SICA-LAB

Next Generation Checkpoints for On-The-Move Threat Detection

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1. Introduction: from "portal" to "on-the-move"

*What is the problem being solved?

Existing: Checkpoints

- Slow throughput, long lines
- Frequent false alarms (pat-downs, bag searches)
- Significant passenger divestment and re-collection.
- Threat detection is not automated.

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Vision: 2020 Checkpoint

- **Passengers walking** at a normal pace through the checkpoint.
- **No divestiture** of clothing or removal of liquids or electronics from carry-on
- **Lower false alarm** rate
- **Automatic and adapting dynamically** to information provided by Risk-Based Security

Images adapted form Chris Smith's , "Apex: Screening at Speed," ADSA 2015, Northeastern University, Boston, MA.

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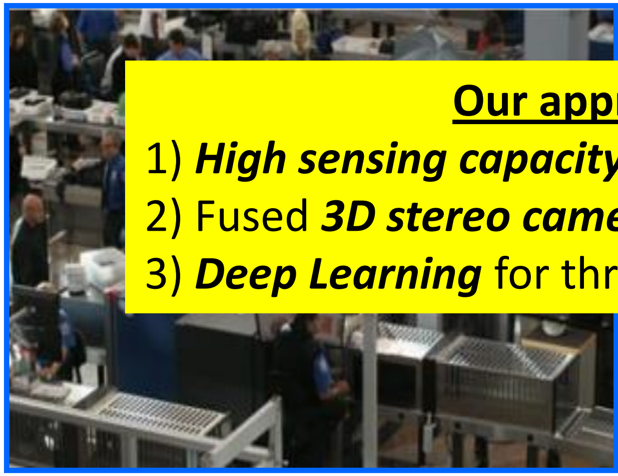

Our approach

1) ***High sensing capacity & CS*** imaging
2) Fused ***3D stereo cameras*** and ***mm-wave***
3) ***Deep Learning*** for threat detection

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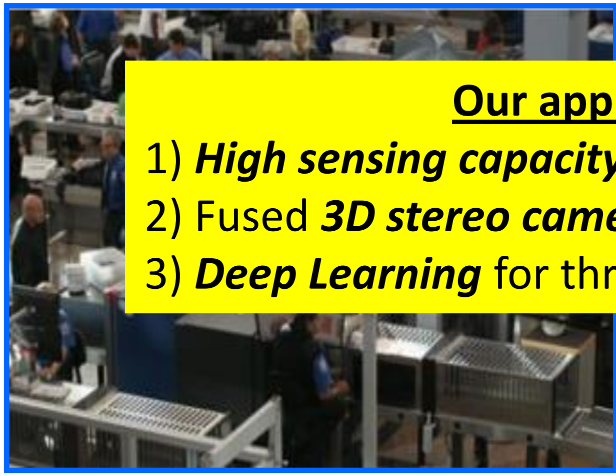

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*Who cares?

- Industrial transition partners: HXI, Inc ; Rapiscan, L3 Communication; Smiths Detection
- Target government customers: TSA, DOJ, CBP, Dept. of State

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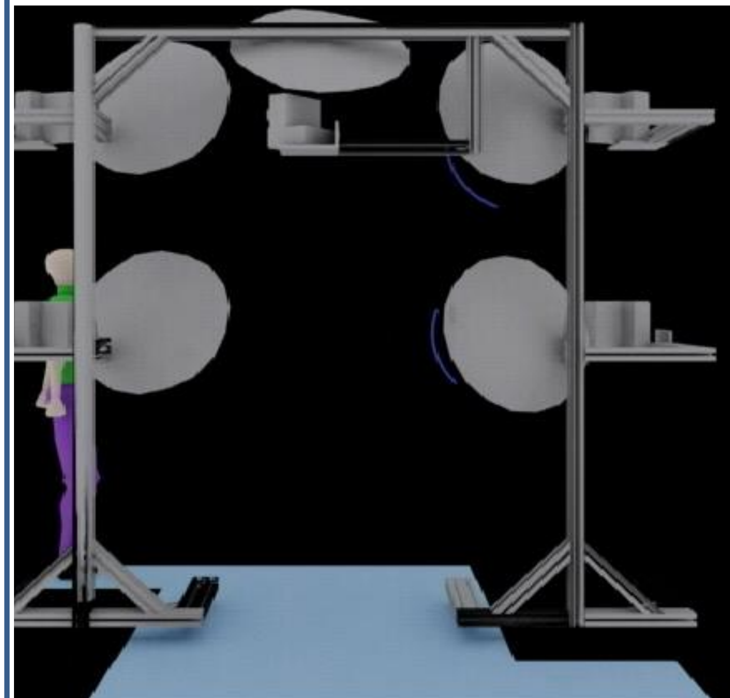
2. Introduction: SICA-LAB Towards real-time imaging



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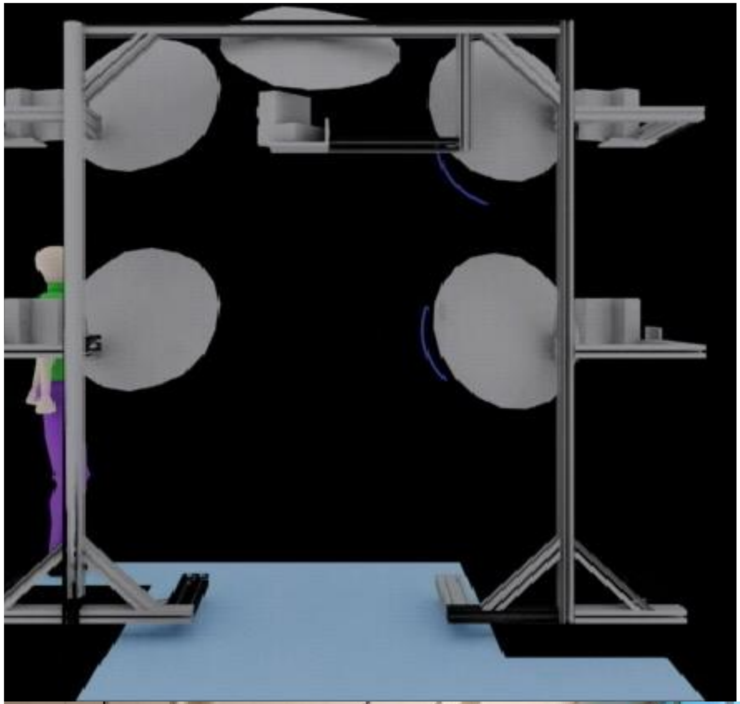
High Sensing Capacity Systems



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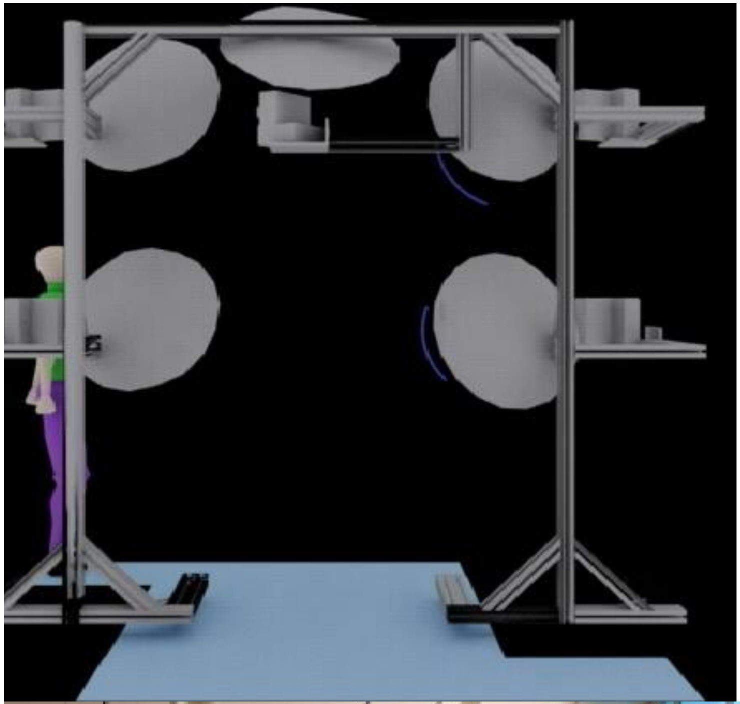
High Sensing Capacity Systems

=

amount of information

over a period of time



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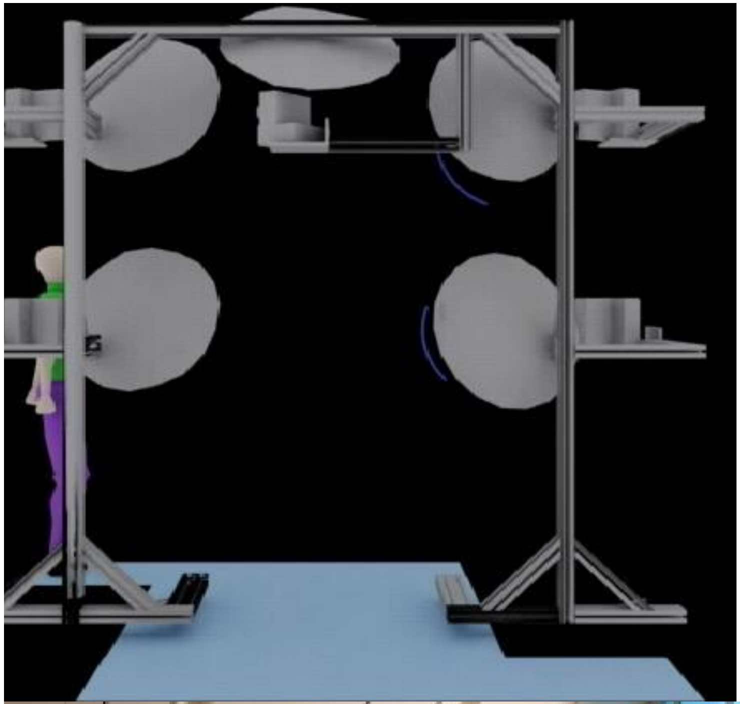

