mmSight: Towards Robust Millimeter-Wave Imaging on Handheld Devices

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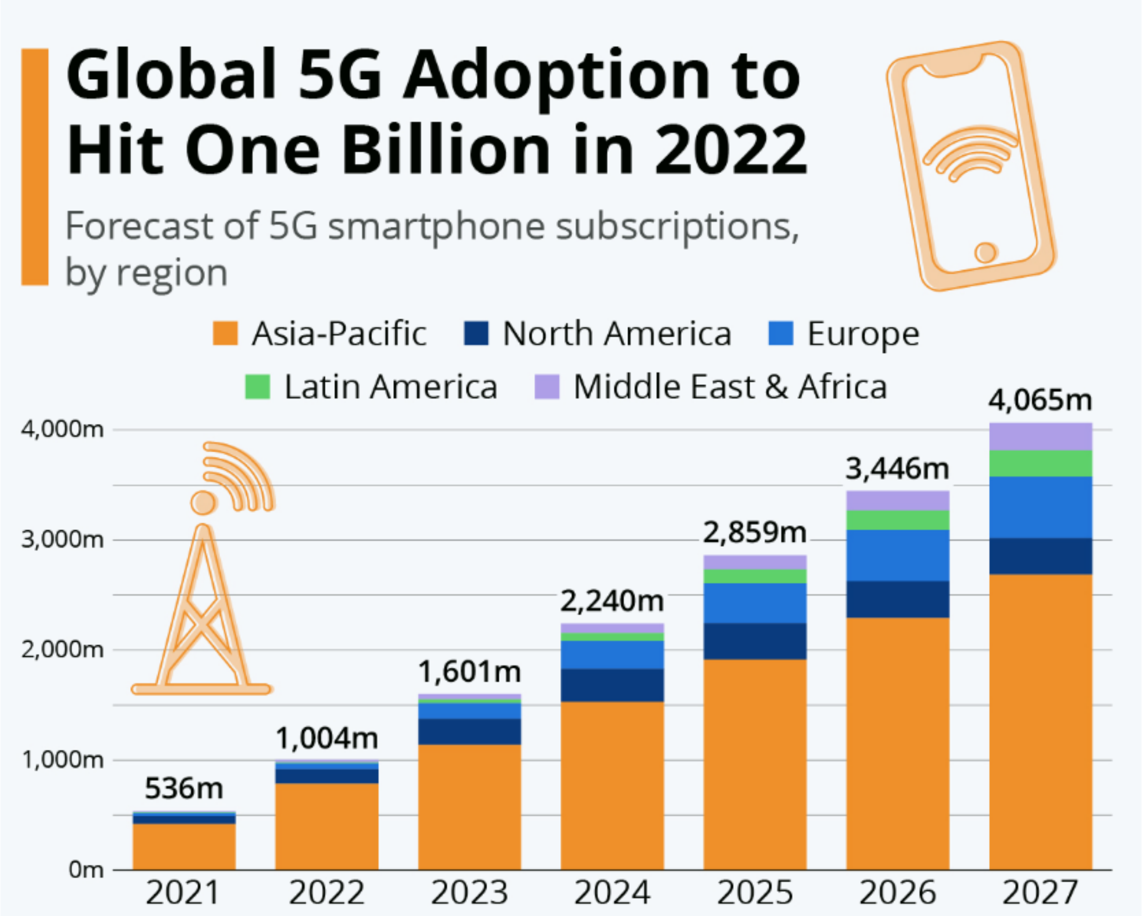
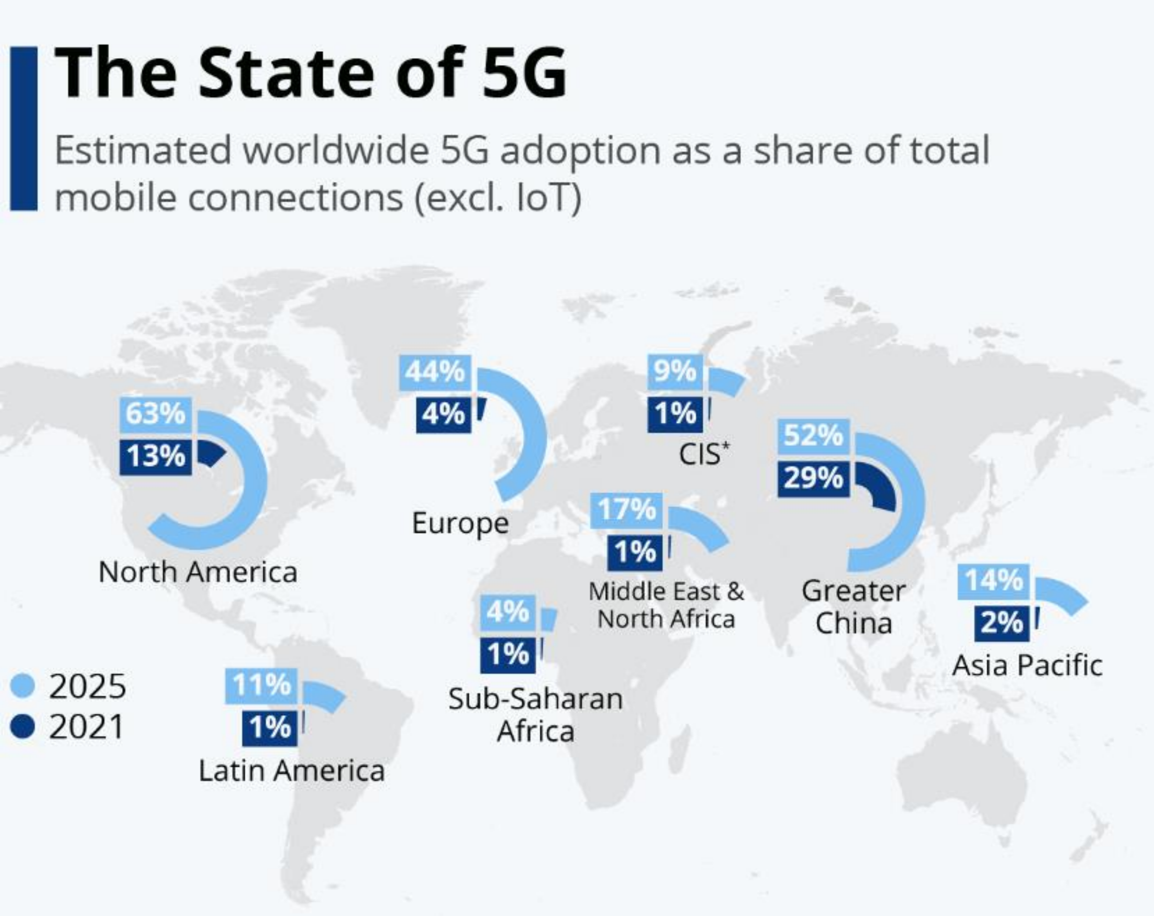
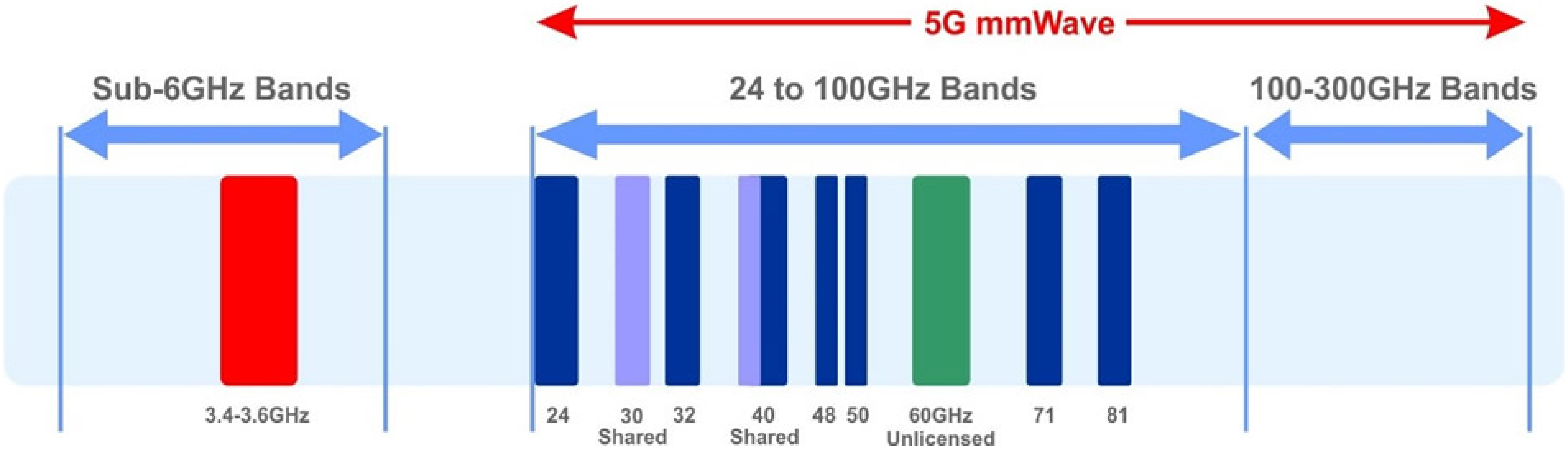
Ubiquity of 5G Mobile Devices





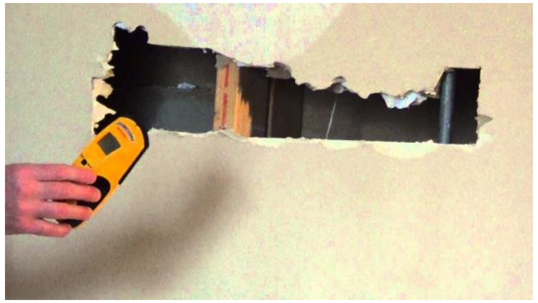
Source: Statista

What is 5G and Millimeter-Wave (mmWave)?



Capability of millimeter-wave signals to penetrate the clothes/wall enables the imaging beyond the vision

Millimeter-Wave Imaging Applications



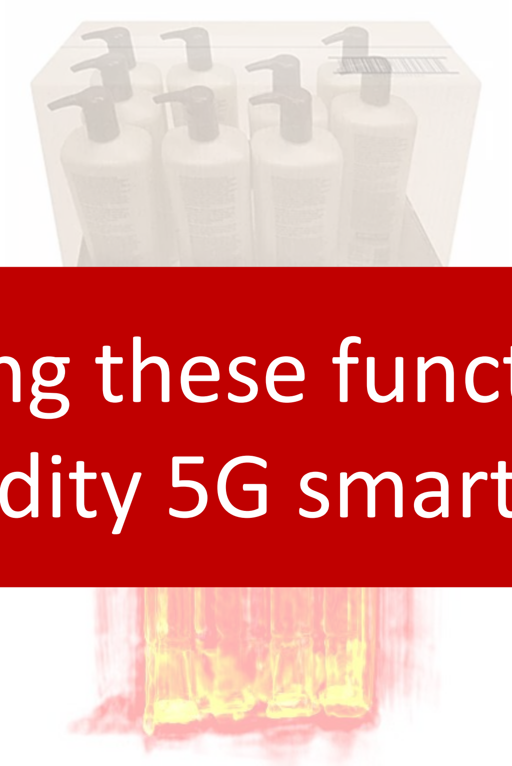
Behind wall detection

Construction
site surveying

Packaging and inventory

Airport contra-band
scanner

Millimeter-Wave Imaging Applications



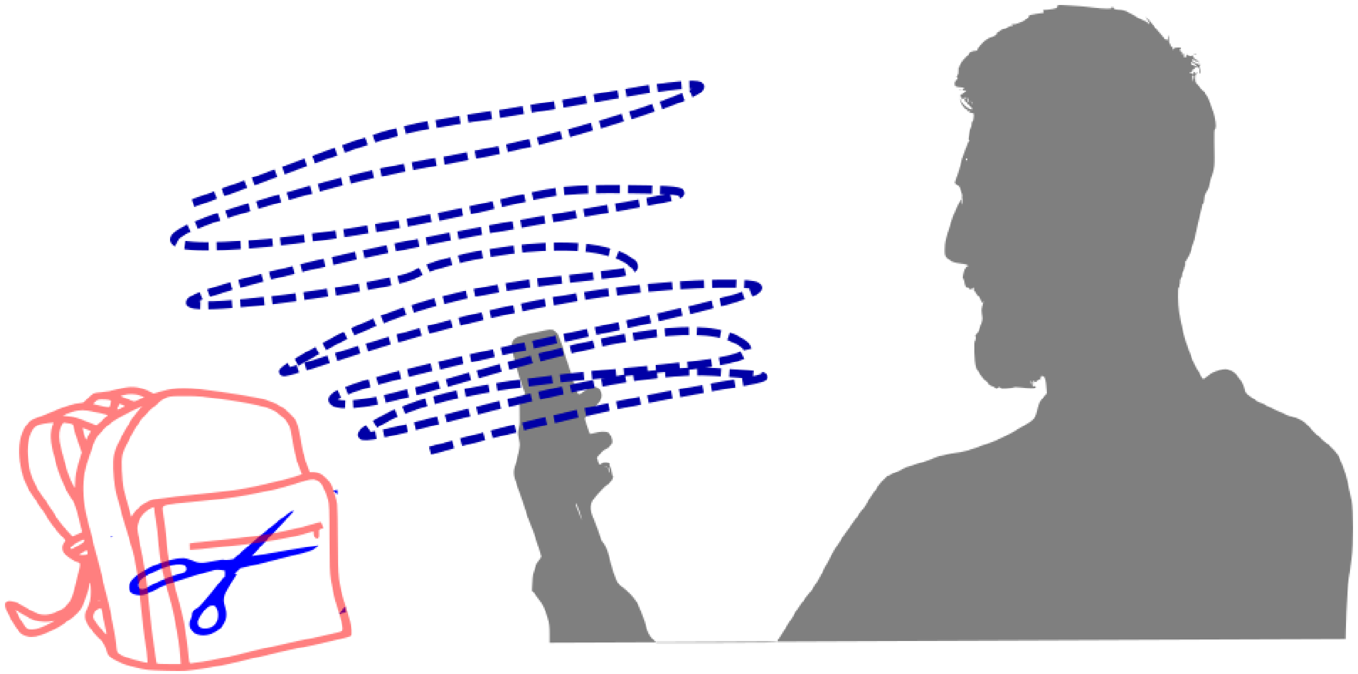
Can we bring these functionalities to commodity 5G smartphones?

