hardware and AR Camera

# Implementation

## Squiggle Pose Collection



# Data Collection

## Real Data Collection

- ❑ Volunteers are asked to squiggle phone to collect pose data
- ❑ Then, we place mmWave in precise mechanical controller
- ❑ It scans the area of  $20 \times 20 \text{ cm}^2$
- ❑ Apply pose to obtain the squiggle data set
  
- ❑ To collect ground-truth 2D shape, we use co-located AR device
- ❑ MmWave 3D image:  $40 \times 1000 \times 236 \Rightarrow 32 \times 64 \times 96$
- ❑ 2D shape ground-truth:  $128 \times 256$  depth image
- ❑ Takes  $\sim 15$  mins/sample

2918 LOS and NLOS Real Samples

Real data collection is slow and ML needs lots of data, what can we do?

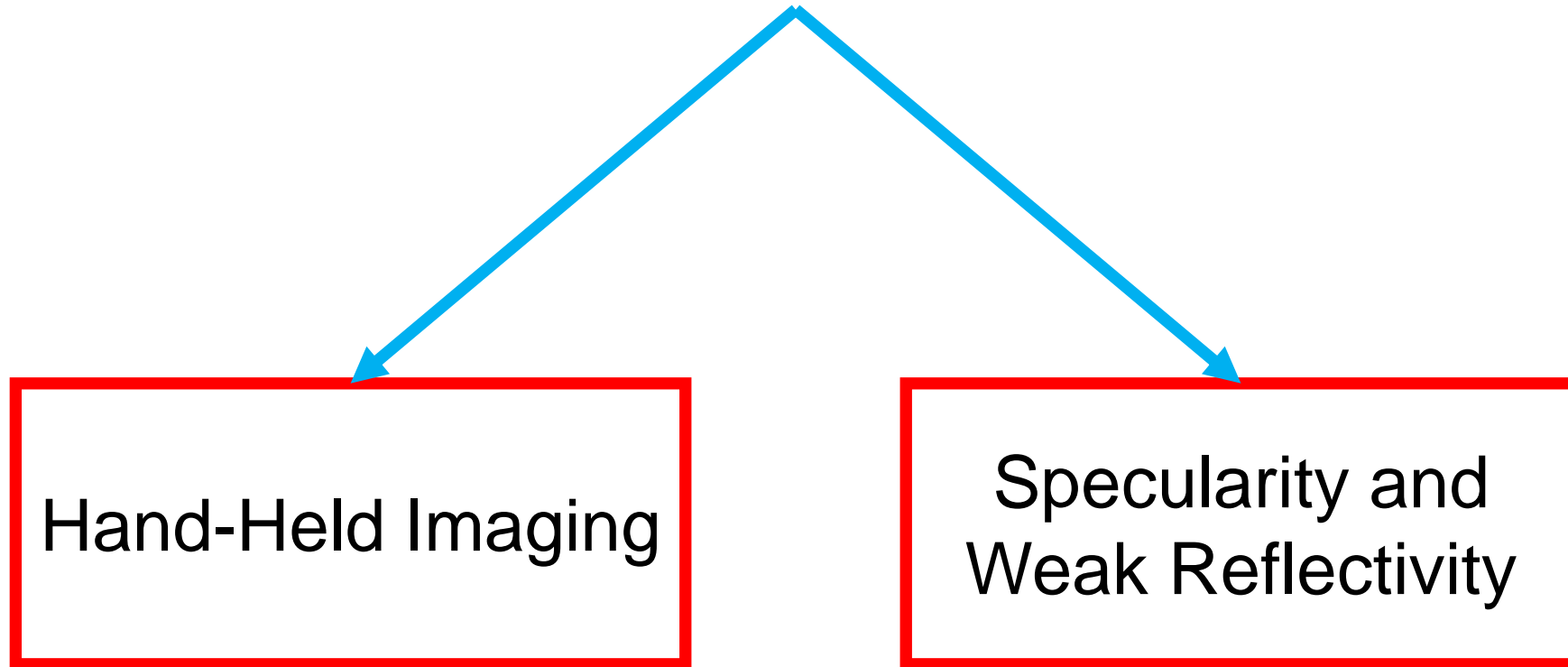
# Data Collection

## Synthetic Data Generation

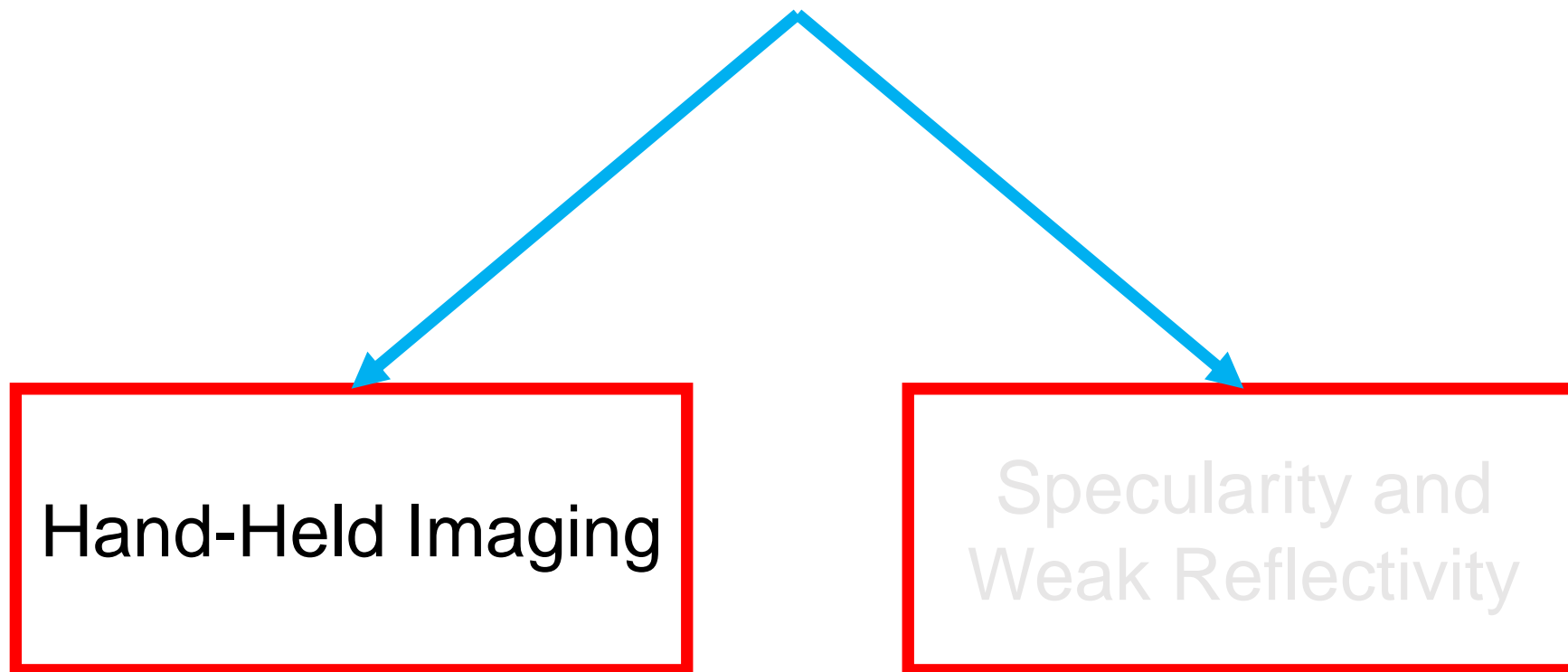
- ❑ Large data scales for mmWave are not available
- ❑ We collected multiple 3D shapes from ShapeNet
- ❑ We projected the image into 2D shape and apply different 3D rotation matrix to generate 3D voxel
- ❑ 3D voxel is then used in **Ray Tracing Algorithm**
- ❑ Introduced various noises in simulation
- ❑ It generates the mmWave image like the images generated by SAR Imaging Devices
- ❑ Single simulation takes ~ 1.5 min in our PC (Intel Xeon @ 32 GB RAM)