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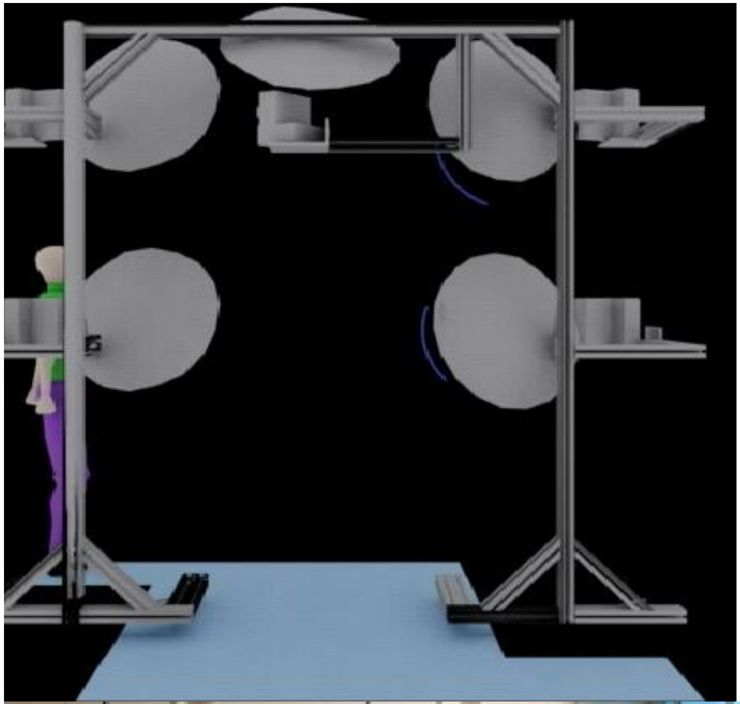
Richard Obermeier and Jose Angel Martinez-Lorenzo, "Generalized Optimization of High Capacity Compressive Imaging Systems," arXiv:1803.08184



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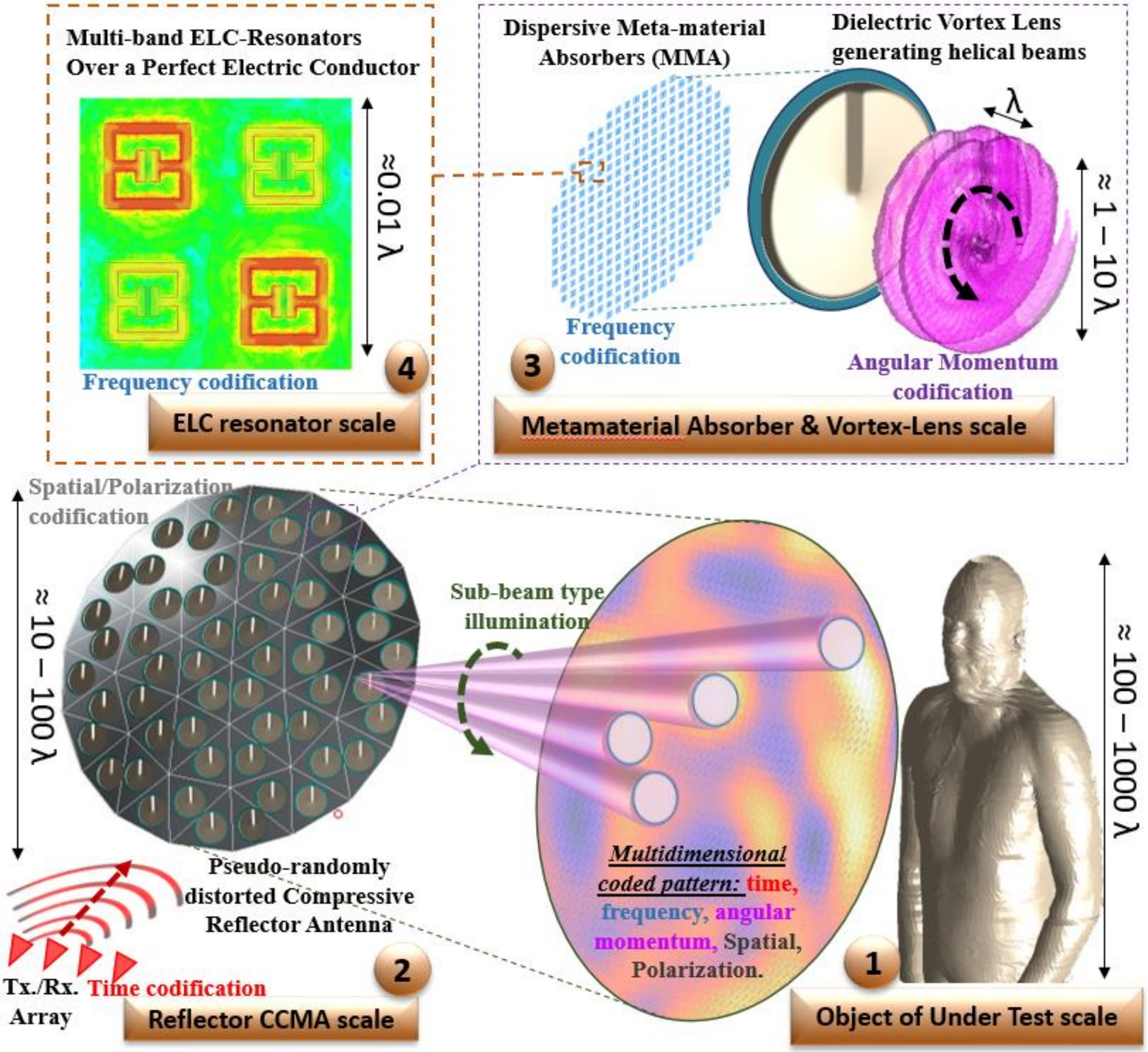

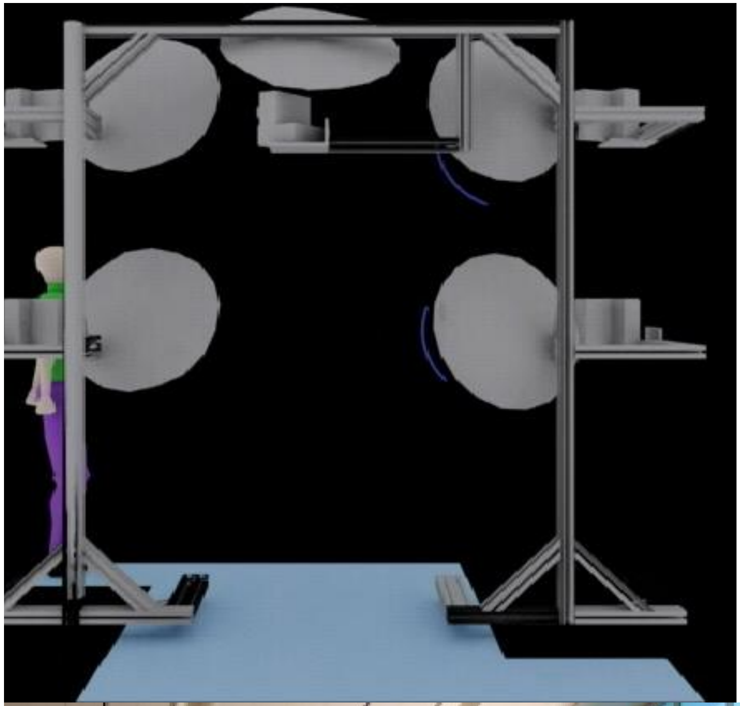

J. A. Martinez-Lorenzo. Compressive Coded Antenna/Meta-Antenna. US Patent Application No. 62/147,363. Date of Filing: March 30, 2016.