Packaging and inventory

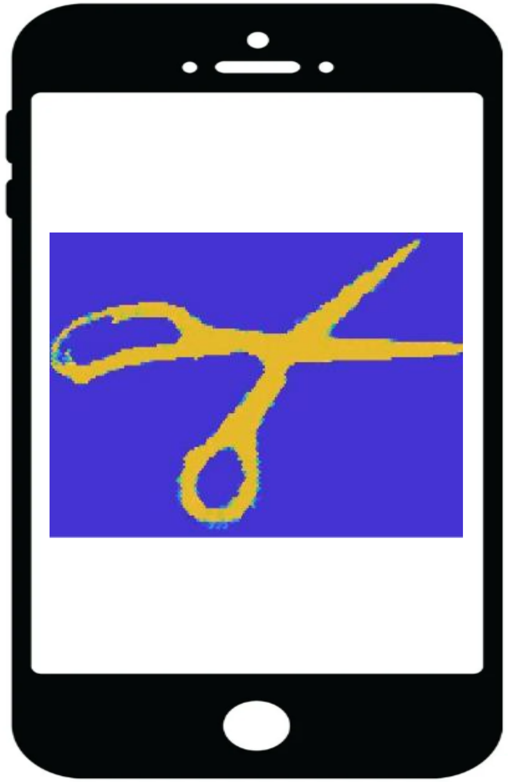
Construction site surveying

Airport contra-band scanner

Our Proposal: mmSight

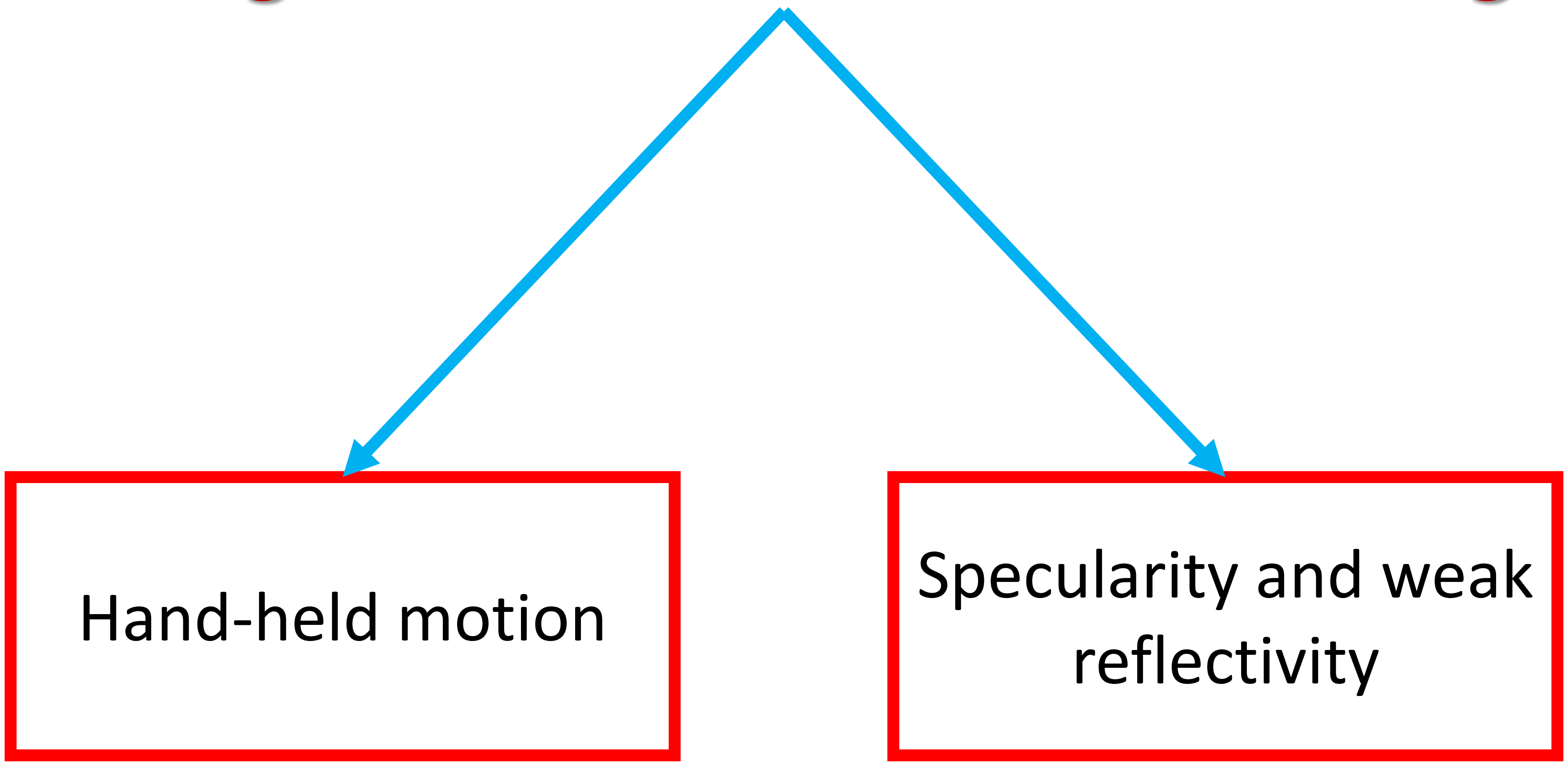


User scans the device in front of region of interest



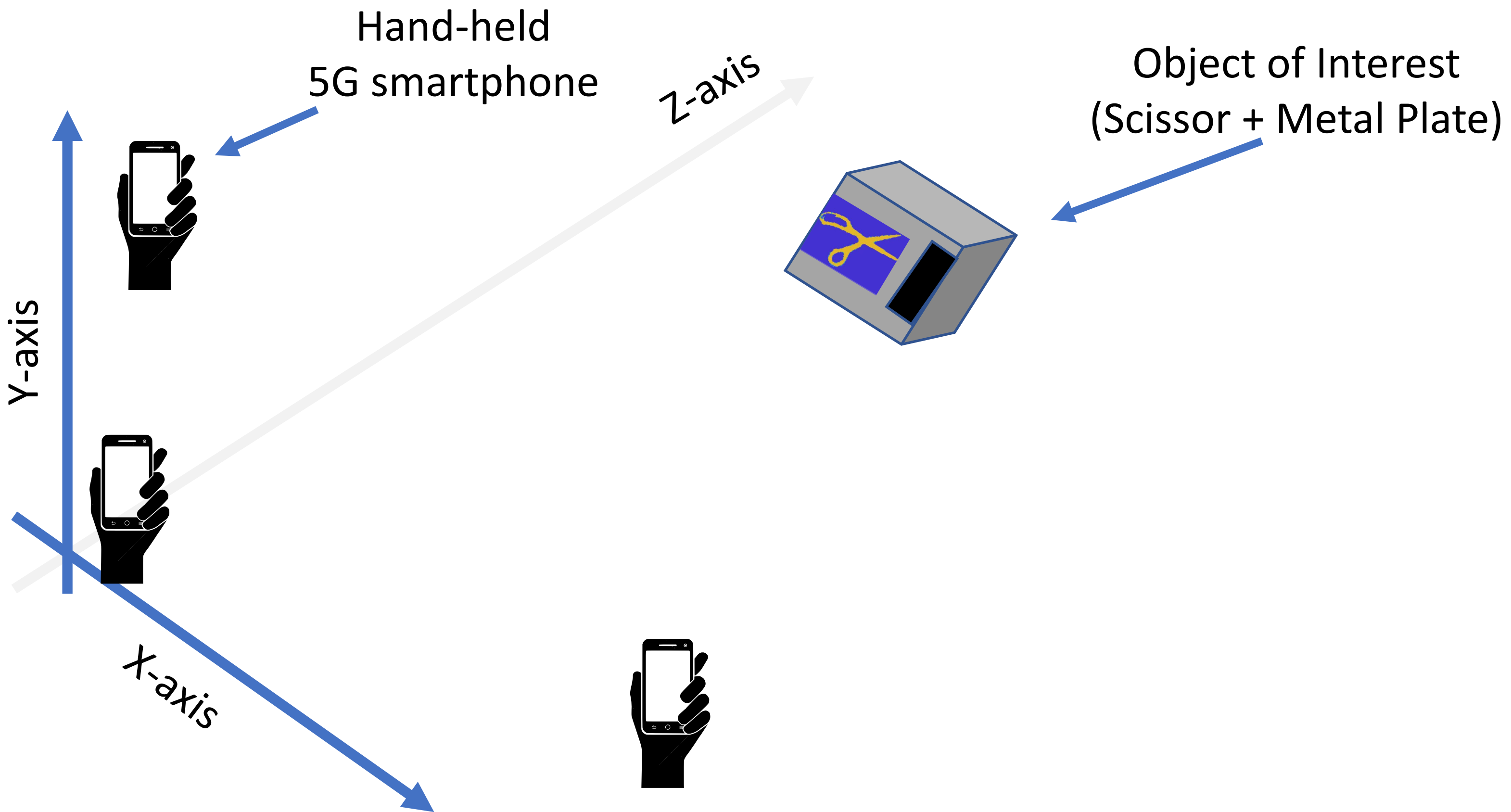
Human perceptible image allows for object classification

Challenges of Millimeter-Wave Imaging

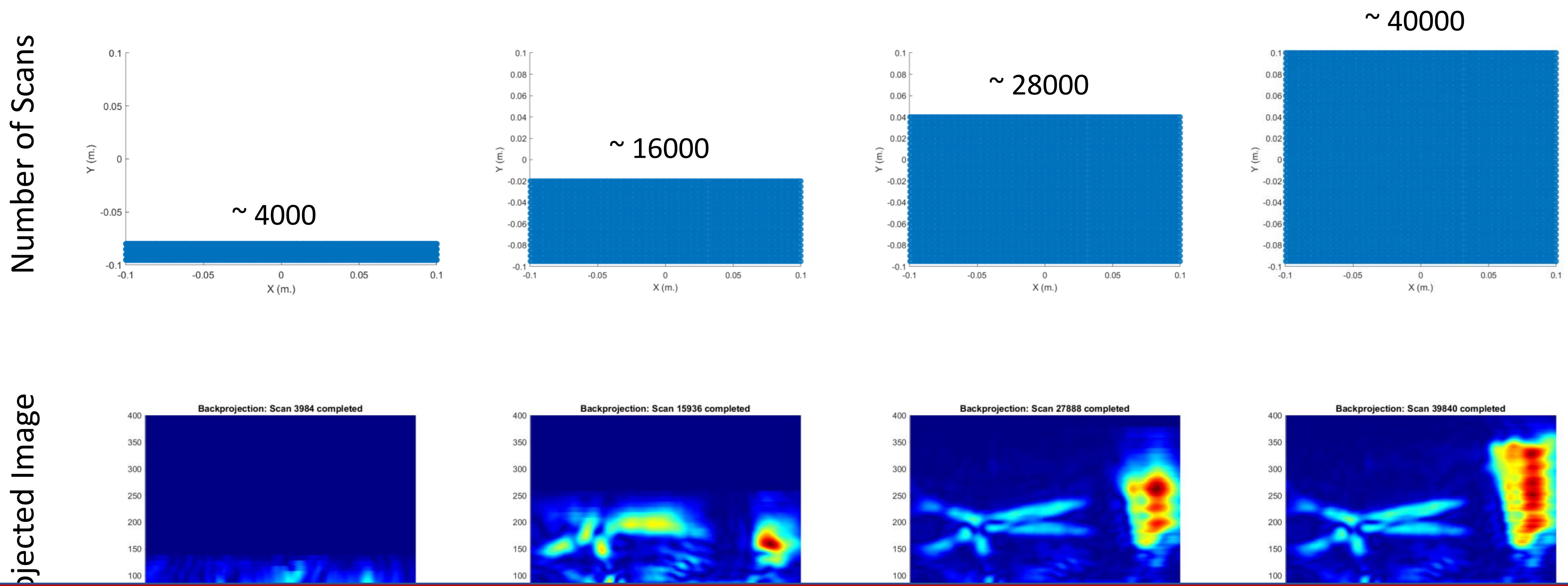


Time Domain Back Projection (TDBP)

- TDBP is widely used imaging technique in the field of Synthetic Aperture Radar (SAR) and medical imaging
- It constructs the image by summing the contribution from individual scattered signals received at different locations and times



Millimeter-Wave Image Generation Process



TDBP supports non-linear motion, but quality of mmWave image generation is dependent on number of scans

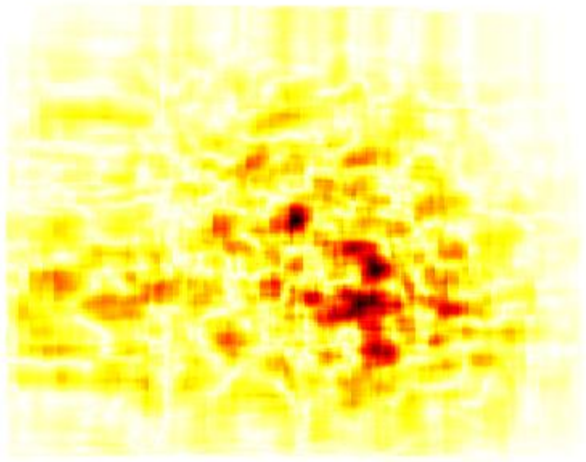
Challenges of Millimeter-Wave Imaging

- Hand-held motion
- Specularity and weak reflectivity

Challenge: Effect of Hand-held Motion

- Hand-held motion causes drift in X and Y direction
- Low-resolution vision tracking devices estimate pose inaccurately
- Error in pose estimation causes signals to combine destructively, and generated images are defocused and noisy

Scissors



Without
pose correction

Challenges of Millimeter-Wave Imaging

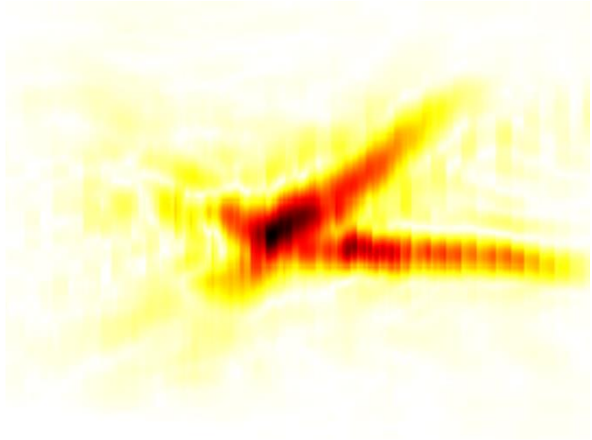
Hand-held motion

Specularity and weak reflectivity

Challenge: Specularity and Weak Reflectivity

- Pose-corrected mmWave images still lack various details necessary for human and machine perception
- Specularity of mmWave causes most reflections to reflect away from the receiver, resulting in missing regions on the mmWave images
- Moreover, weak reflectivity of objects absorbs signal energy and reflected signals are highly attenuated, close to the noise level