9800 Synthetic Samples

# Evaluation



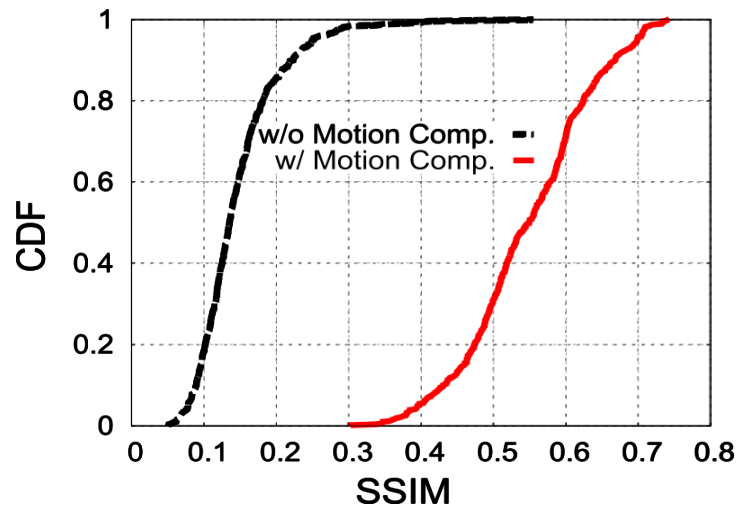
# Evaluation





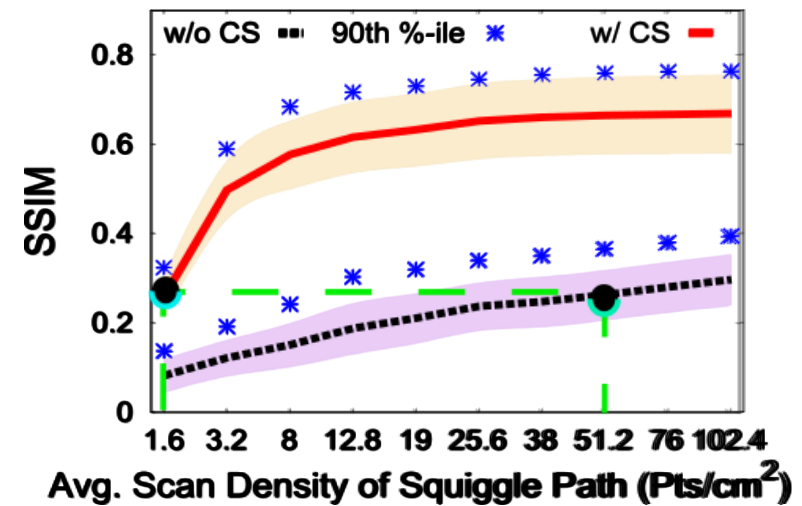
# Hand-held Imaging

## Motion Correction



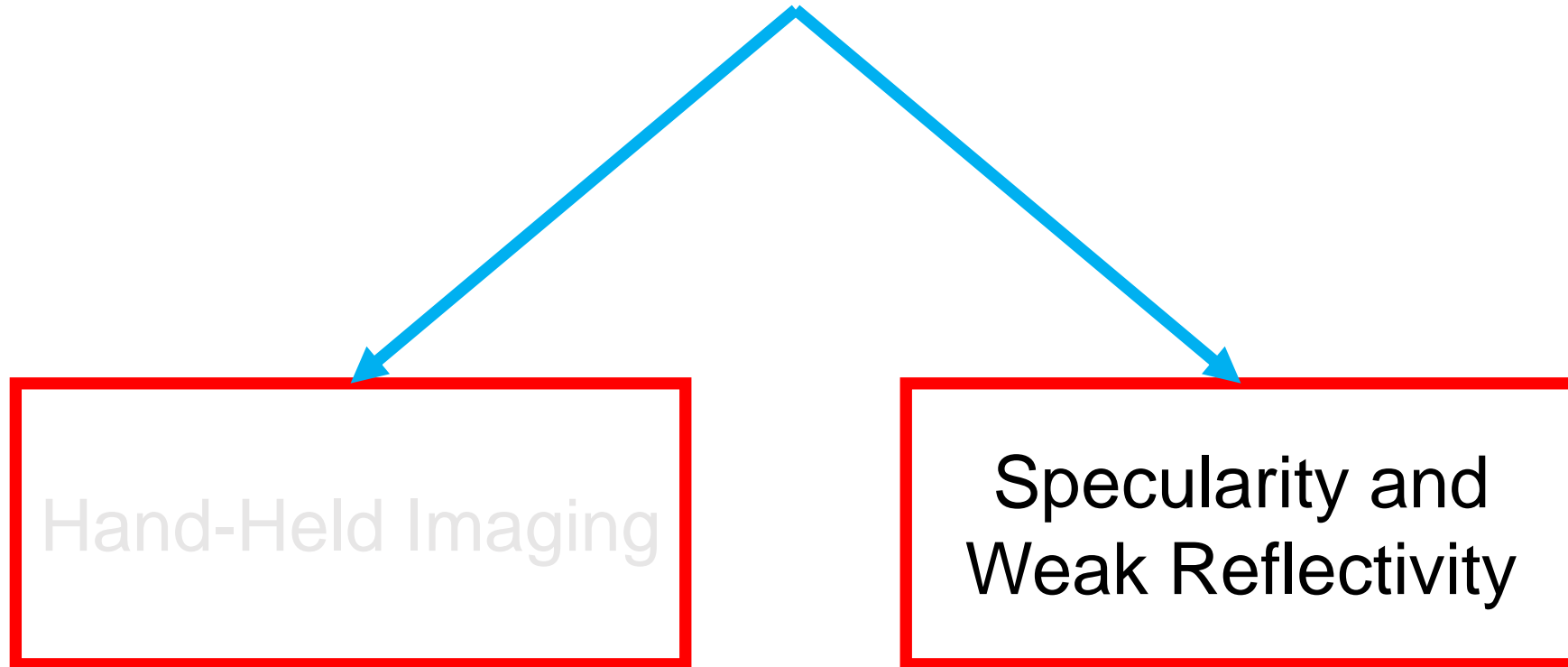
**Shape quality  
improved ~4 times**

## CS Recovery



**Scan Requirement  
Reduced by 30  
times**

# Evaluation



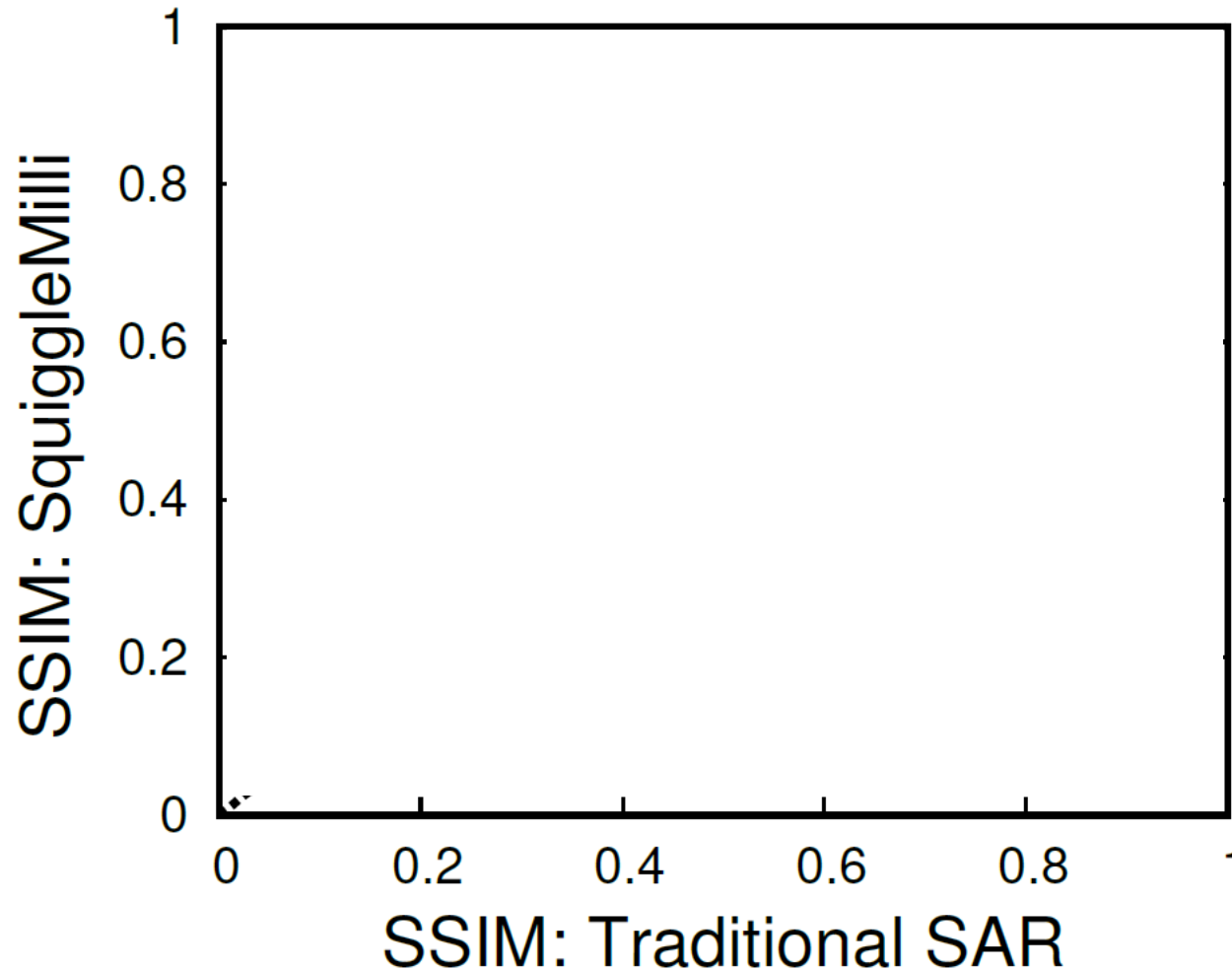
# Full Shape Recovery With SquiggleMilli

Camera image

2D Ground-truth Shape



# Full Shape Recovery With SquiggleMilli



**LOS:** Line of Sight  
**NLOS:** None Line of Sight  
**Unseen:** Objects not included in Training but looks like the Category of objects trained

**Median similarity to ground-truth is 90% for NLOS**

# Object Classification

Actual/Predicted	Boxcutter	Cellphone	Explosive	Hammer	Knife	Pistol	Scissor	Screw	Other
Boxcutter	94	0	0	0	0	0	1	0	5
Cellphone	0	69	0	4	0	2	0	0	25
Explosive	0	0	85	8	0	0	0	0	7
Hammer	0	0	0	93	0	0	3	0	4
Knife	5	0	0	0	67	0	8	0	20
Pistol	2	0	0	0	0	87	2	1	8
Scissor	0	0	0	0	0	0	100	0	0
Screw	0	0	0	3	0	0	19	45	33
Other	0	0	19	6	0	21	2	0	52