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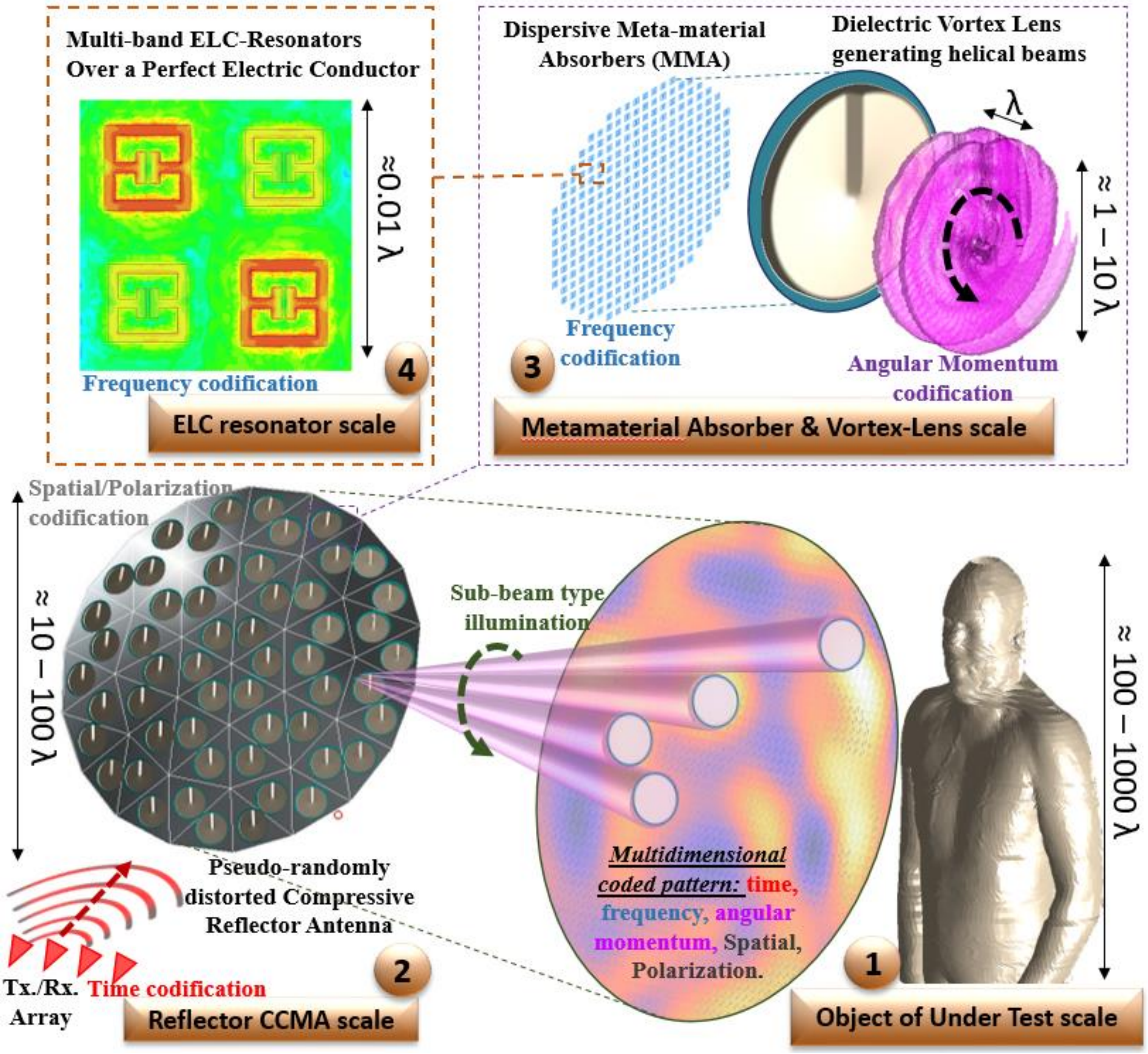

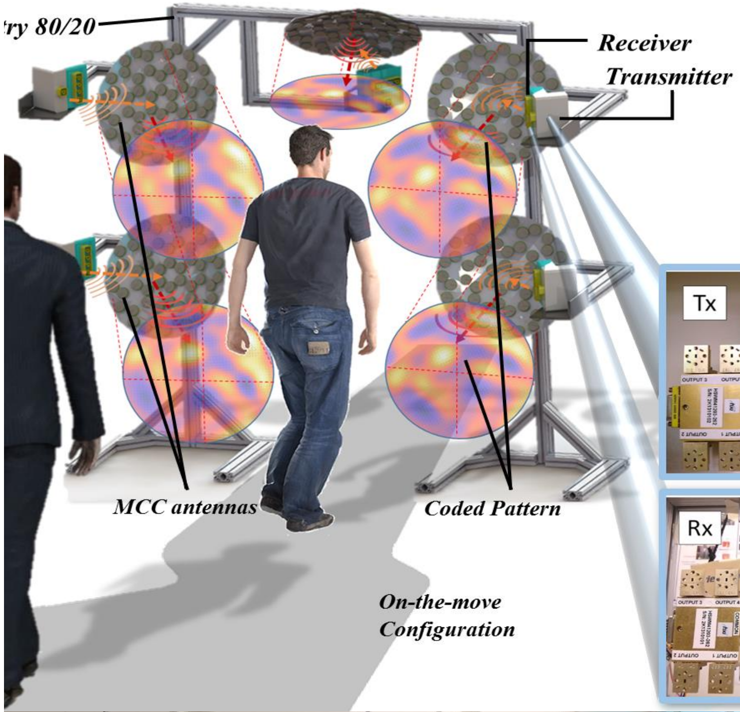

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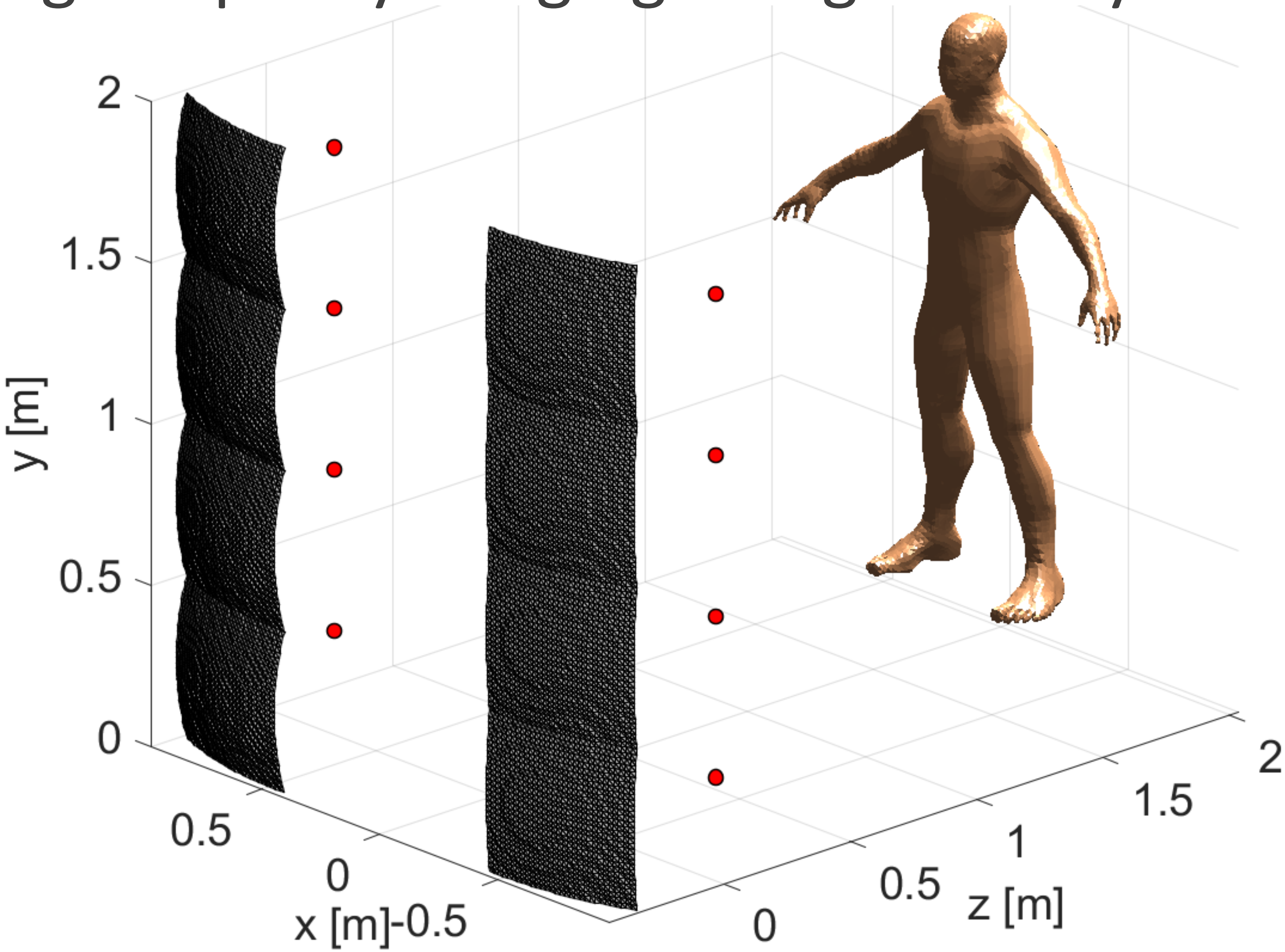