Scissors

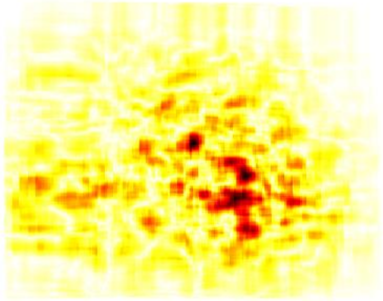


With
pose correction

Summary of Challenges

- Pose error due to hand-held motion and low-resolution vision-based tracking

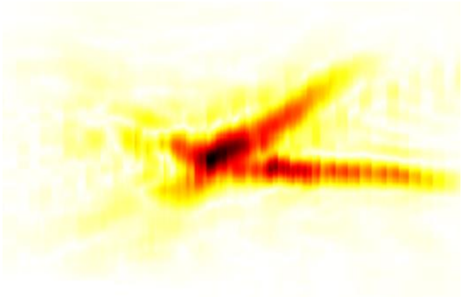
Scissors



Without
pose correction

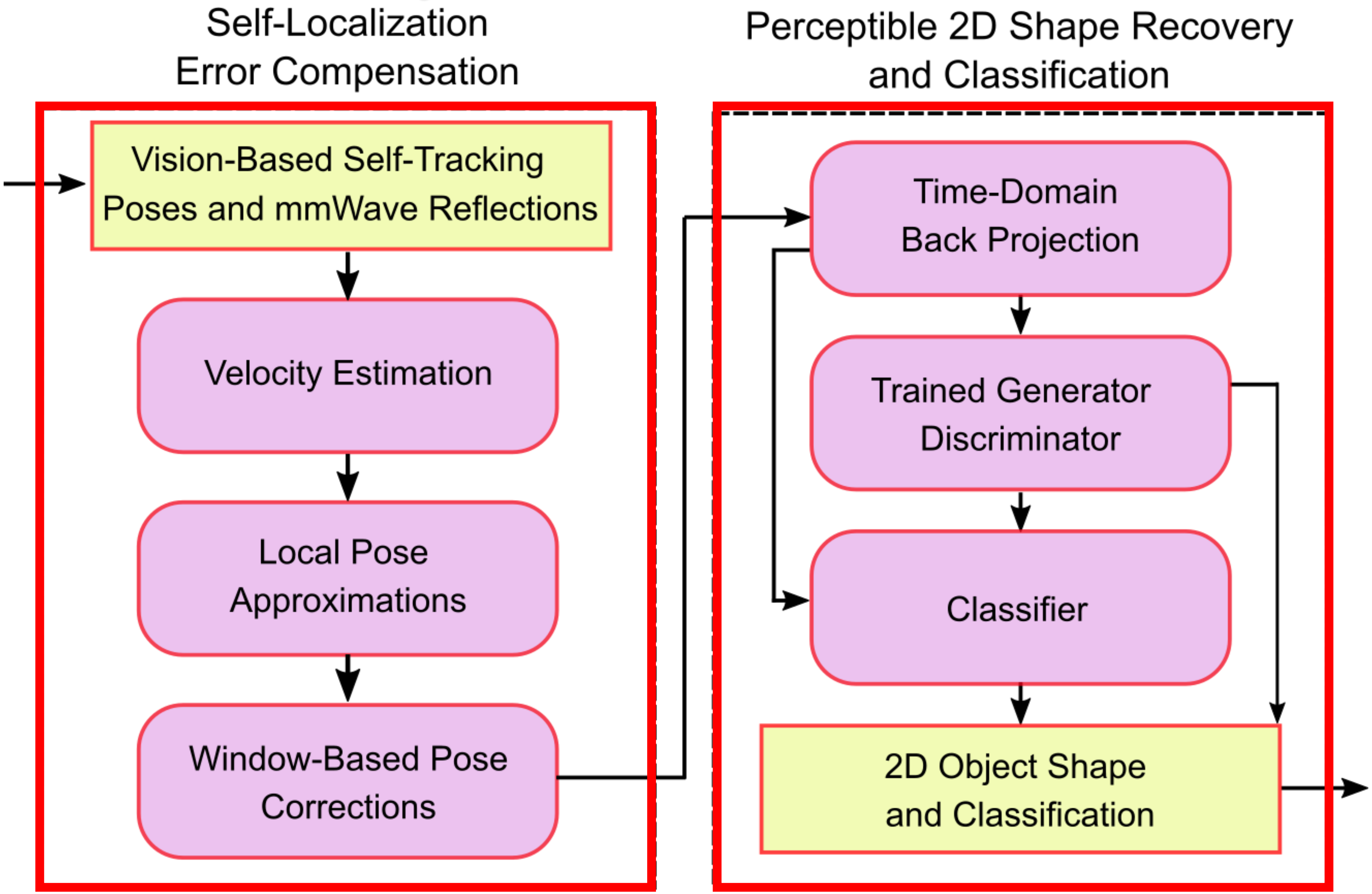
- Specularity of mmWave and weak reflectivity of object

Scissors

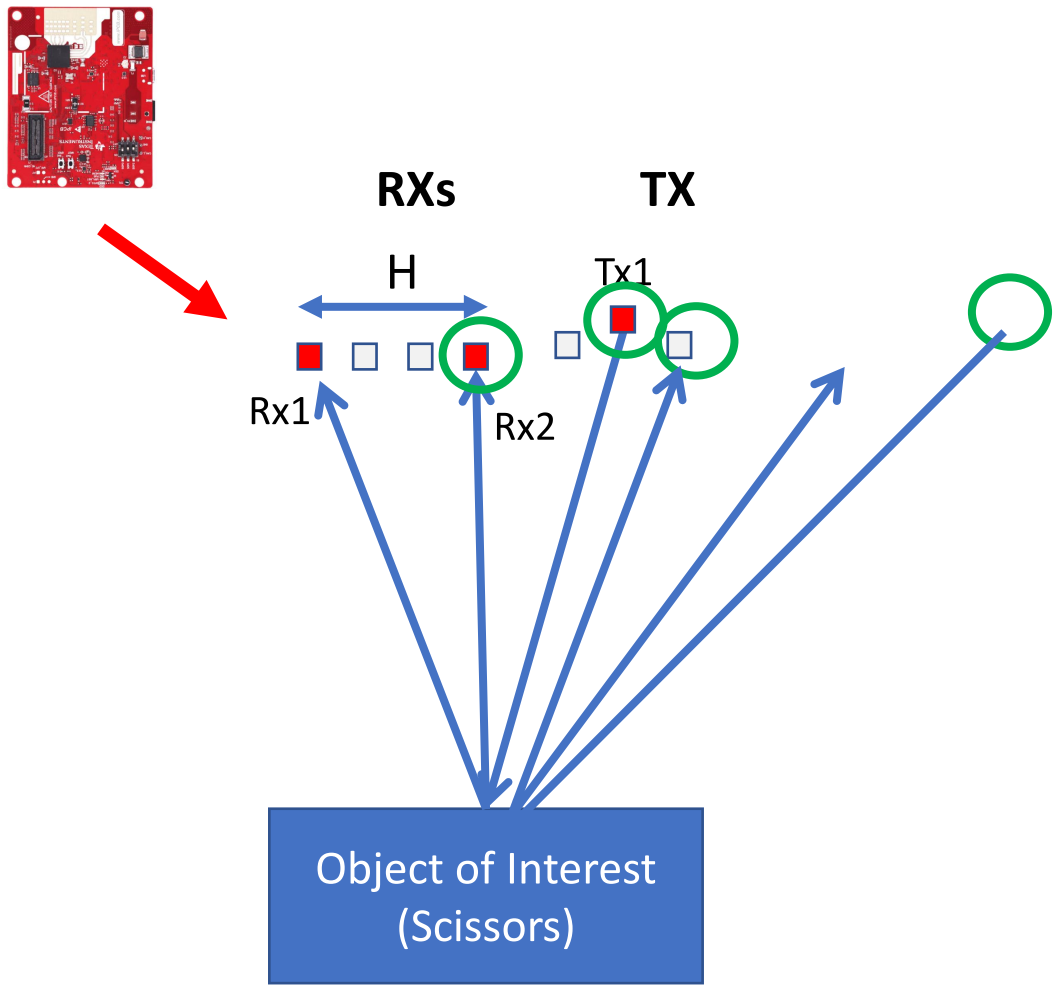


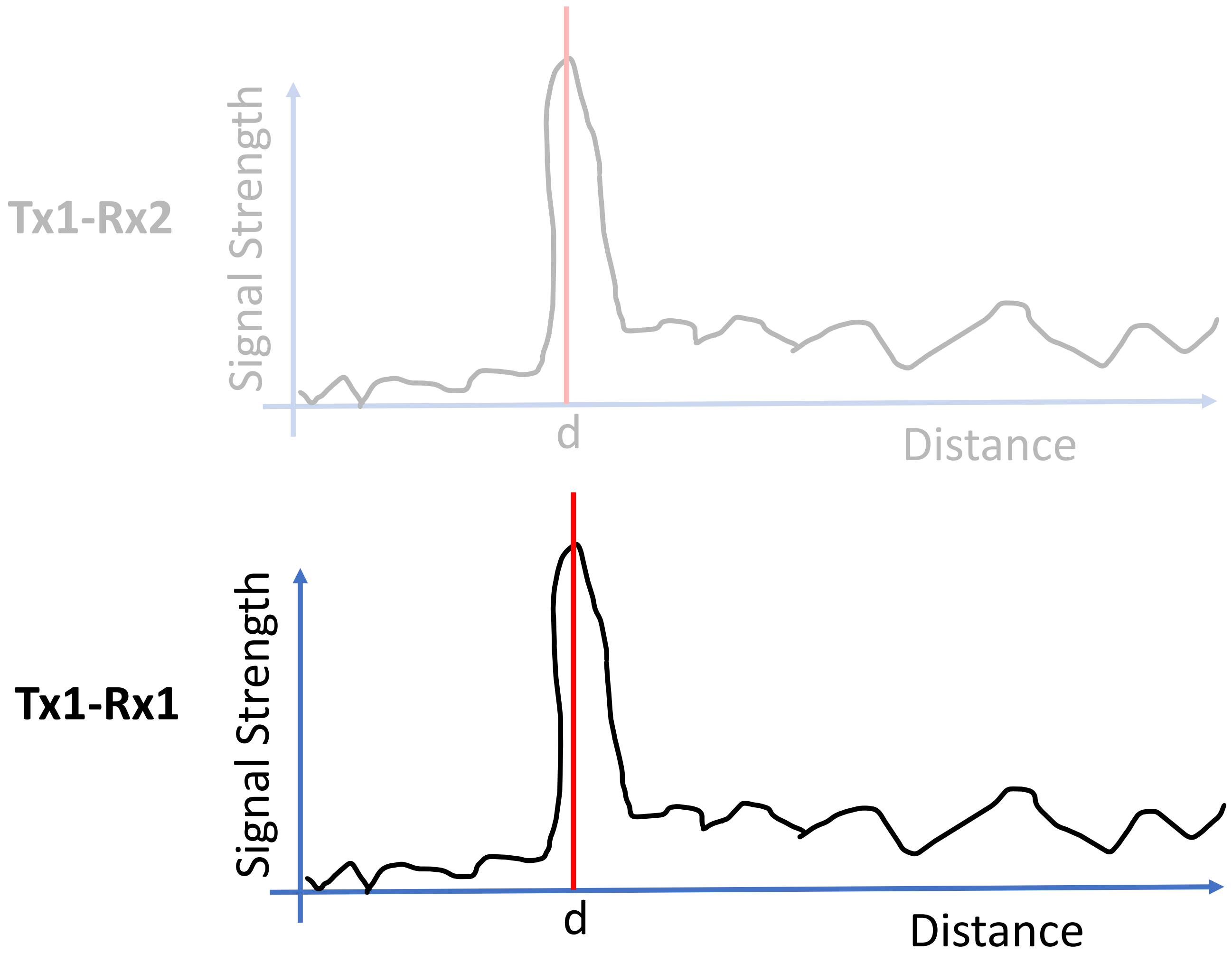
With
pose correction

System Overview

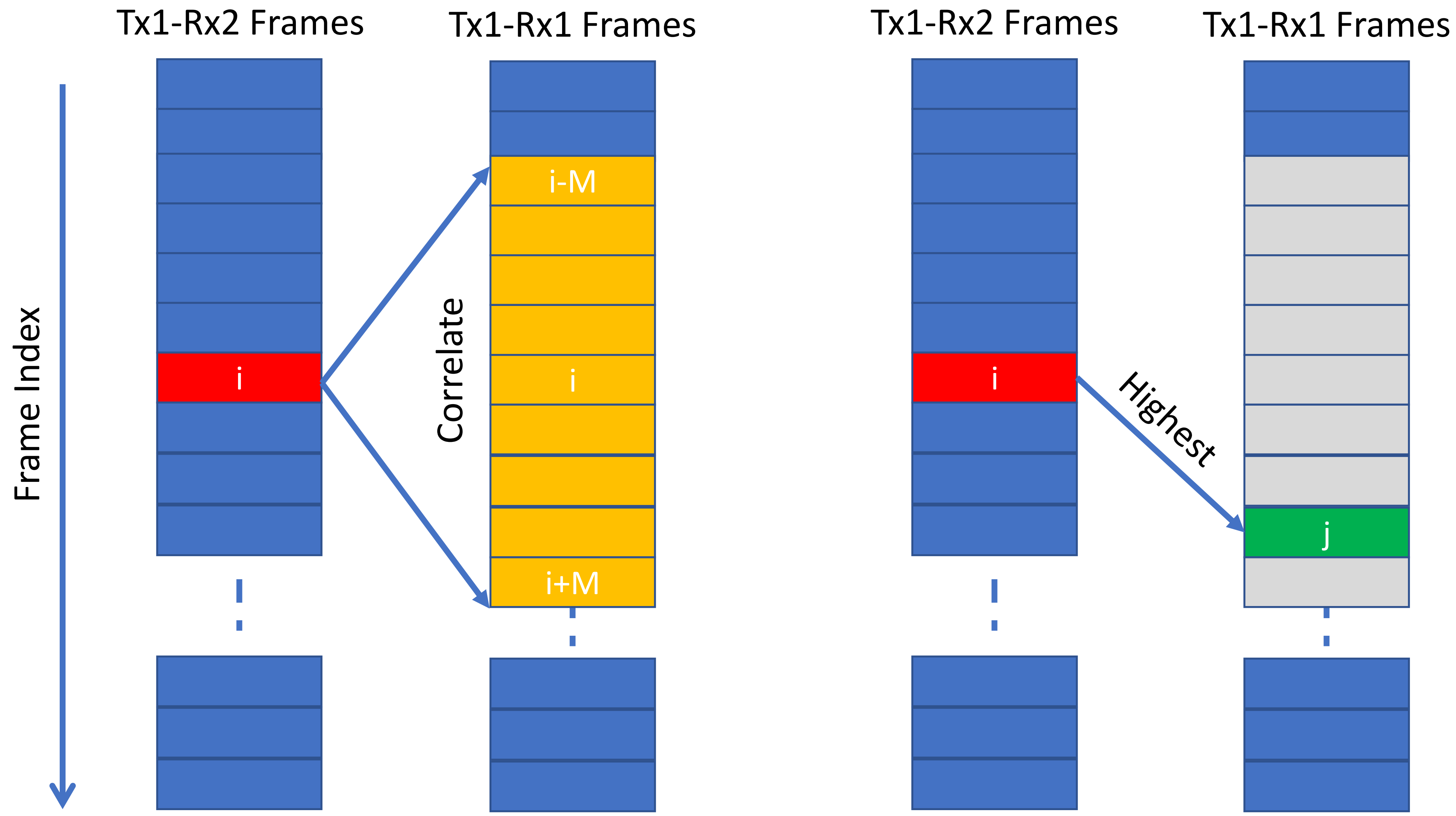


Millimeter-Wave Based Velocity Estimation





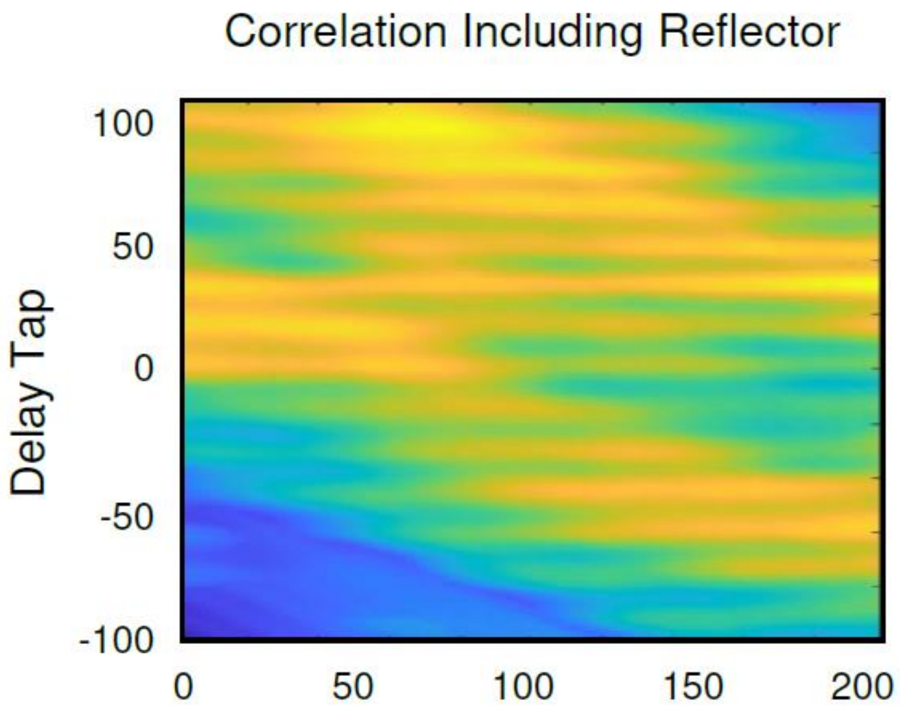
Millimeter-Wave Based Velocity Estimation