**Objects are selected which are use used in TSA Screening**

**Objects are correctly classified to respective classes**

# Field Trials

Camera image

**Pistol semi-occluded**



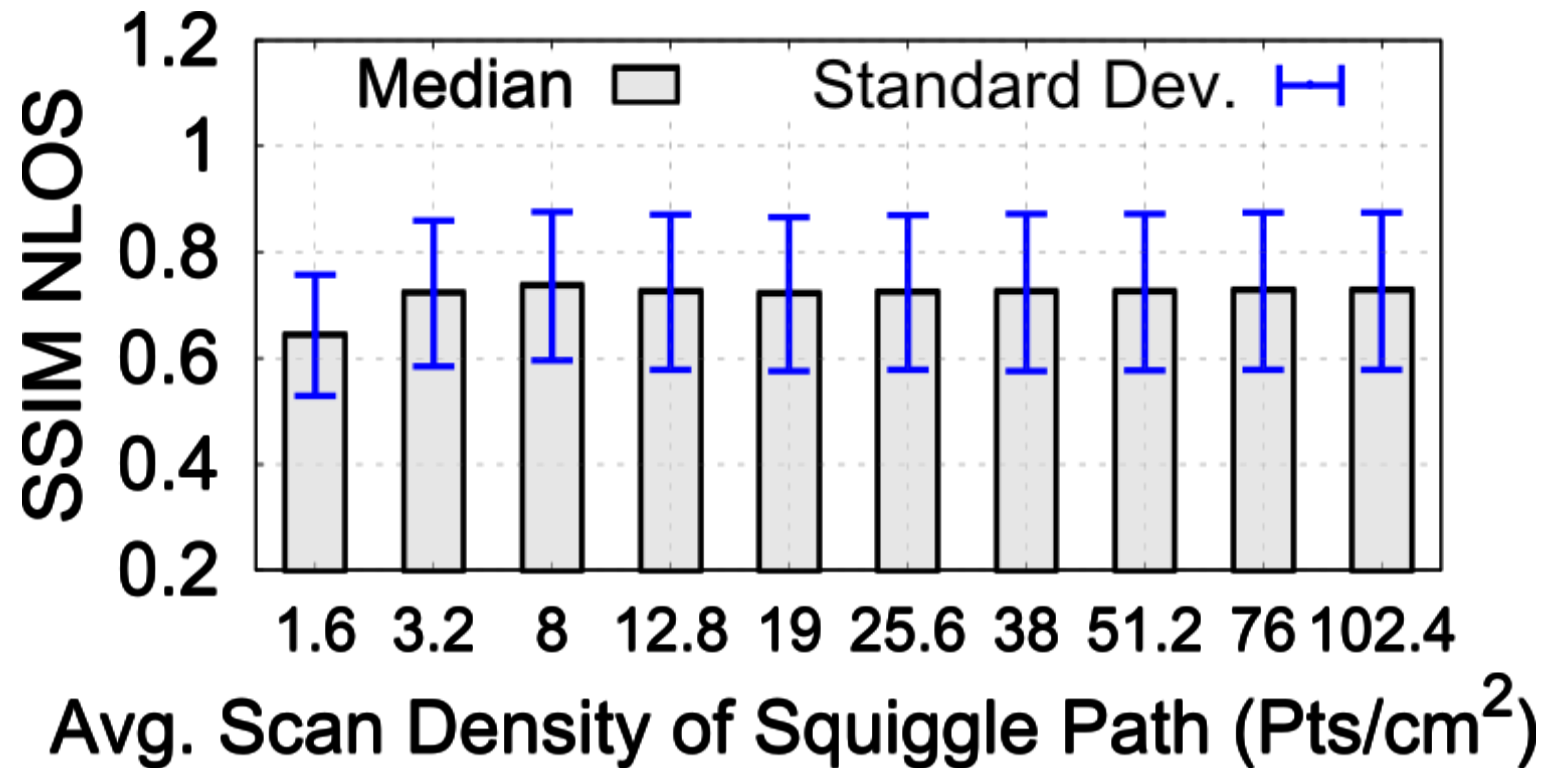
**Pistol fully-occluded**



**Scissors semi-occluded**



# Field Trials



**Achieved 72% shape similarity with  
just 3.2 pts/cm<sup>2</sup> scan density**



# Conclusion

- ❑ SquiggleMilli brings **high-resolution**, through-obstruction imaging into cheap, **ubiquitous mobile devices**

## Thank you!

Please check out our paper for more results:

<https://github.com/hregmi77/SquiggleMilli>

Any Questions: Please email to [hregmi@email.sc.edu](mailto:hregmi@email.sc.edu)