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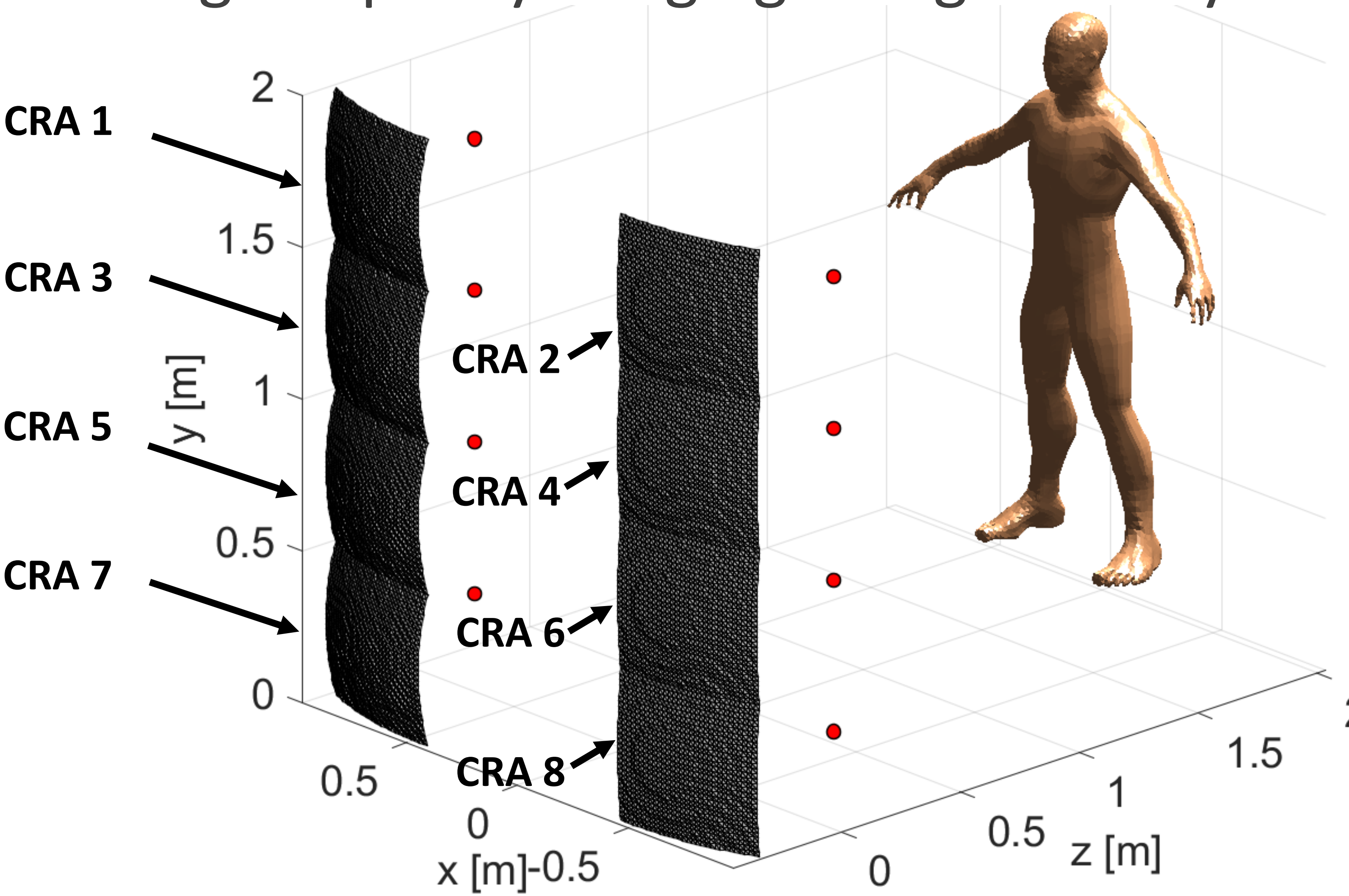

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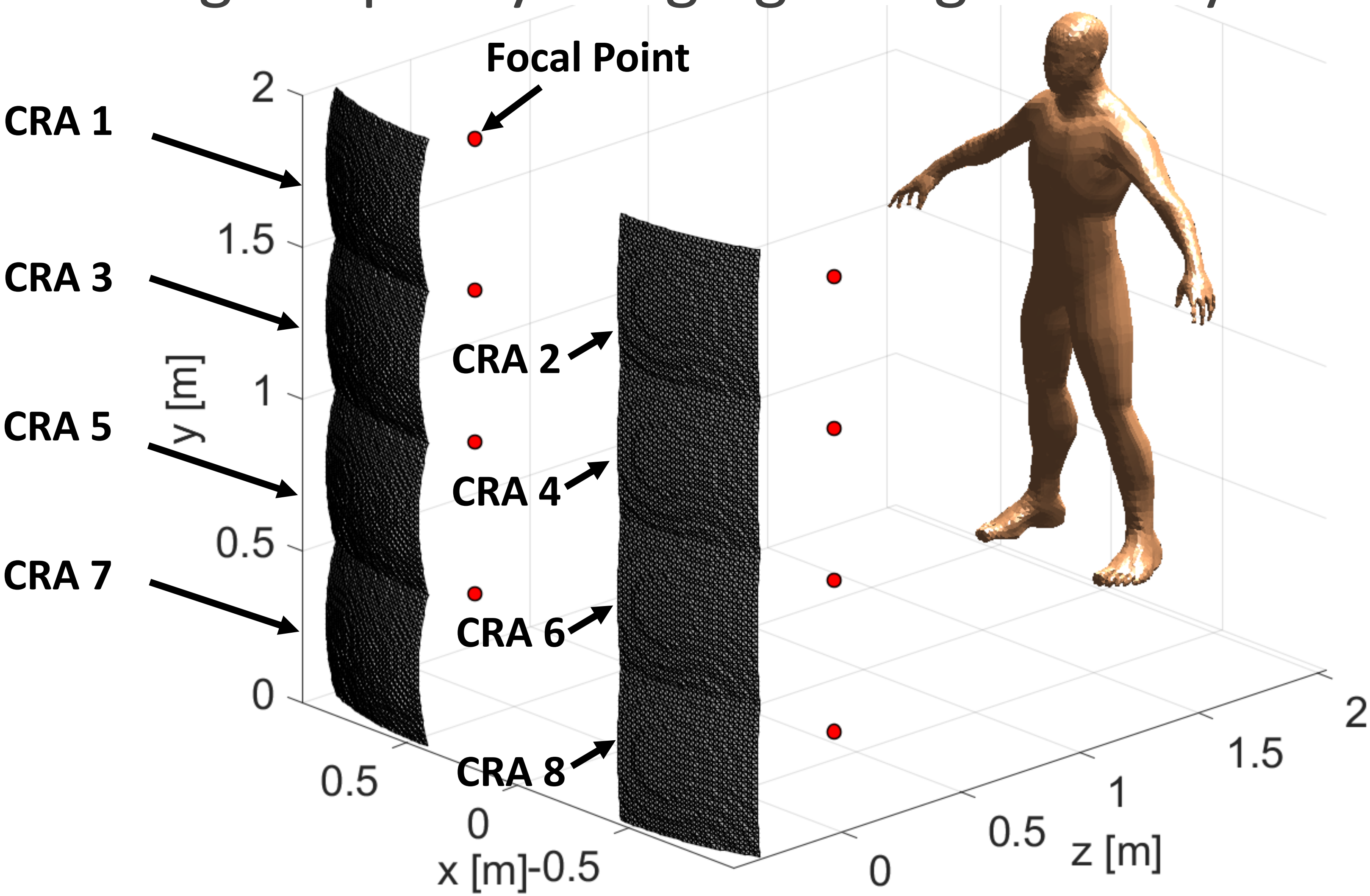

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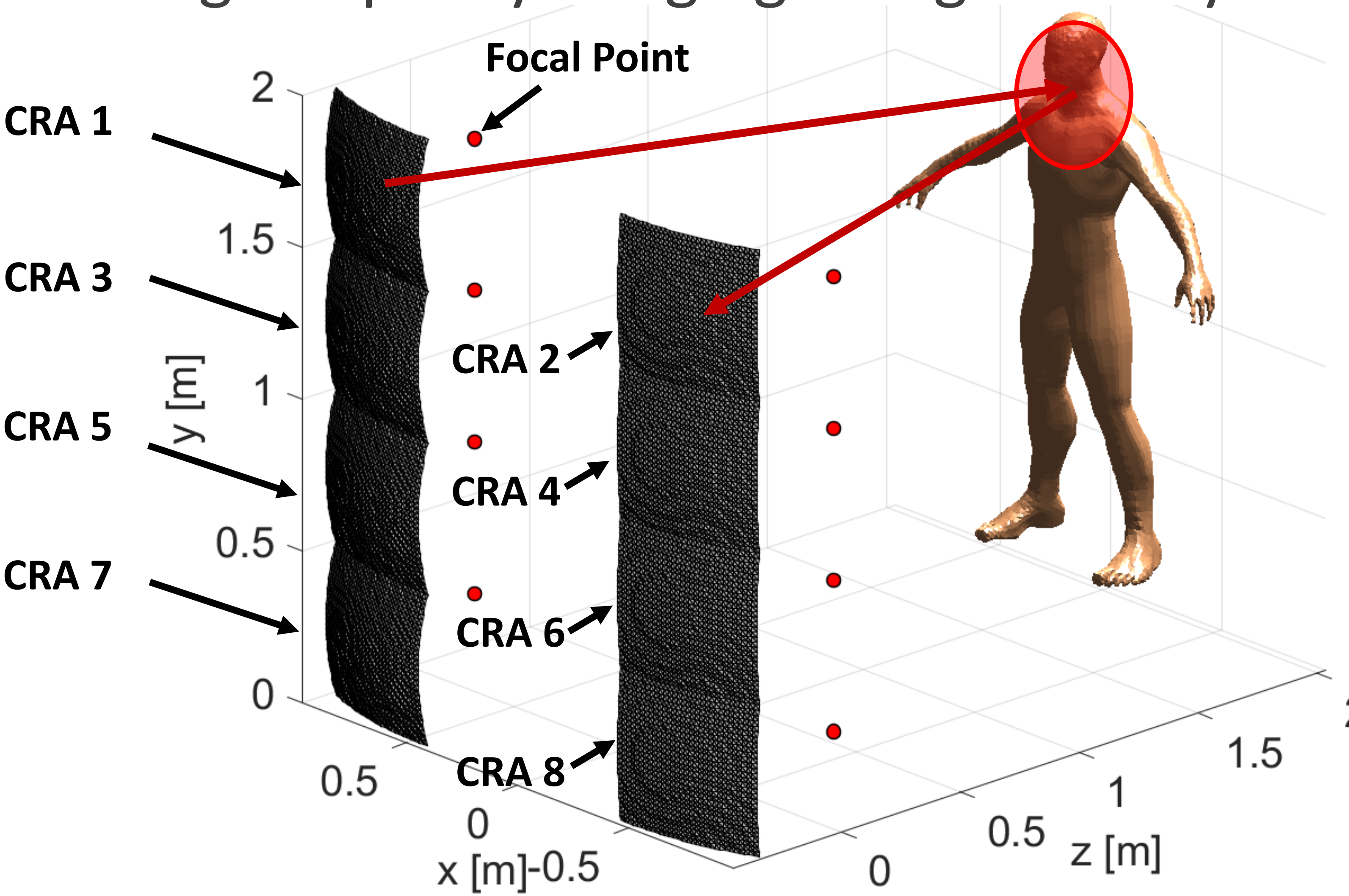