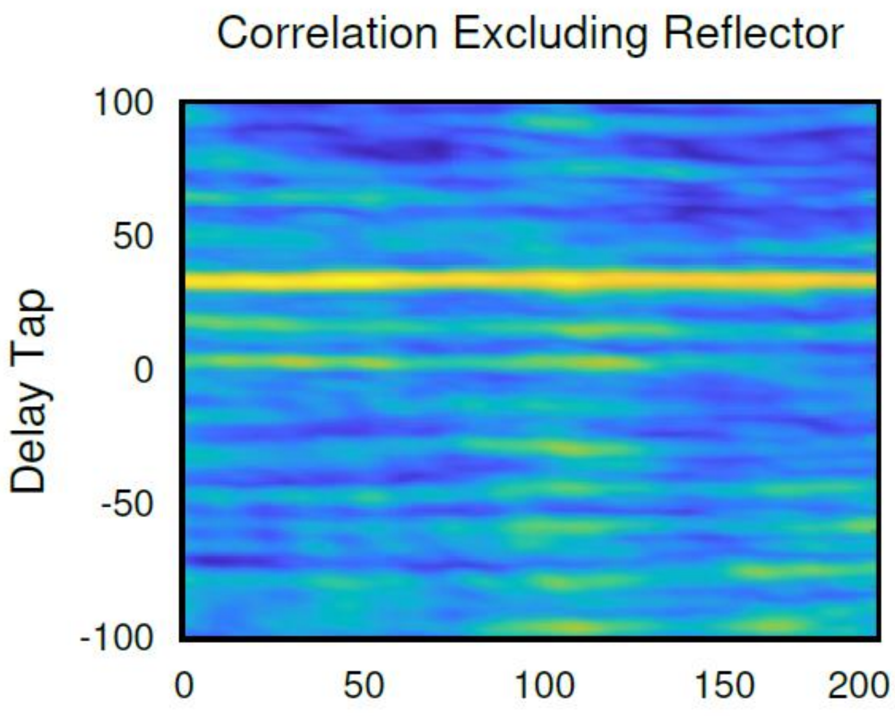


Millimeter-Wave Based Velocity Estimation

$$delay(i) = j - i$$

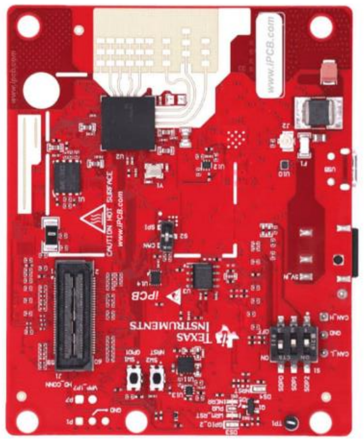
$$V(i) = \frac{H \cdot fps}{2 \cdot delay(i)}$$





Excluding strong reflectors provides better correlation for velocity estimation

Pose Correction



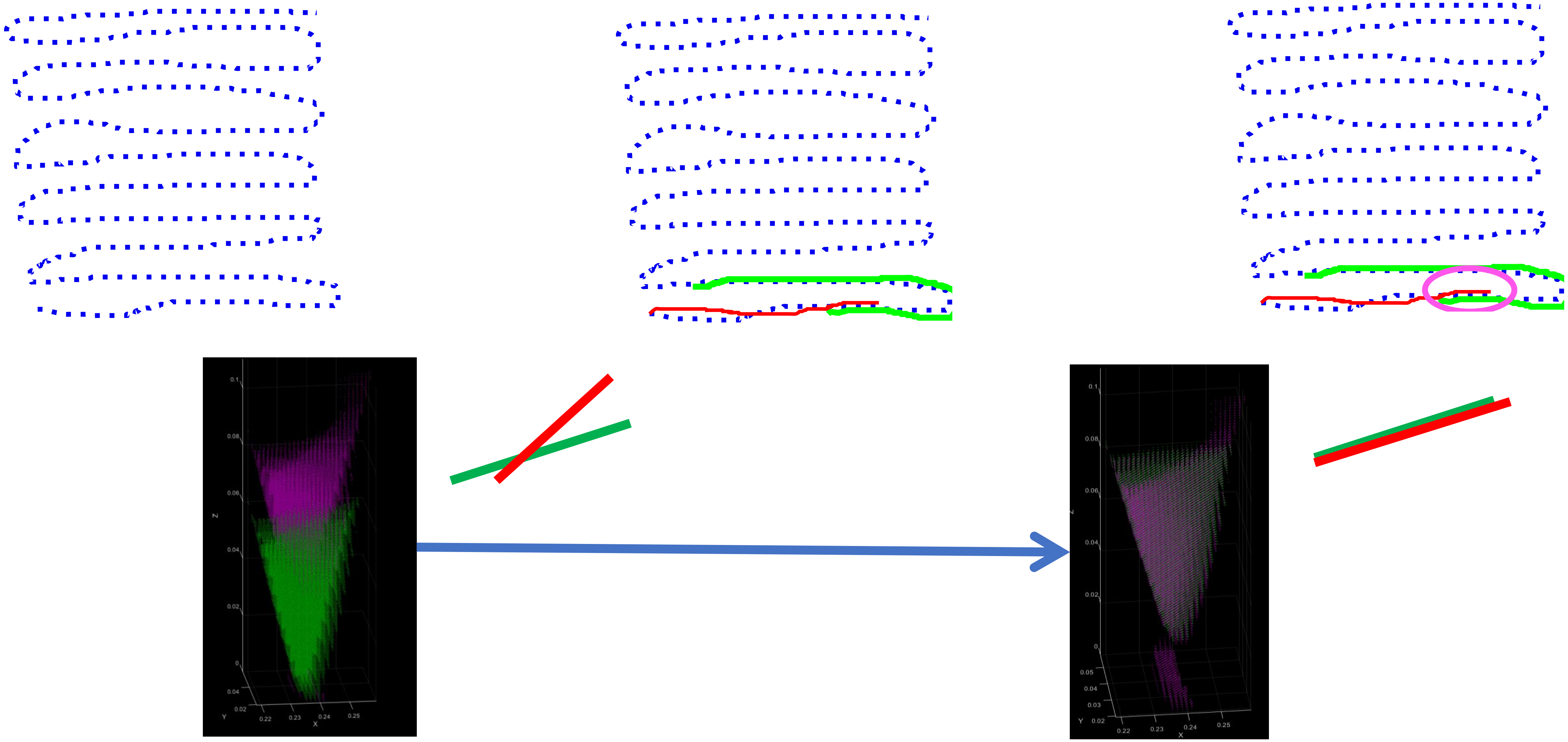
Local Pose Correction

- Low resolution inaccurate poses
- Velocities in X and Y direction
- Accurate local poses

Global Pose Correction

- Multiple windows
- Align overlap regions
- Accurate global pose

Window Based Pose Correction

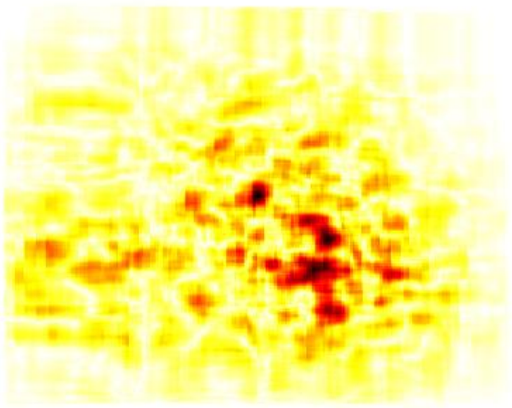


Before Alignment

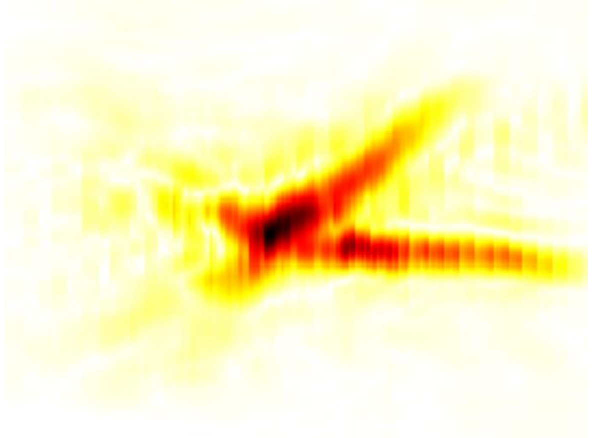
After Alignment

Before and After Pose Correction

Scissors

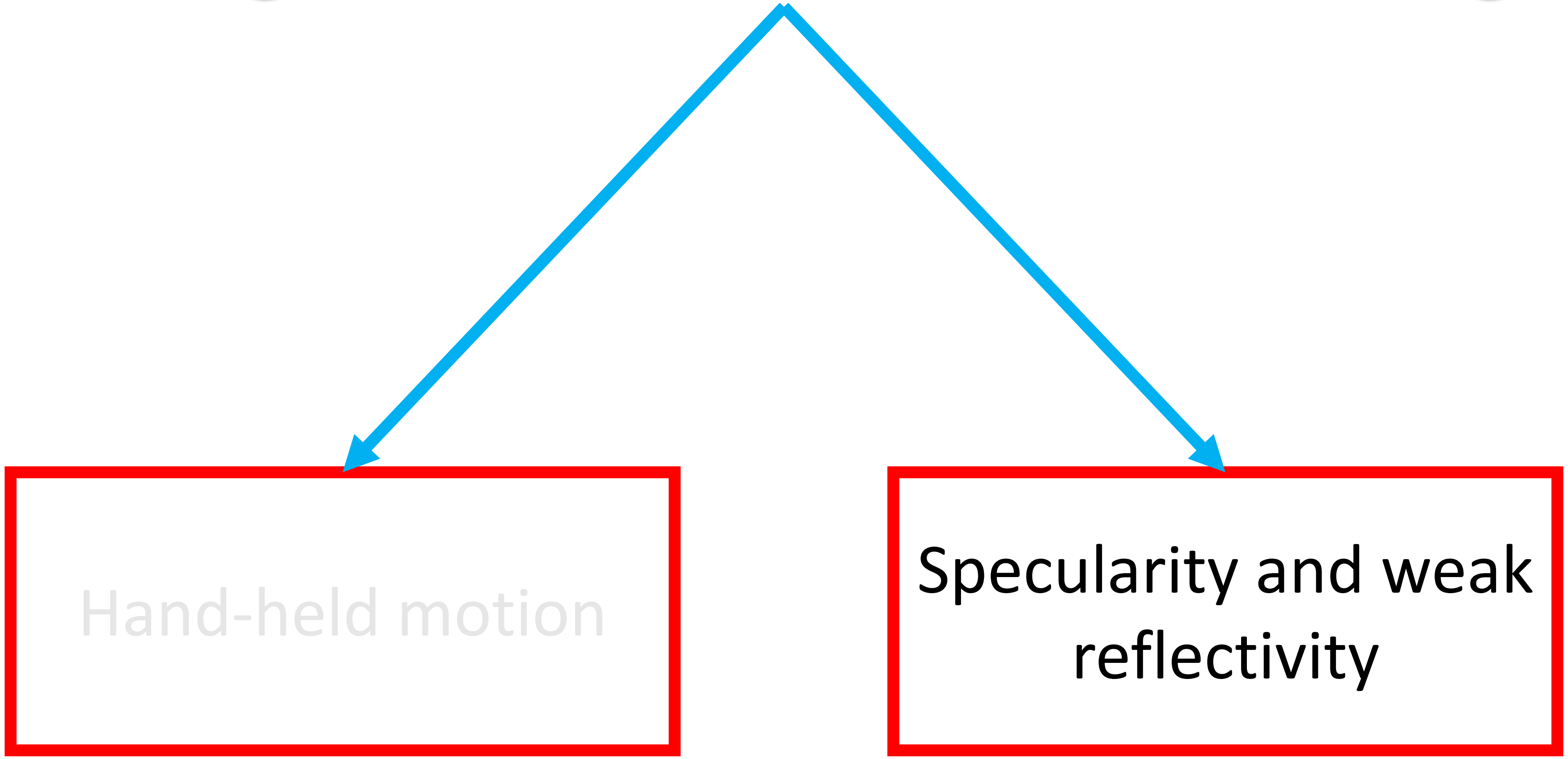


Before
pose correction



After
pose correction

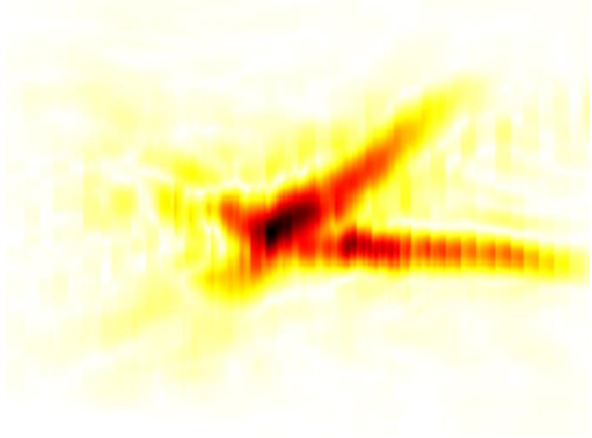
Challenges of Millimeter-Wave Imaging



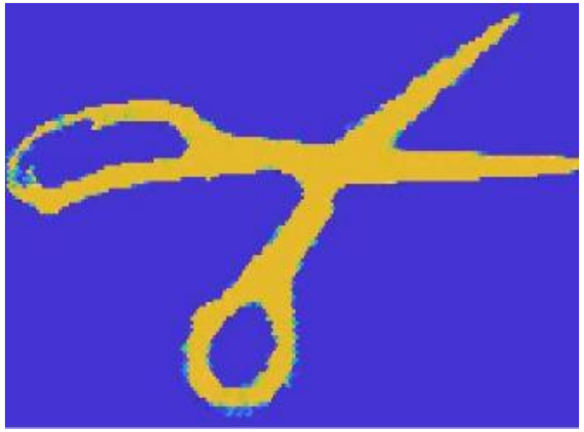
Deep Learning Based Shape Improvement

- Generative models can generate high quality images from low resolution random noise
- So, the idea is to use mmWave image as a low-resolution input and improve shape from learning

Scissors



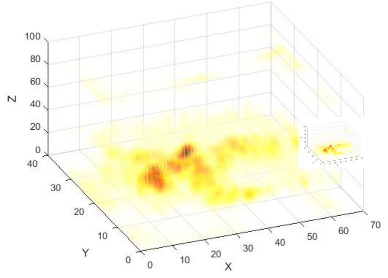
With
pose correction



Improvement by
deep learning

Learning Process

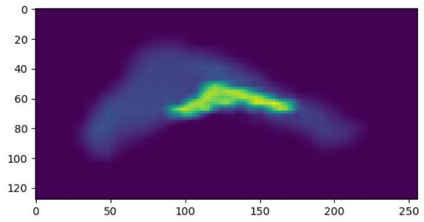
3D mmWave Image



Ground-Truth Image

Conditional Generative Adversarial Networks (cGAN)

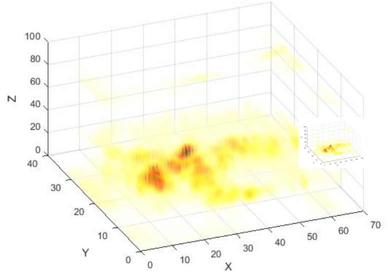
Epoch: 1



Difficult to Recognize Shape

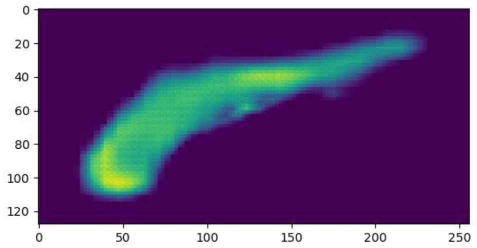
Learning Process

3D mmWave Image



Ground-Truth Image

Conditional Generative Adversarial Networks (cGAN)