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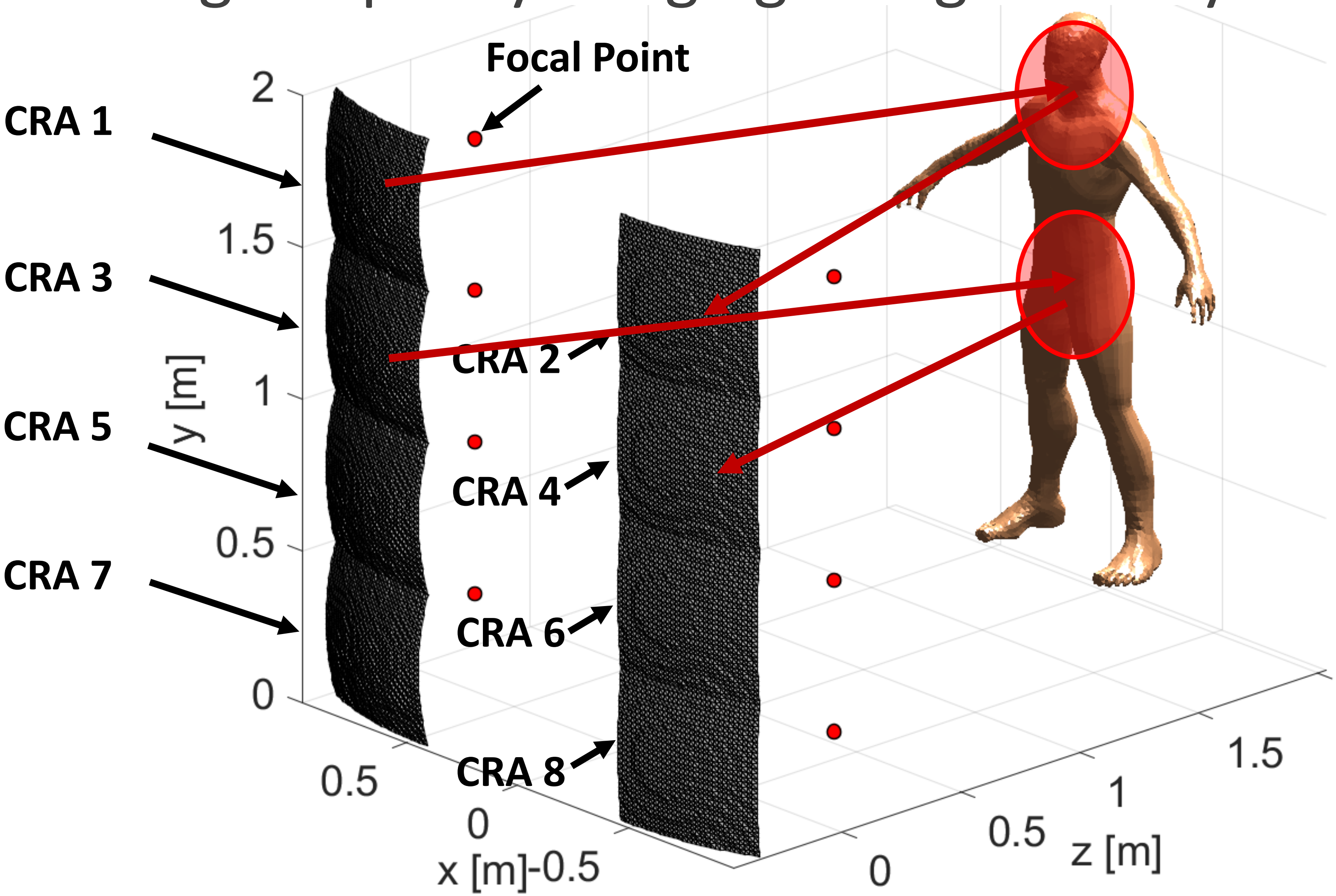

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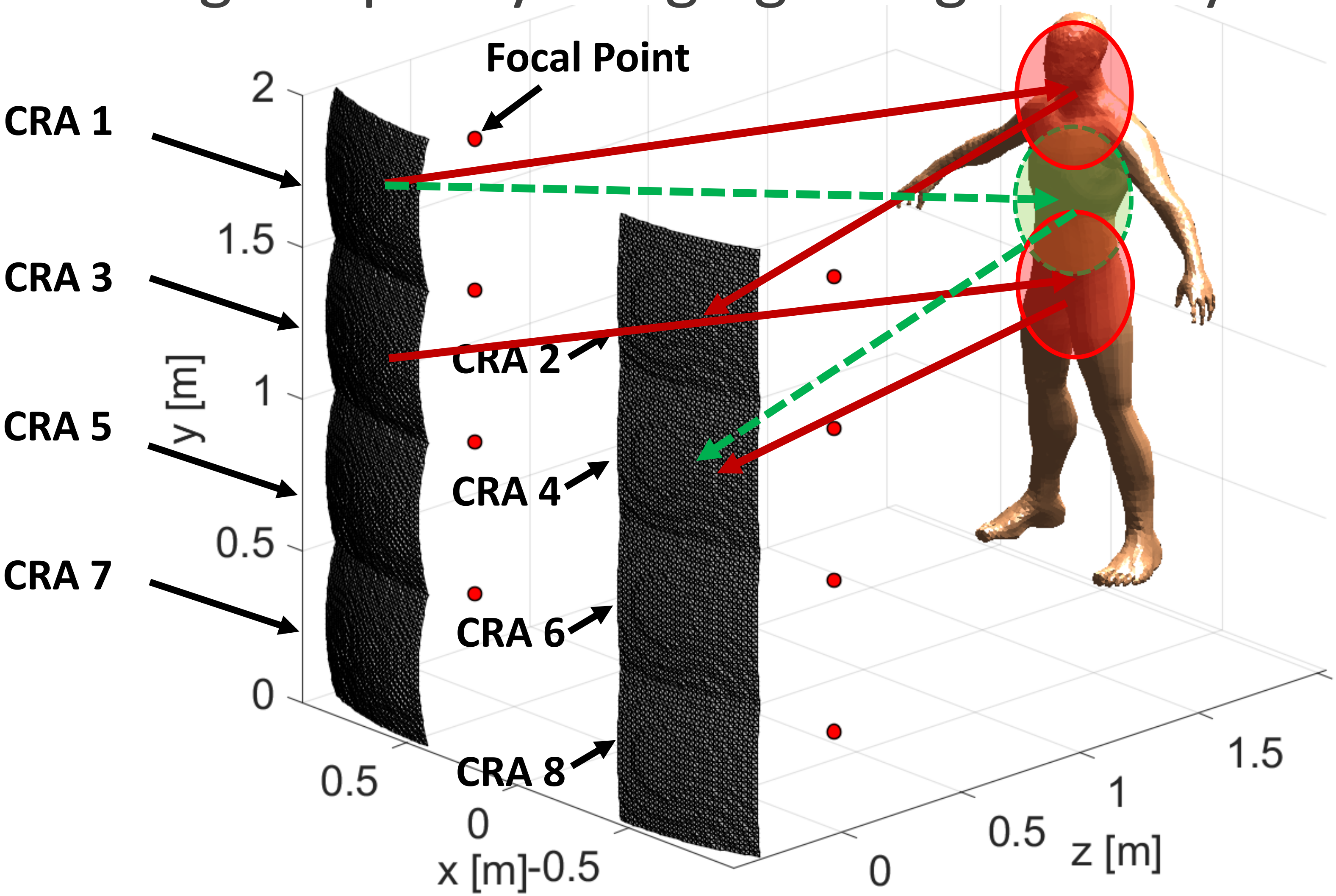

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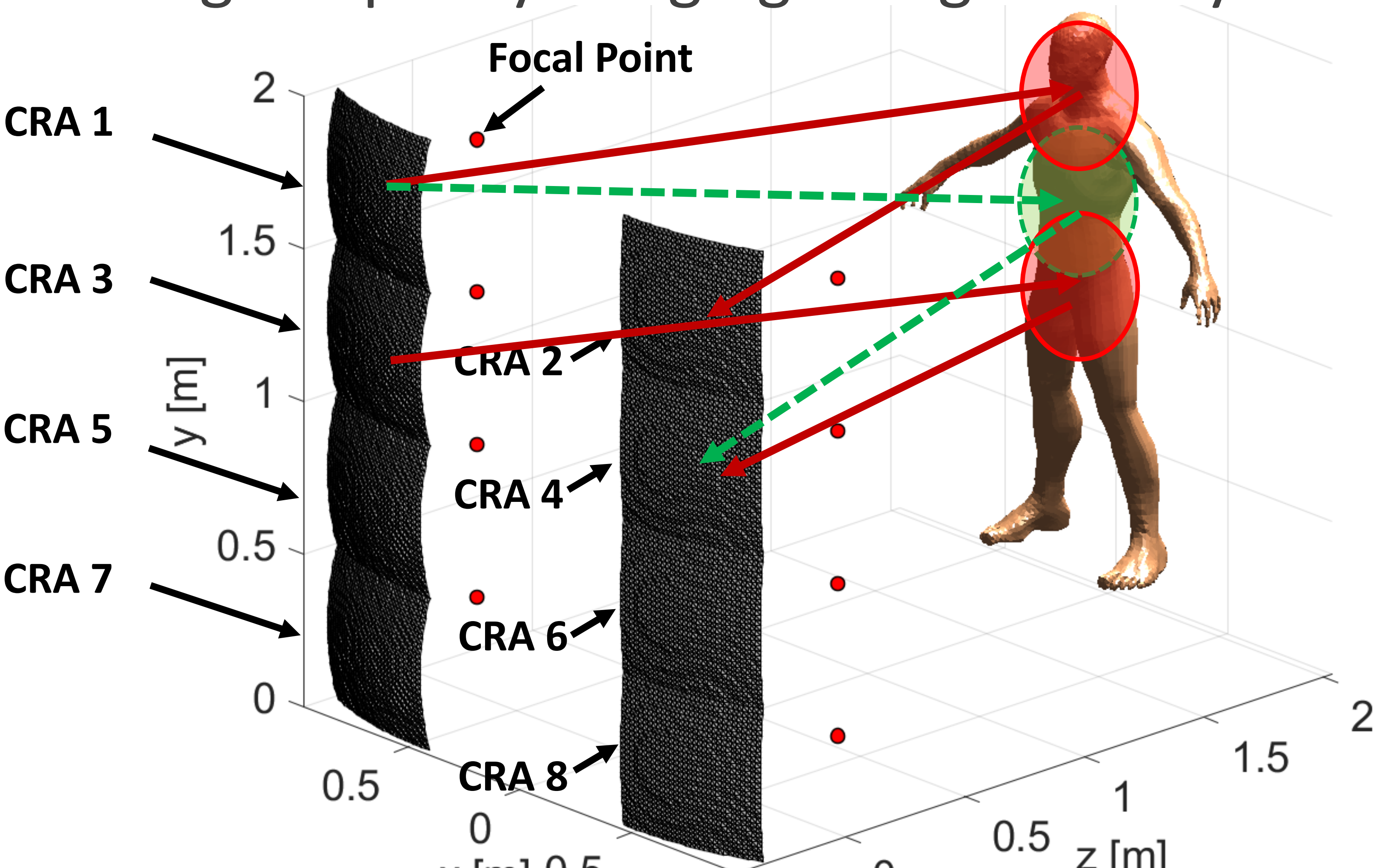

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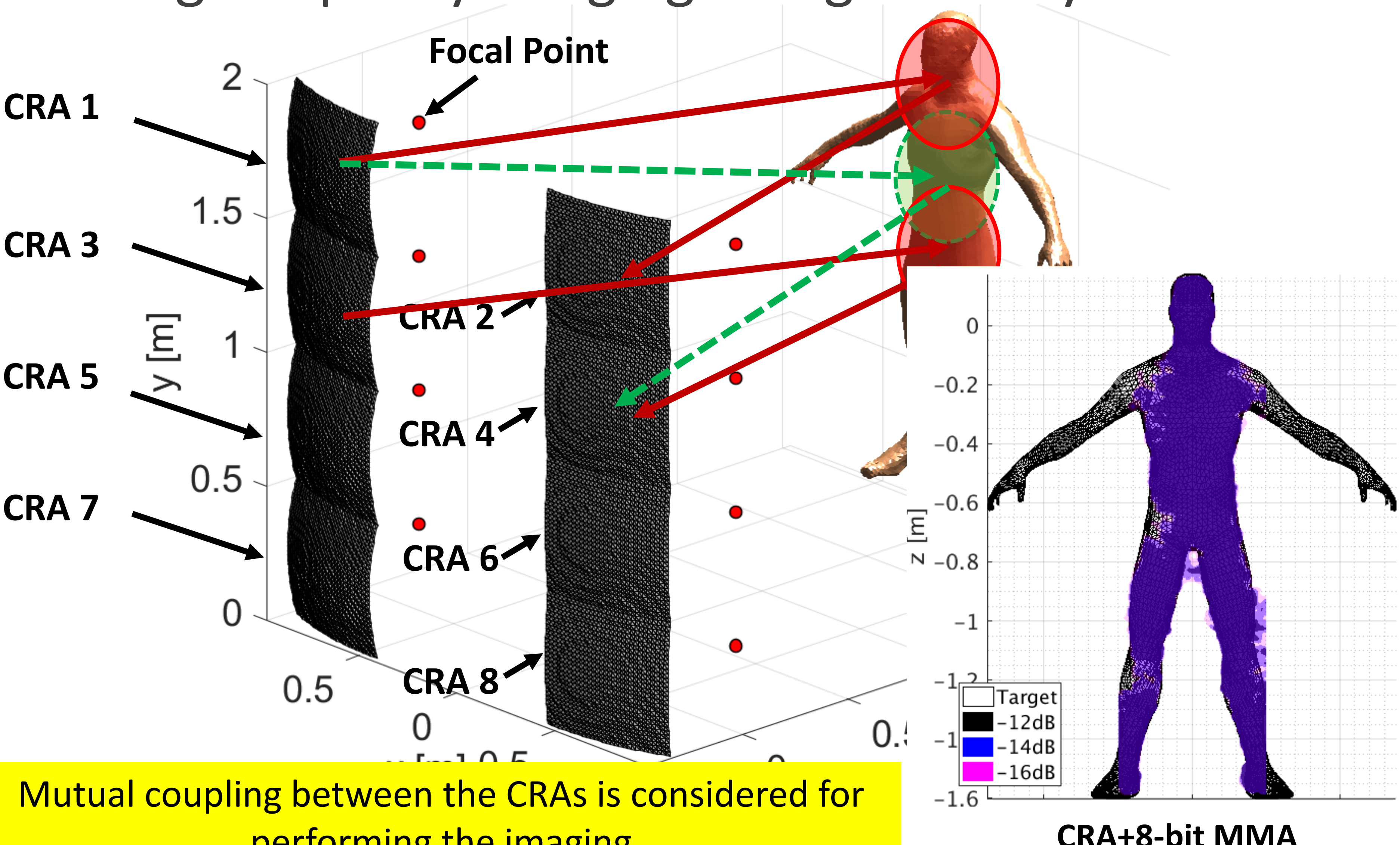

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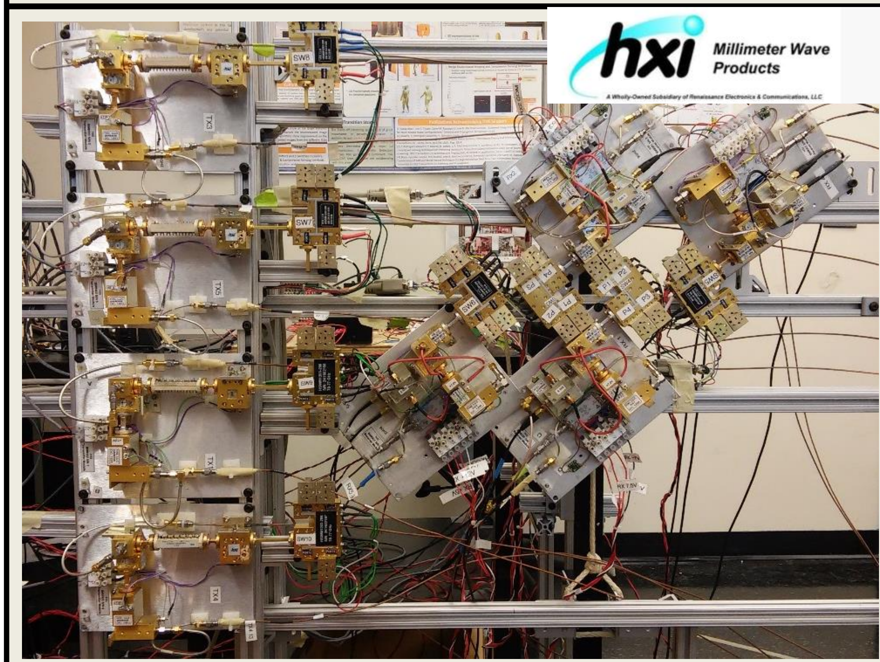
MIMO ARRAY: **400 Coherent Channels**

Front view



- Video: number of people in scene
- 3D stereo camera: imaging location for mm-wave
- mm-Wave: looking under clothing

Anthony Bisulco, Luis Tirado, Shaan Patel, Luigi Annese, Galia Ghazi and J. A. Martinez-Lorenzo. Massive MIMO Millimeter Wave Radar Imaging System. AP-S 2016— IEEE AP-S International Symposium, Fajardo, Puerto Rico, Jul. 2016.