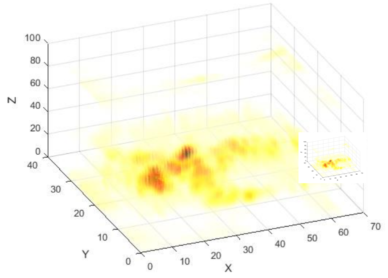


Epoch: 10

Learning real image distribution

Learning Process

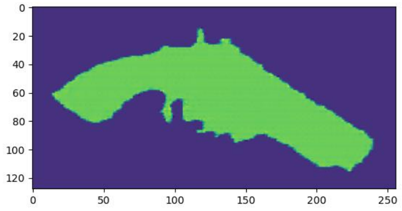
3D mmWave Image



Ground-Truth Image

Conditional Generative Adversarial Networks (cGAN)

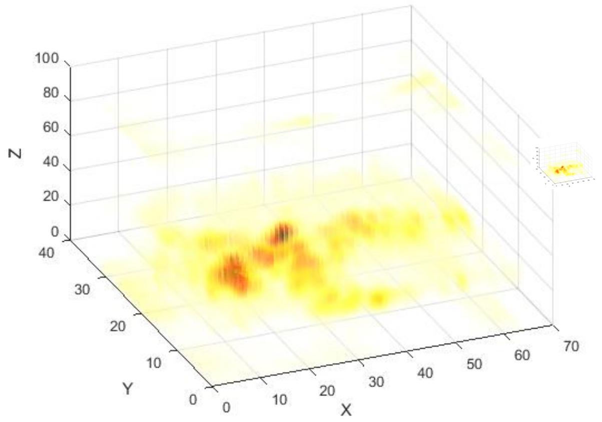
Epoch: 1000



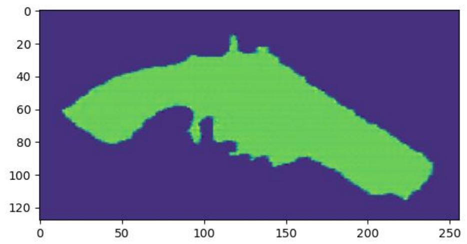
Shape Fully Recovered

Learning Process

3D mmWave Image



Generator

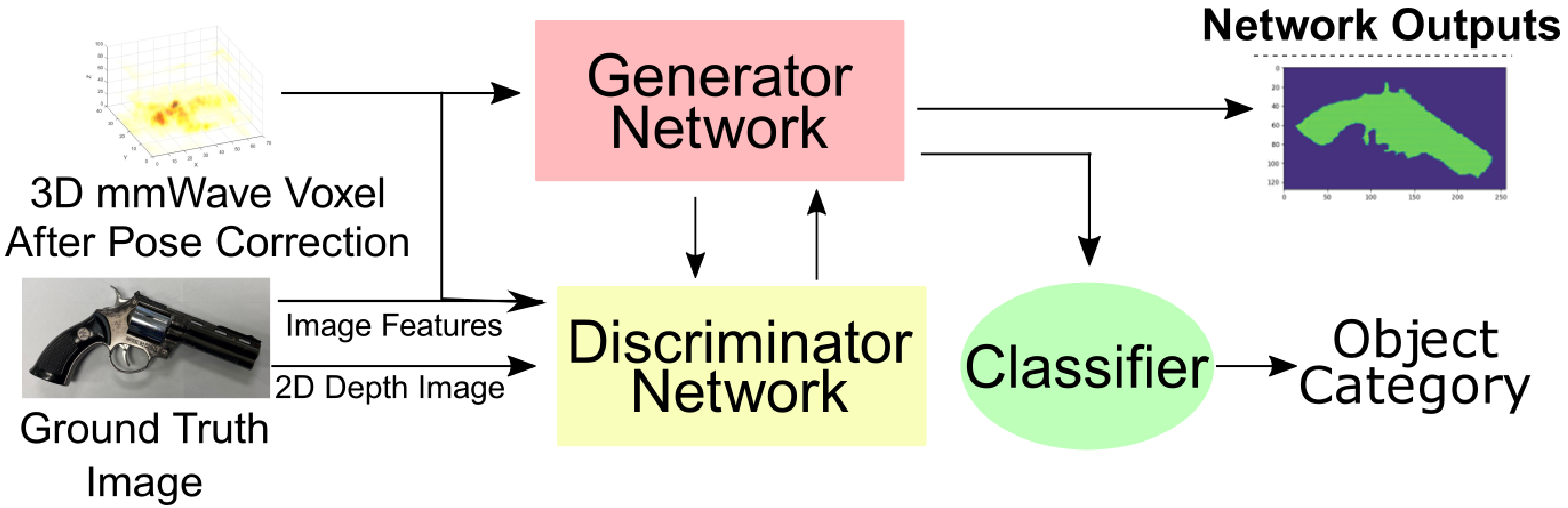


Post Training

Object is human perceptible

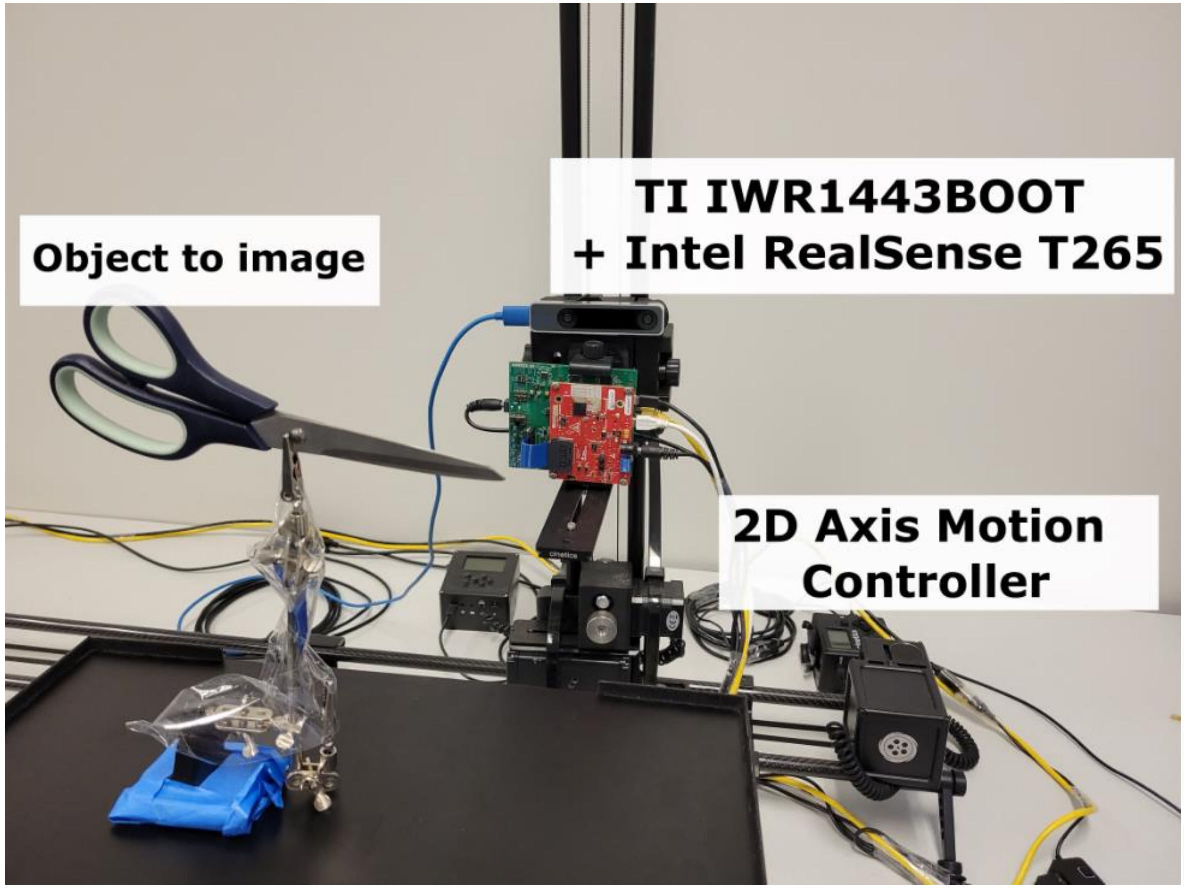
Conditional Generative Adversarial Network Architecture

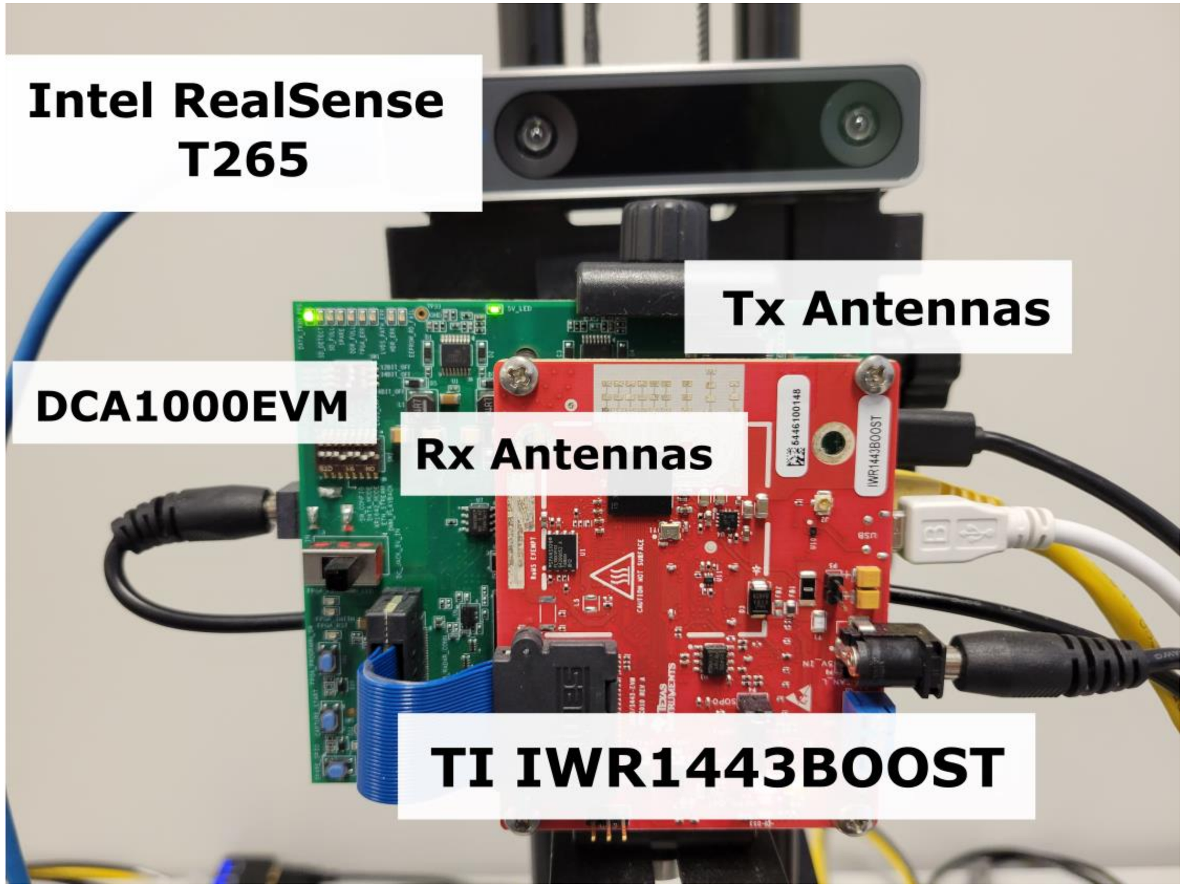
- We pass pose-corrected 3D mmWave voxels to Generator Network
- Generator network produces 2D shape with multiple convolution layers with skip connections
- Discriminator takes 3D mmWave voxels and either generated 2D shape or 2D ground-truth shape to calculate loss



Experimental Setup

- 77-81 GHz mmWave radar with 3 Tx, 4 Rx antennas, 4 GHz bandwidth
- T265 vision-based self-tracking device for poses
- 2D axis motion controller to move mmWave device in x and y direction





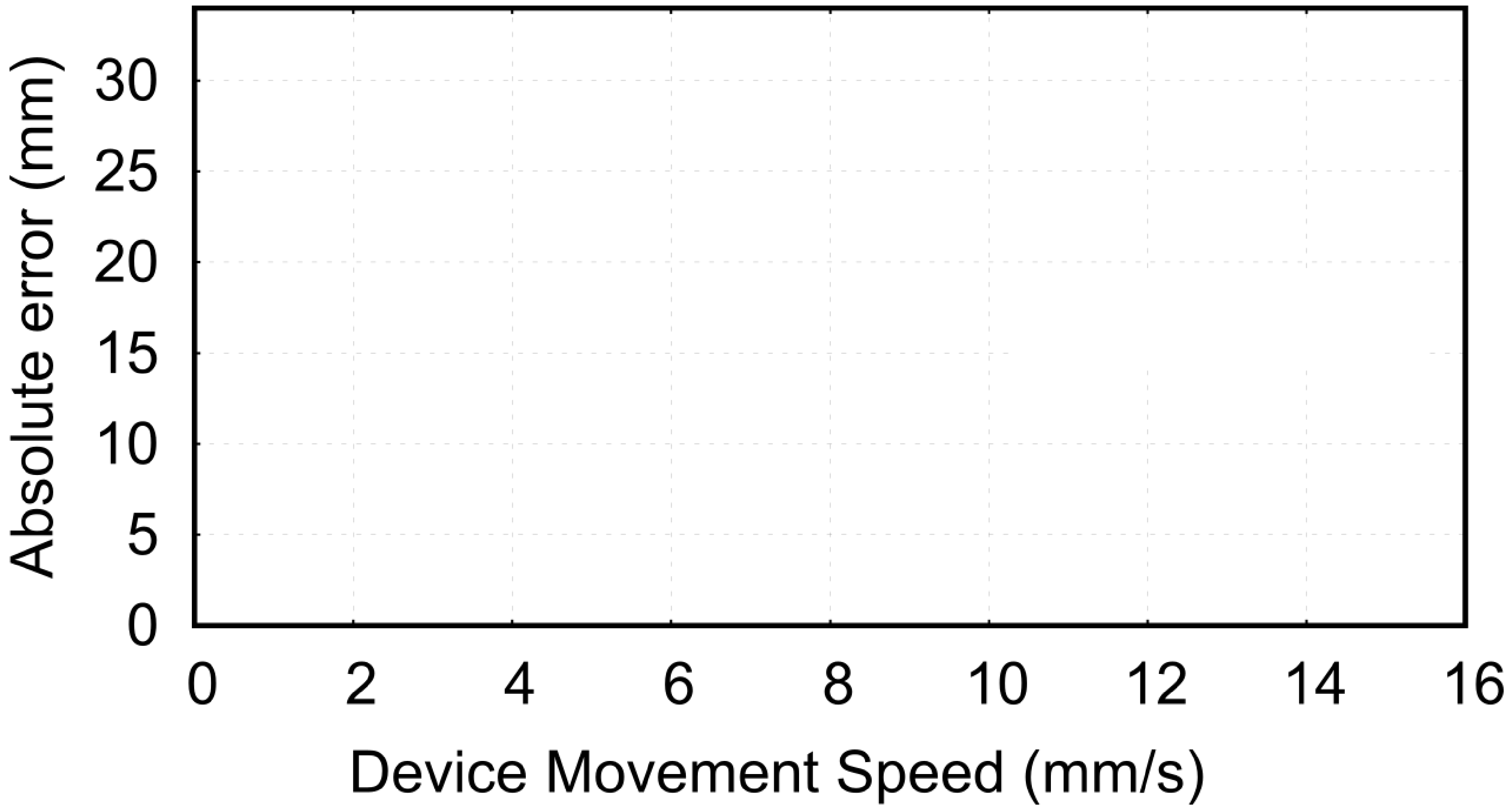
Summary of Datasets

- **Real Data**: Collect mmWave sample and pose via 2D motion controller
  - 90 real data samples
  - Data processed using pose-correction and TDBP