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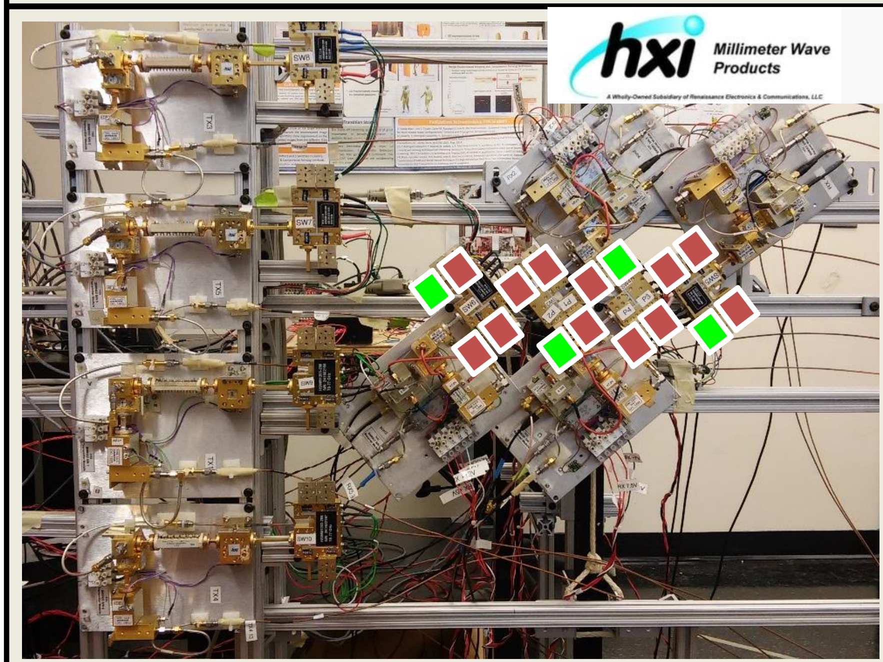

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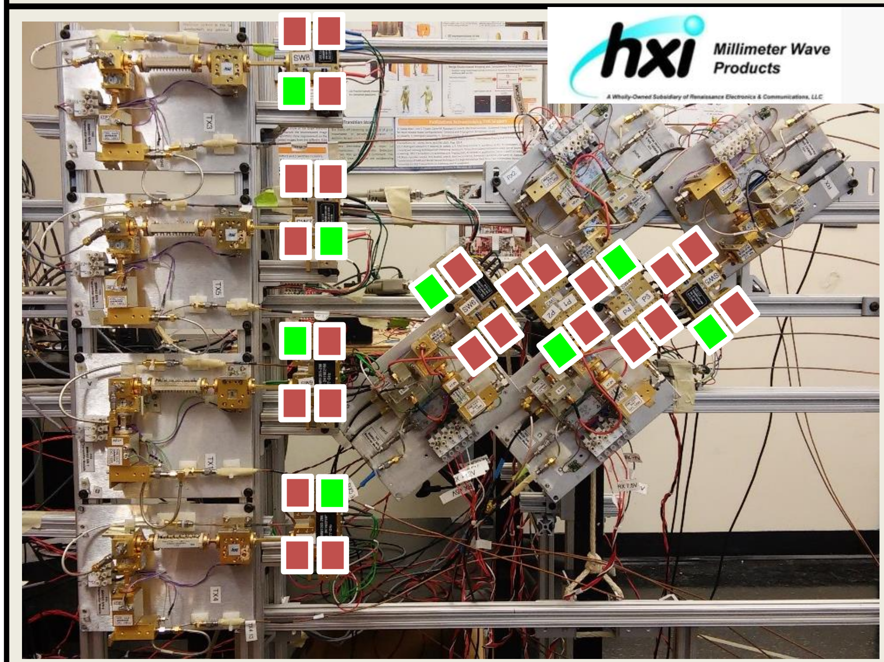

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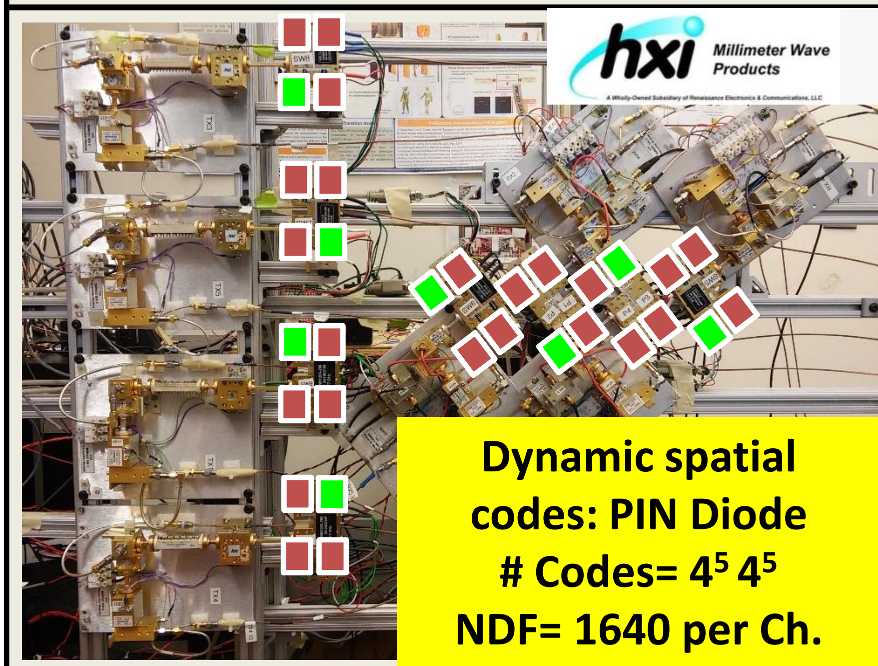

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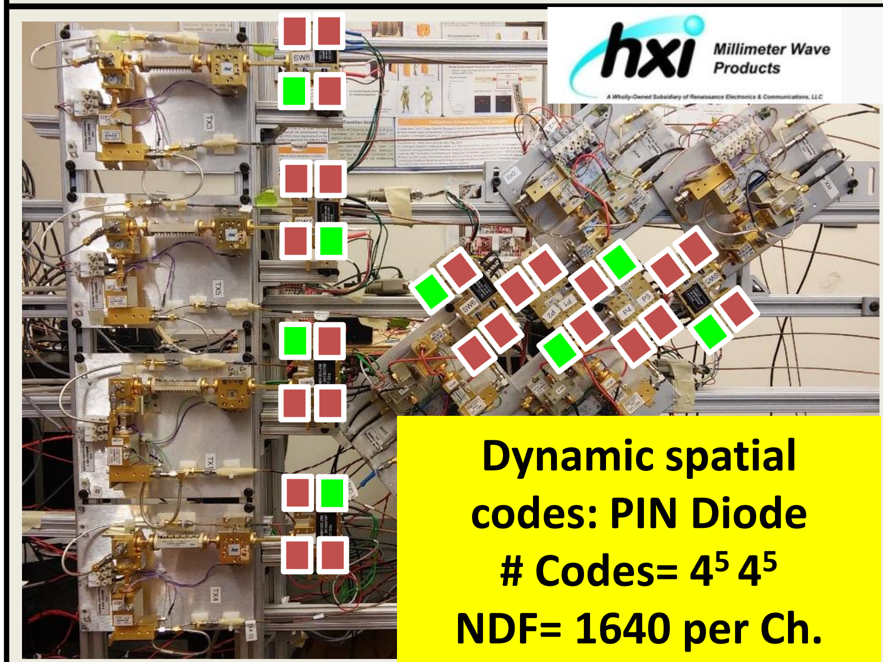

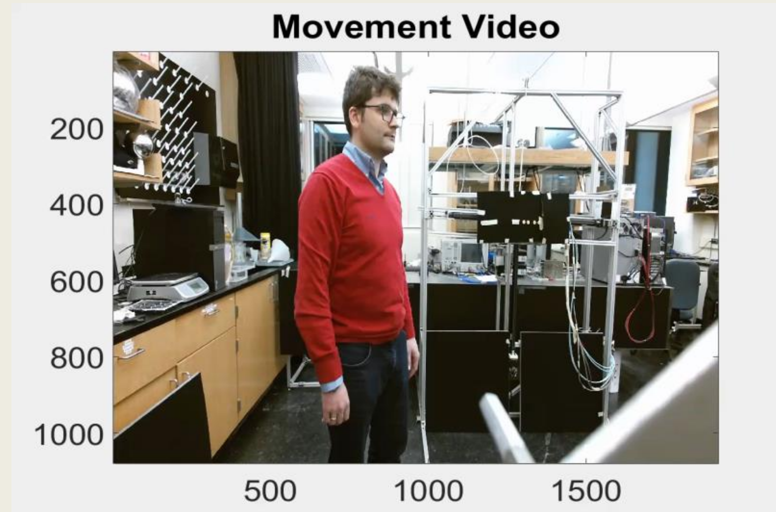

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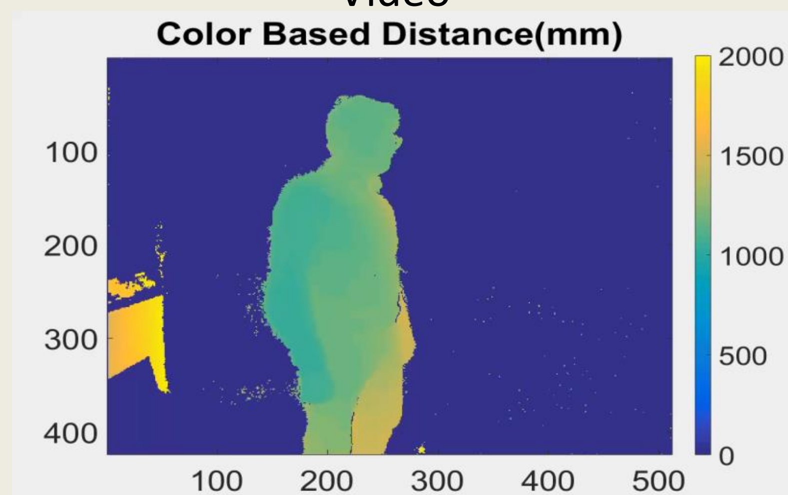