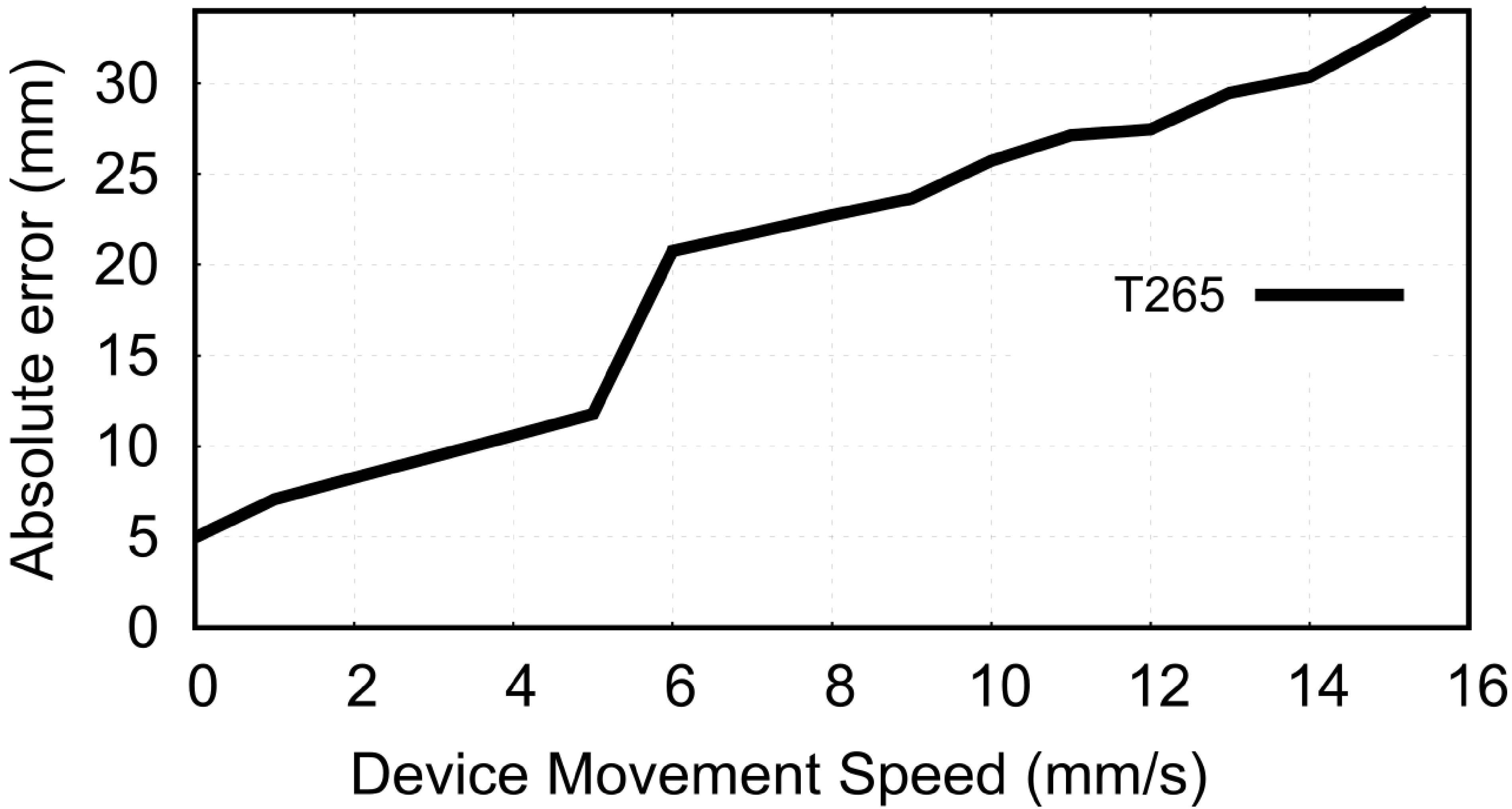
- **Synthetic Data**: Passing 3D object layout to ray-tracing simulator
  - Actual hardware parameters, 8500 samples
  - Helps machine learning models to learn features
  - Different orientation of objects are included

- **Classification Categories**: CD, scissor, box cutter, metal pen, screw-driver, hammer, metal mug, miscellaneous

Device Pose Estimation After Velocity Based Correction



Device Pose Estimation After Velocity Based Correction



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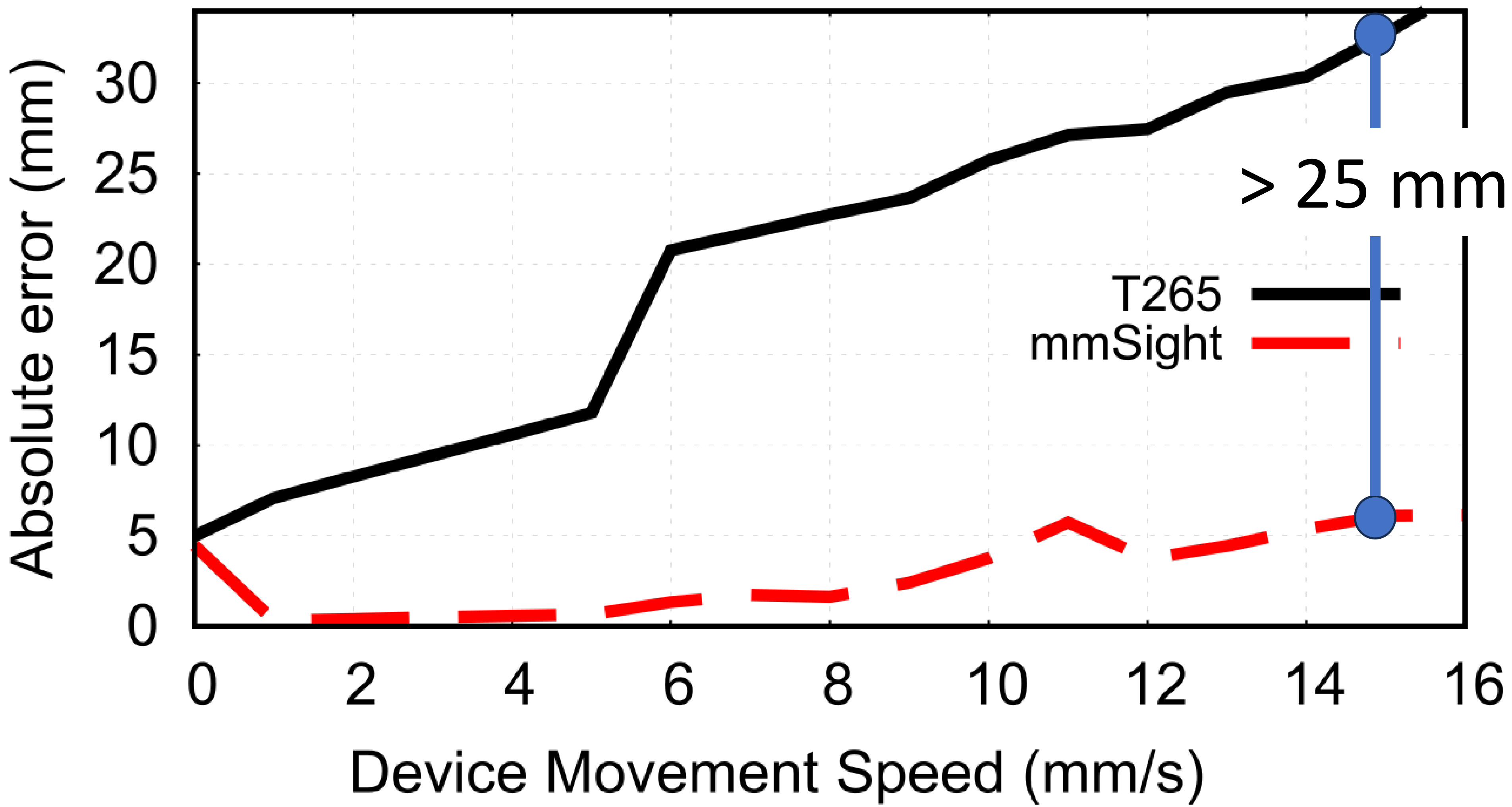
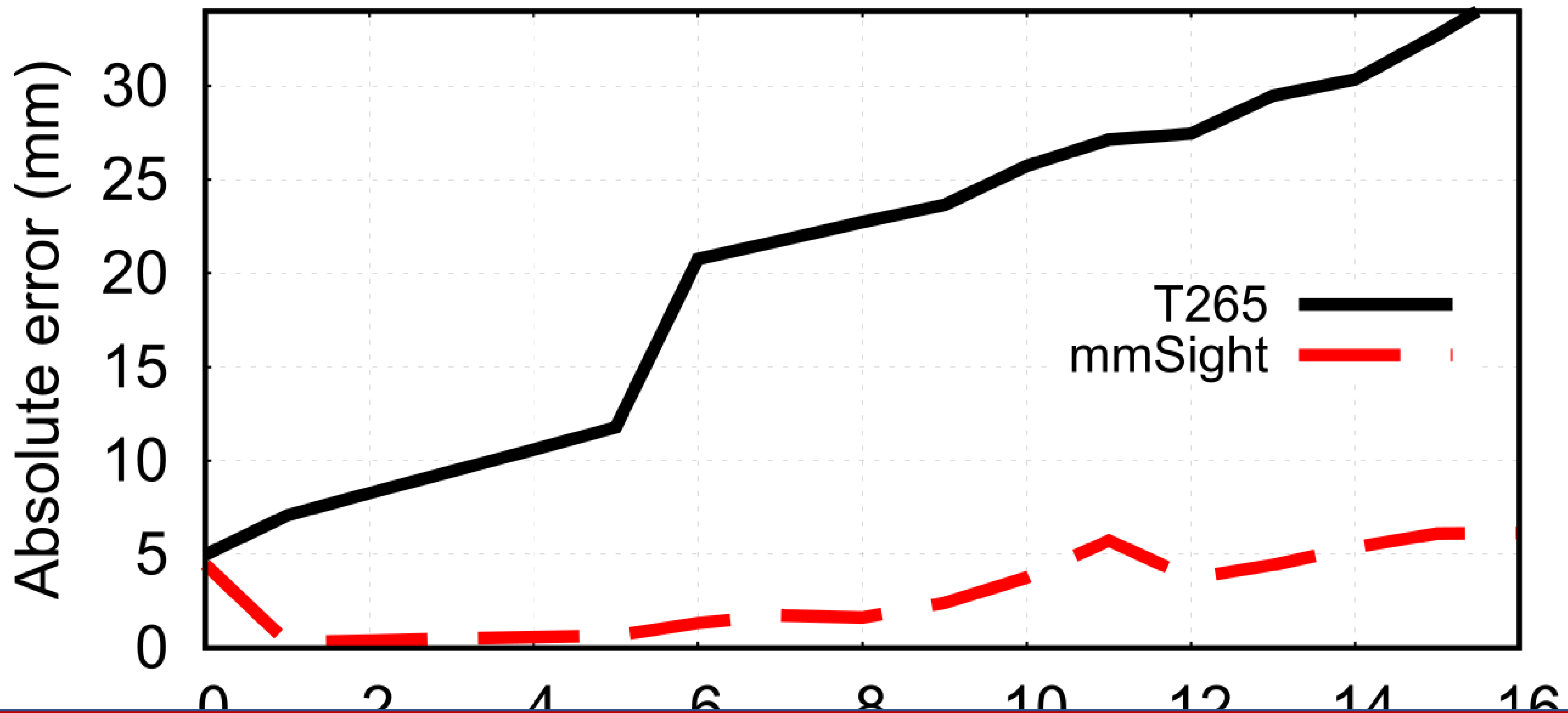
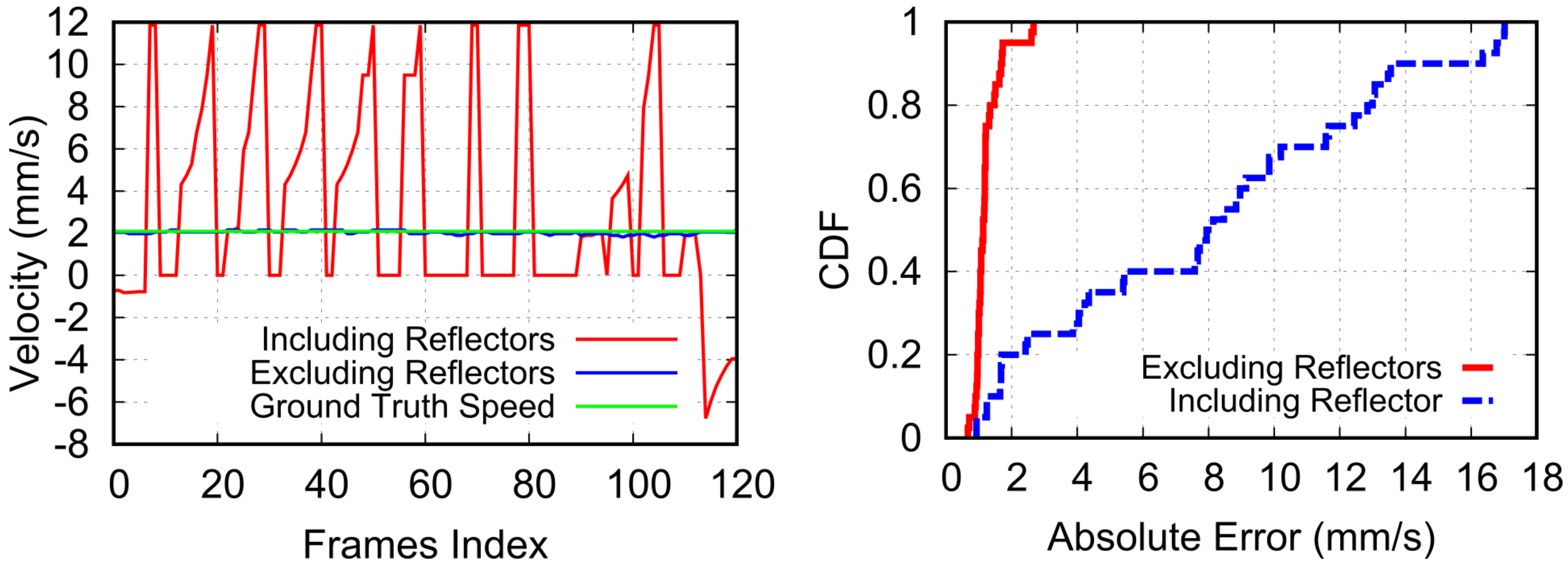


Device Pose Estimation After Velocity Based Correction



Device poses after velocity-based correction is more accurate than raw poses from optical camera

Velocity Estimation After Excluding Reflectors

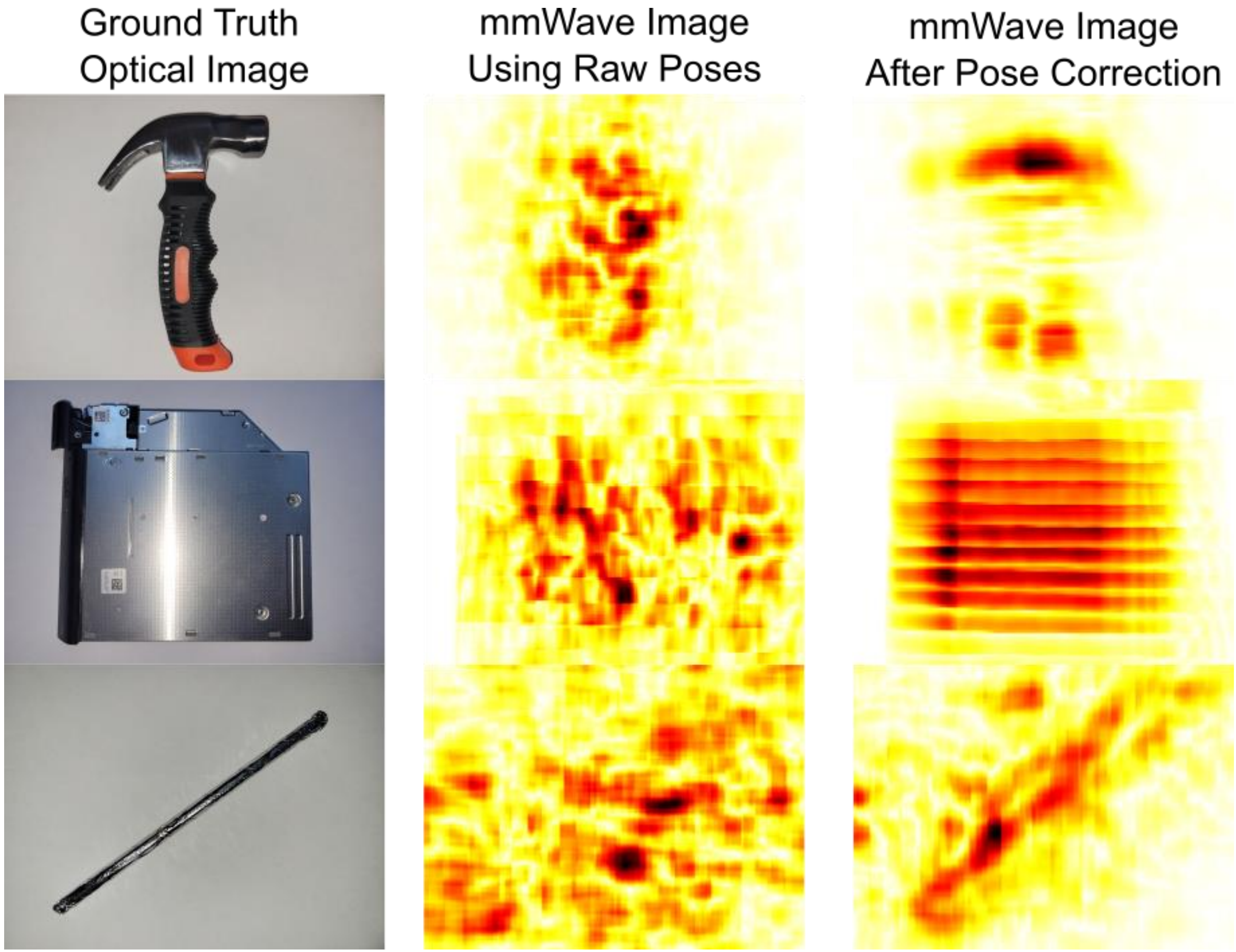


Shape Improvement by Pose Correction

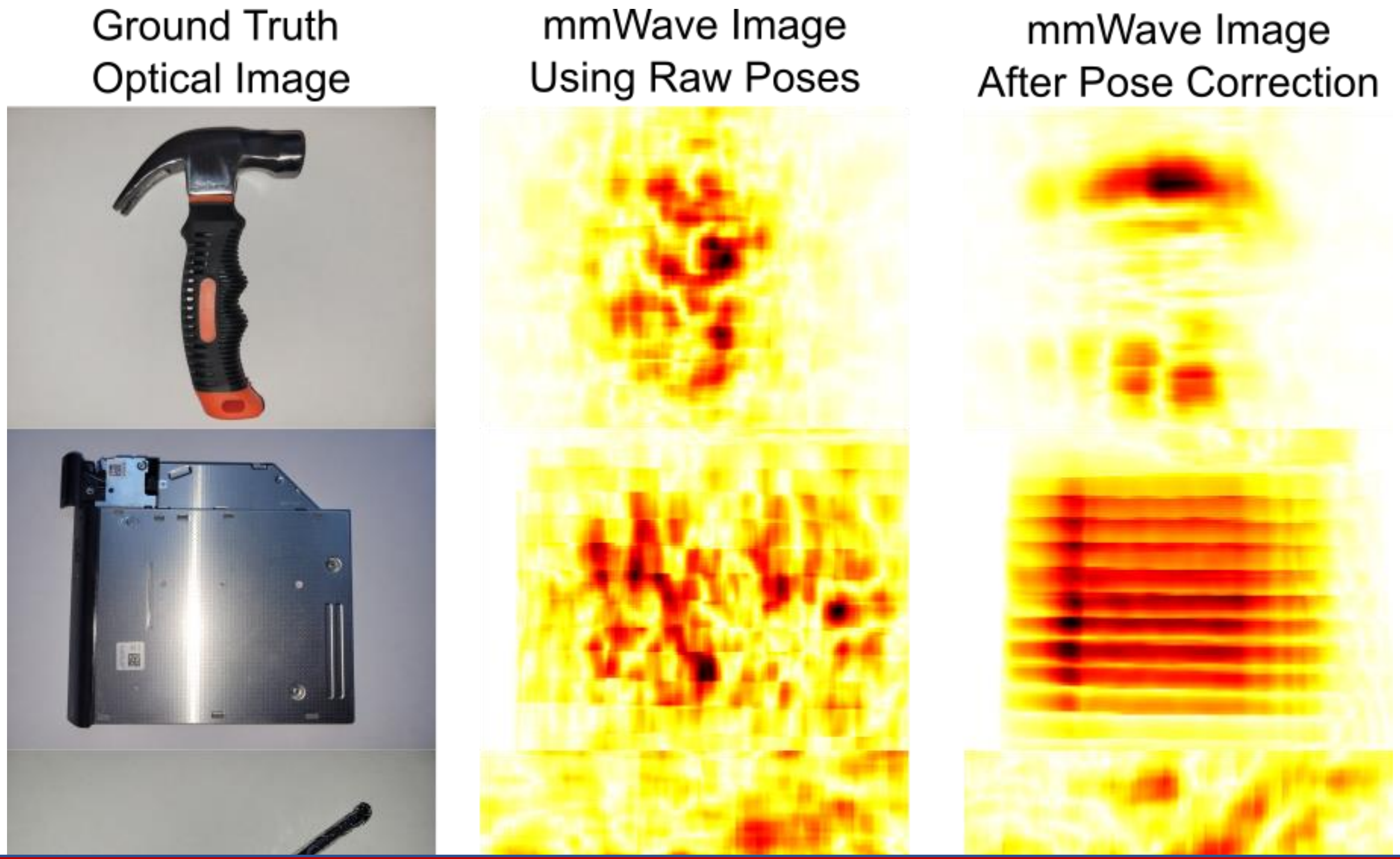
Ground Truth
Optical Image

Shape Improvement by Pose Correction

Shape Improvement by Pose Correction



Shape Improvement by Pose Correction

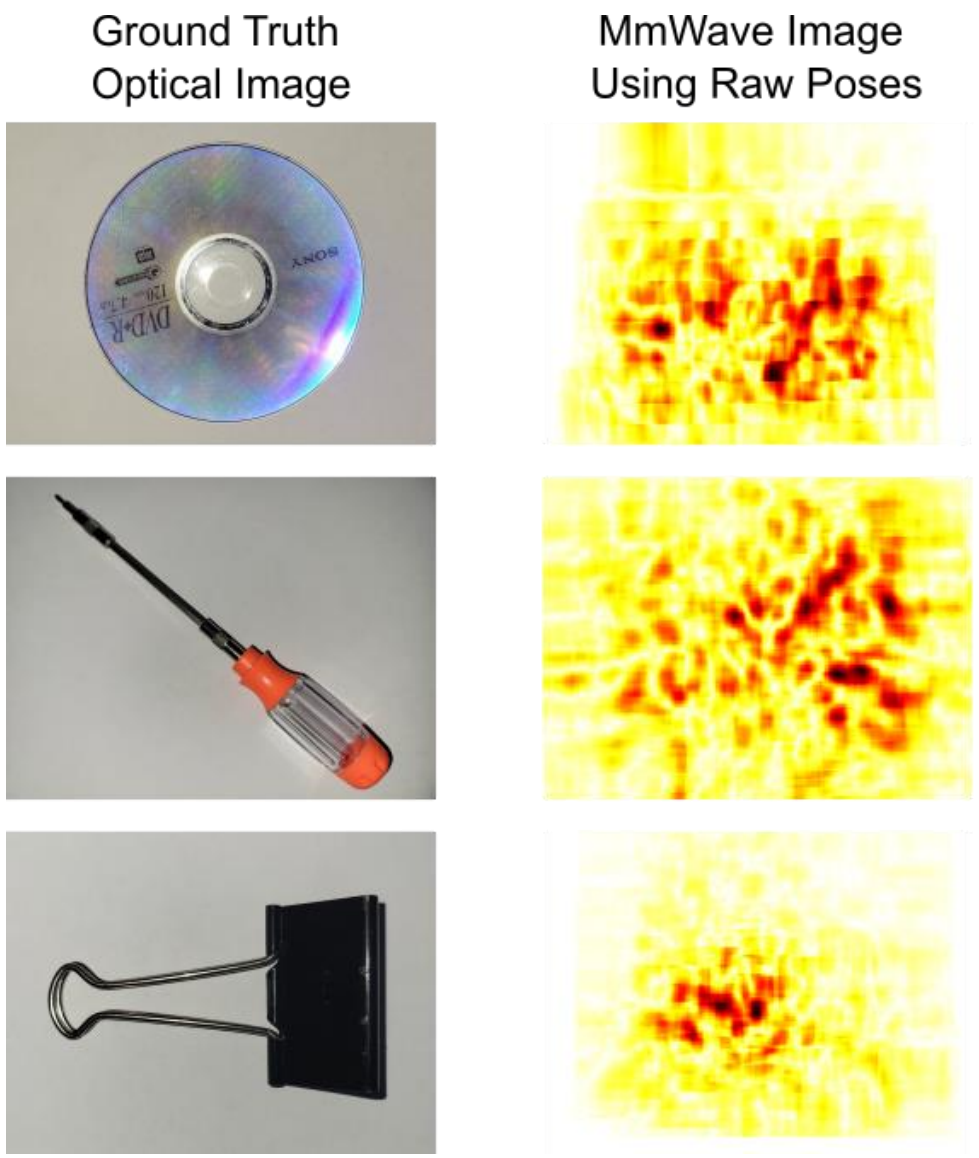


Pose correction produces focused mmWave images,
but are still human imperceptible

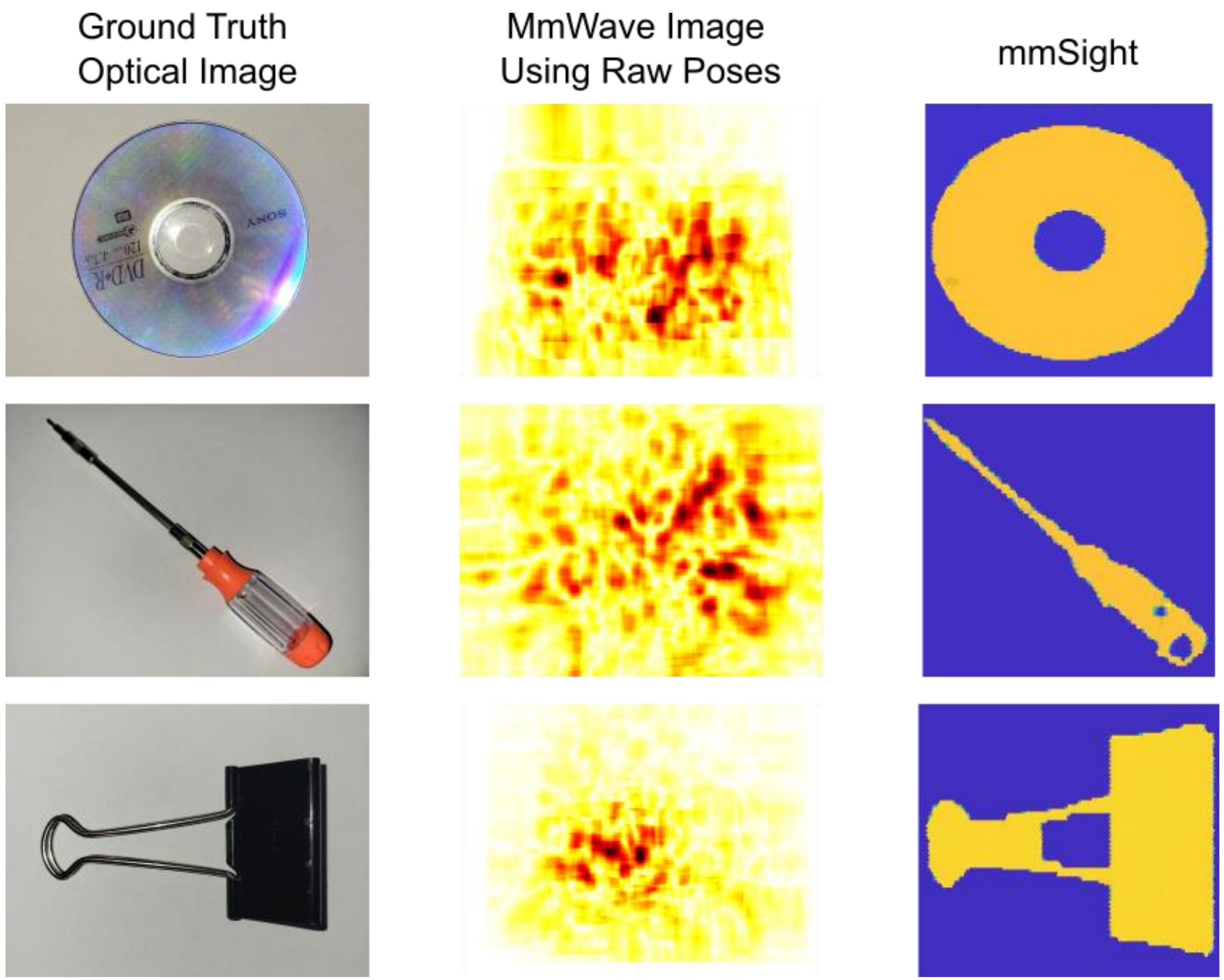
Shape Improvement by cGAN

Ground Truth
Optical Image

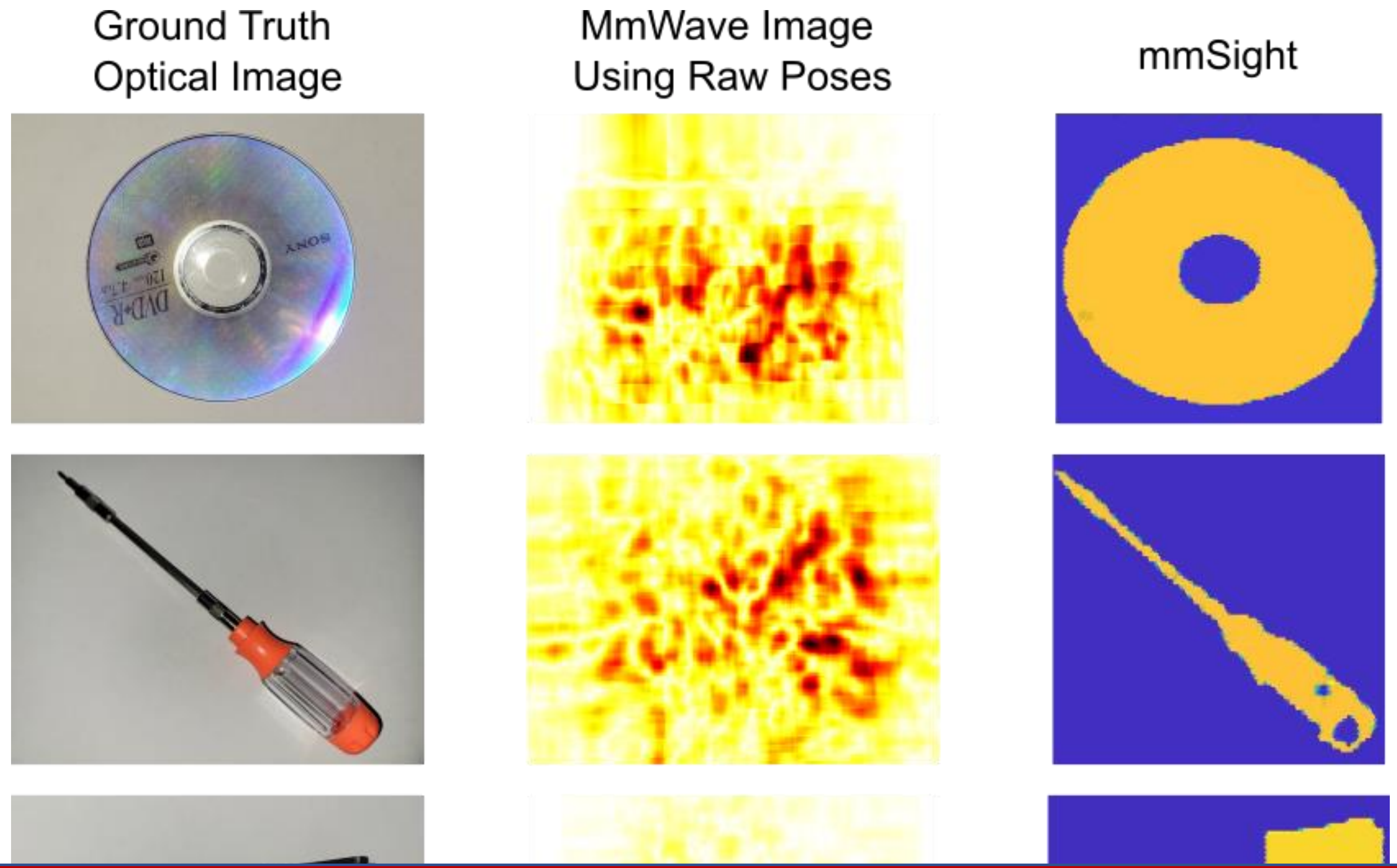
Shape Improvement by cGAN



Shape Improvement by cGAN

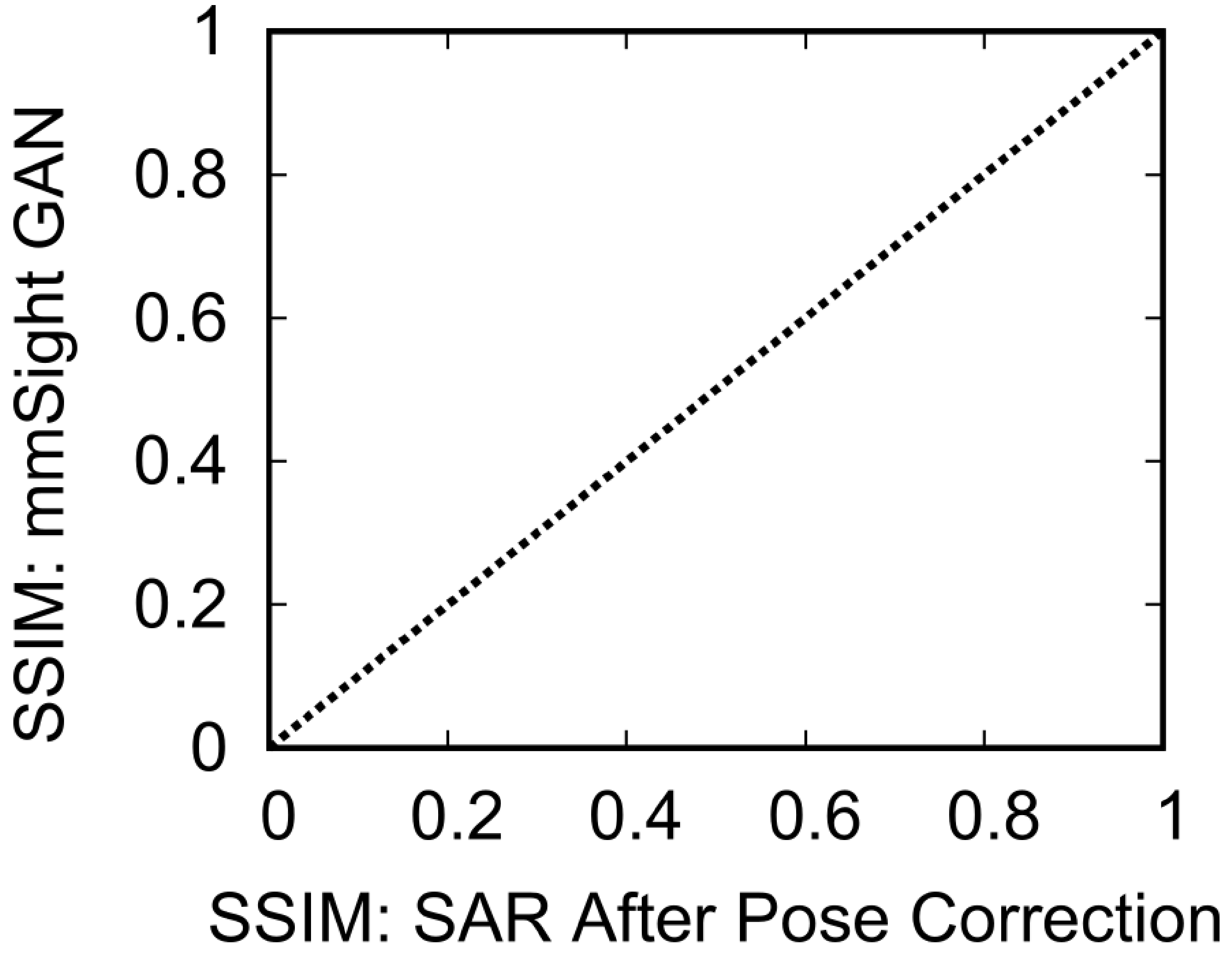


Shape Improvement by cGAN

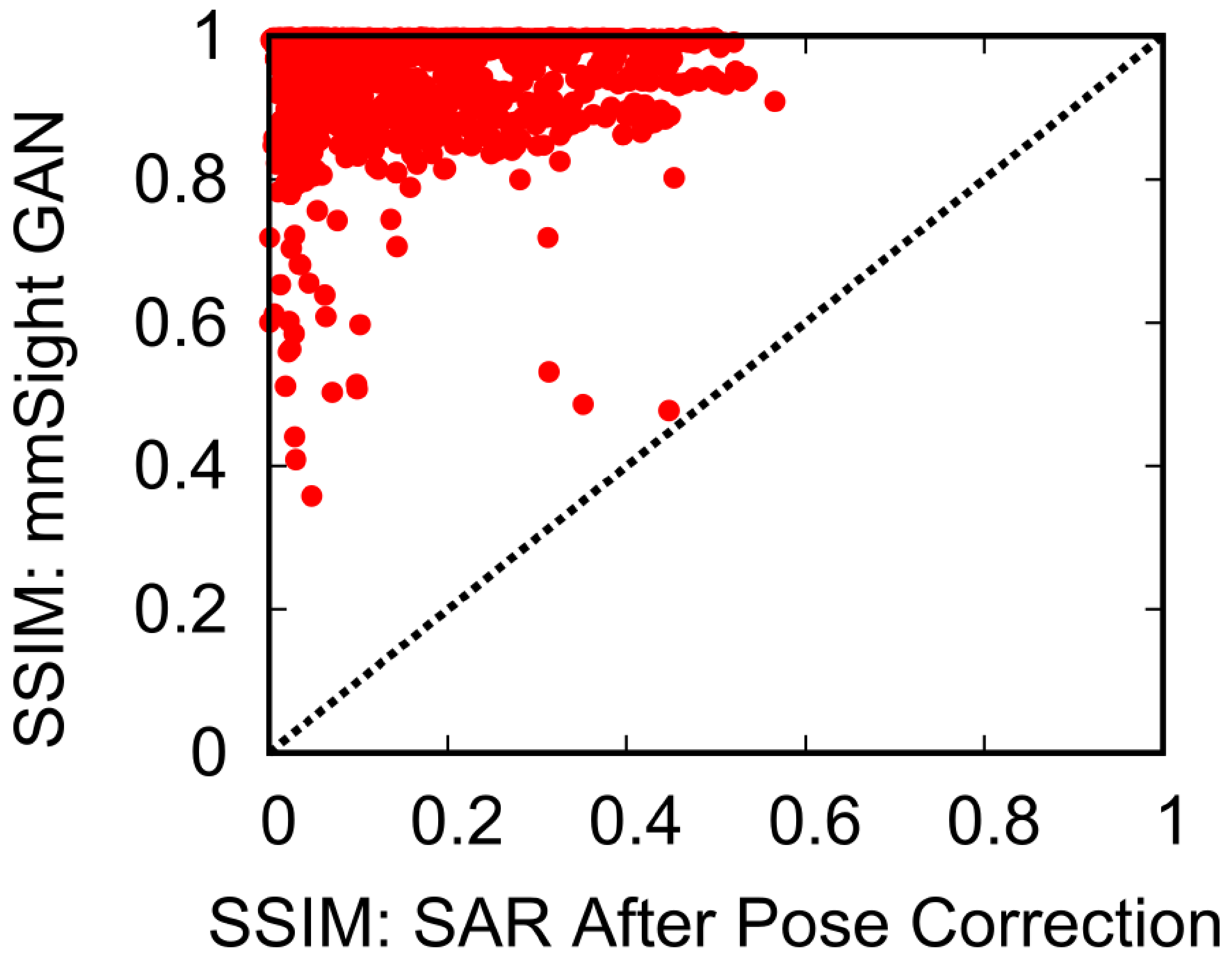


cGAN further improves the shape of the pose-corrected mmWave images

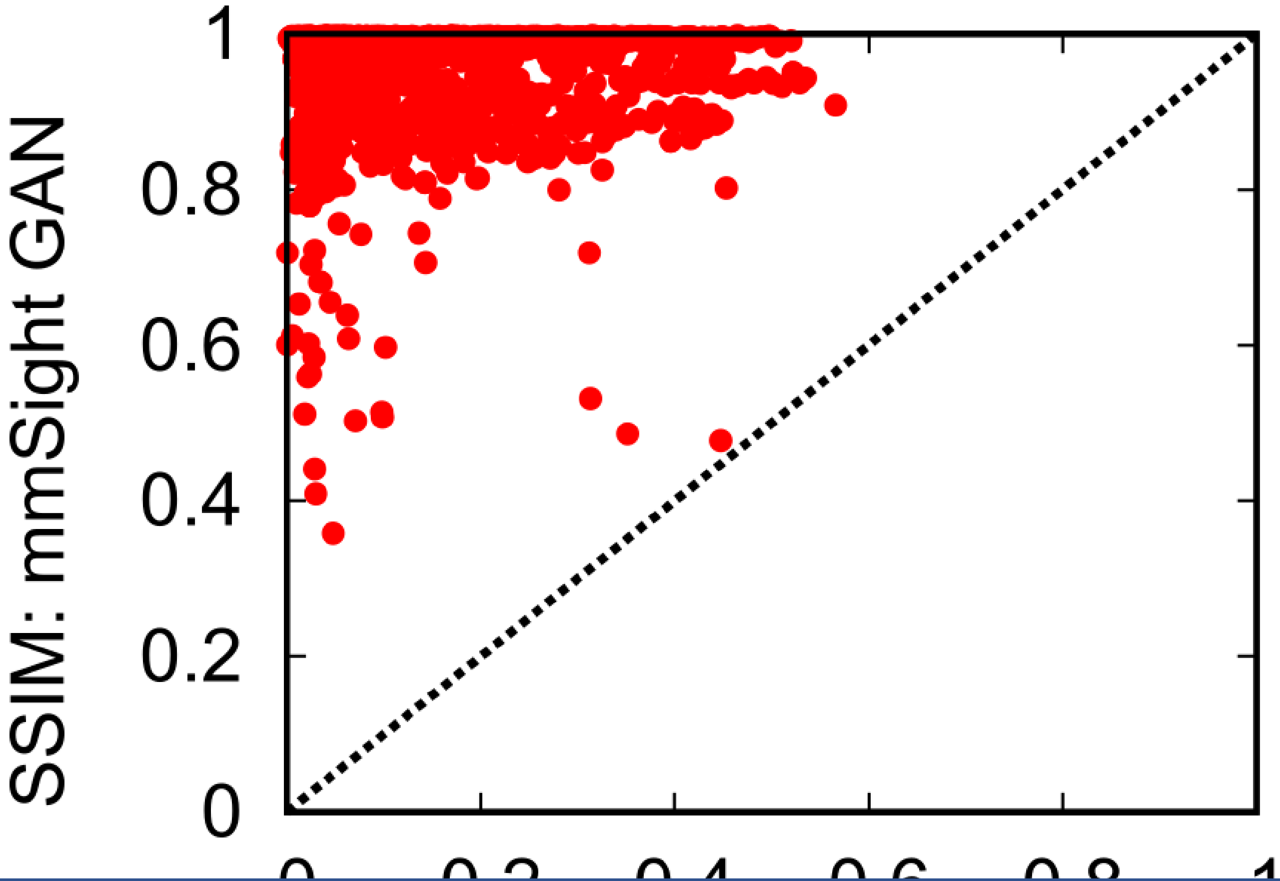
SSIM Improvement by cGAN



SSIM Improvement by cGAN



SSIM Improvement by cGAN



cGAN improves SSIM from 0.08 to 0.9
for 1000 generates shapes

Classification Confusion Matrix

Predicted/Actual	Knife	Toy Gun	Scissor	CD	Pen	Hammer	Clip	Screwdriver	Other
Knife	**98.5**	0	1.5	0	0	0	0	0	0
Toy Gun	0	**100**	0	0	0	1.5	0	0	0
Scissor	0	0	**98.5**	0	0	0	1.5	0	1.5
CD	0	0	0	**98.5**	0	0	0	0	1.5
Pen	0	0	0	0	**100**	0	0	0	0
Hammer	0	0	0	0	0	**98.5**	0	0	0
Clip	1.5	0	0	1.5	0	0	**98.5**	0	1.5
Screwdriver	0	0	0	0	0	0	0	**100**	0
Other	0	0	0	0	0	0	0	0	**95.5**

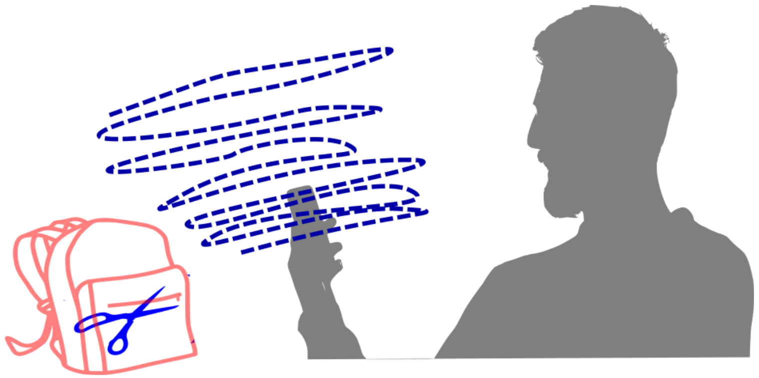
cGAN based shape improvement achieves high classification accuracy for object tagging

Conclusion

- mmSight utilizes device antennas to **estimate velocity and local pose-correction**
- **Window-based pose correction** method improves mmWave image compared to **raw poses**
- **Conditional Generative Adversarial Networks** further improves pose corrected mmWave images and make shape **human perceptible**

Thank you!

Check out our group website for more results



Contact:
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SyReX
Systems Research on X