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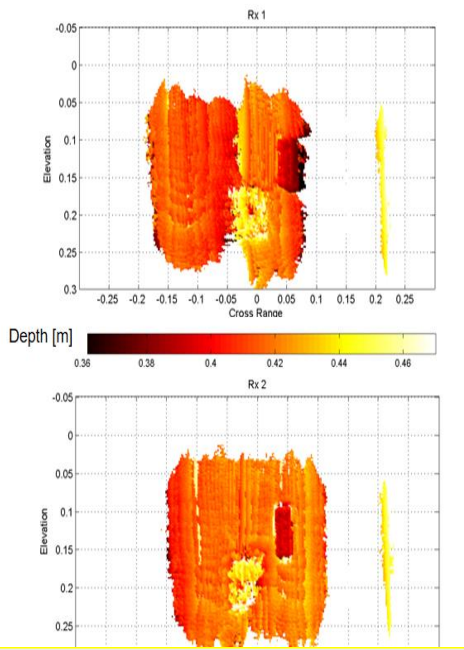
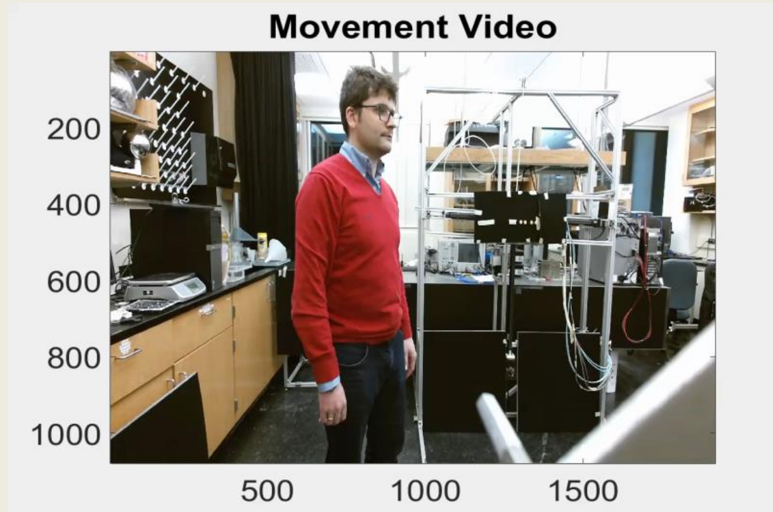
- Metallic channel
- Dielectric





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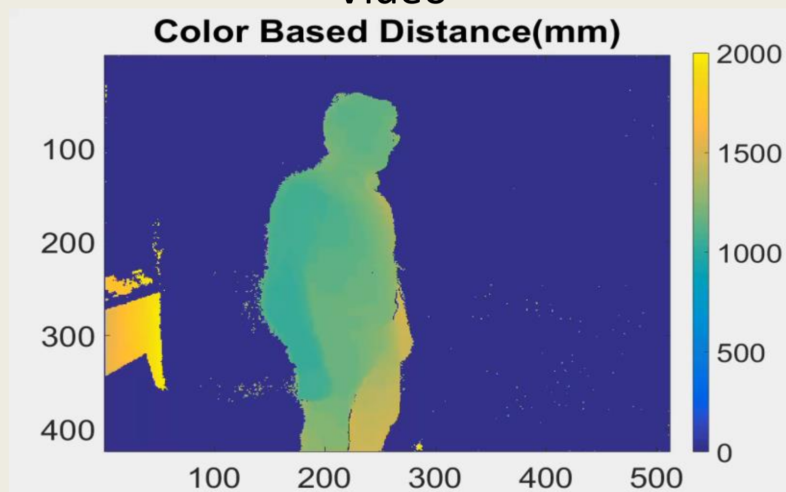

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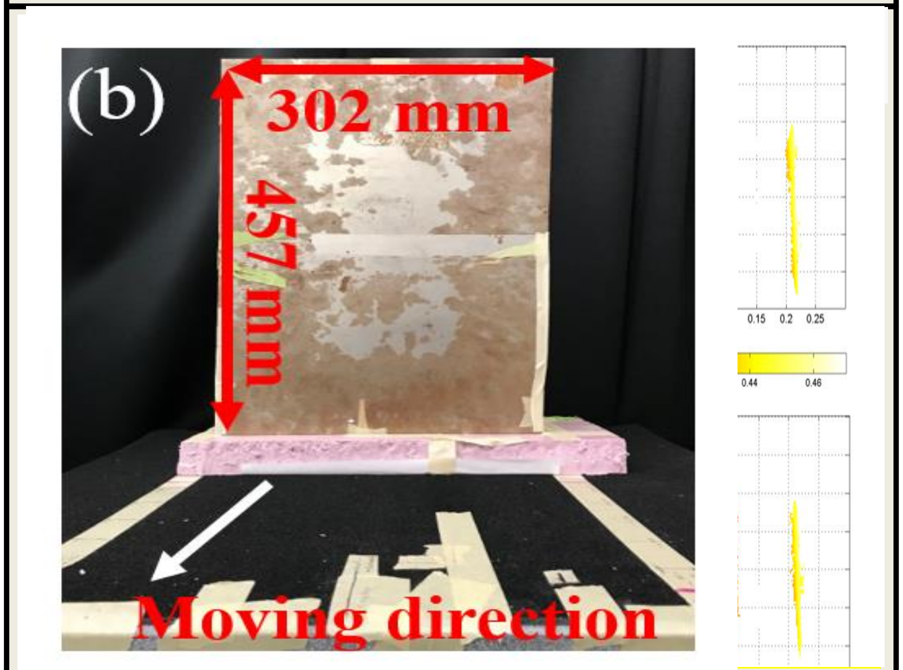

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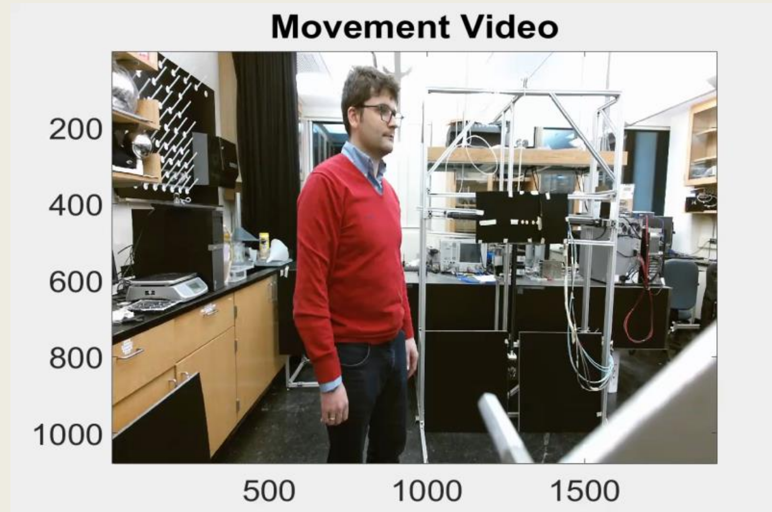

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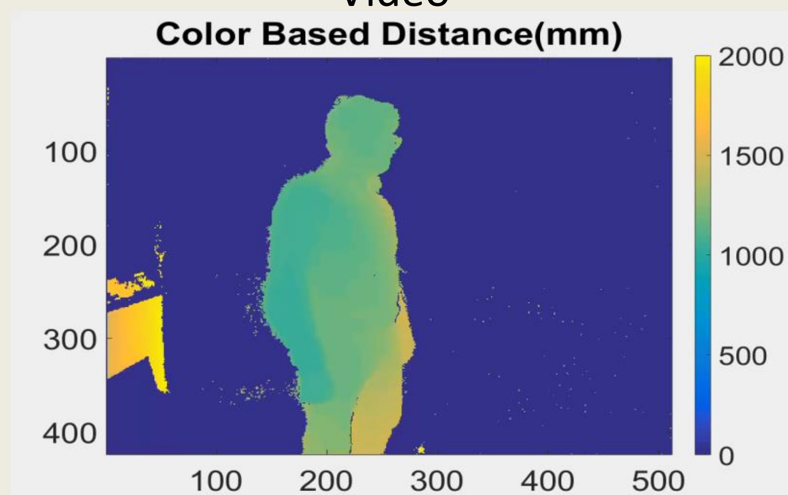

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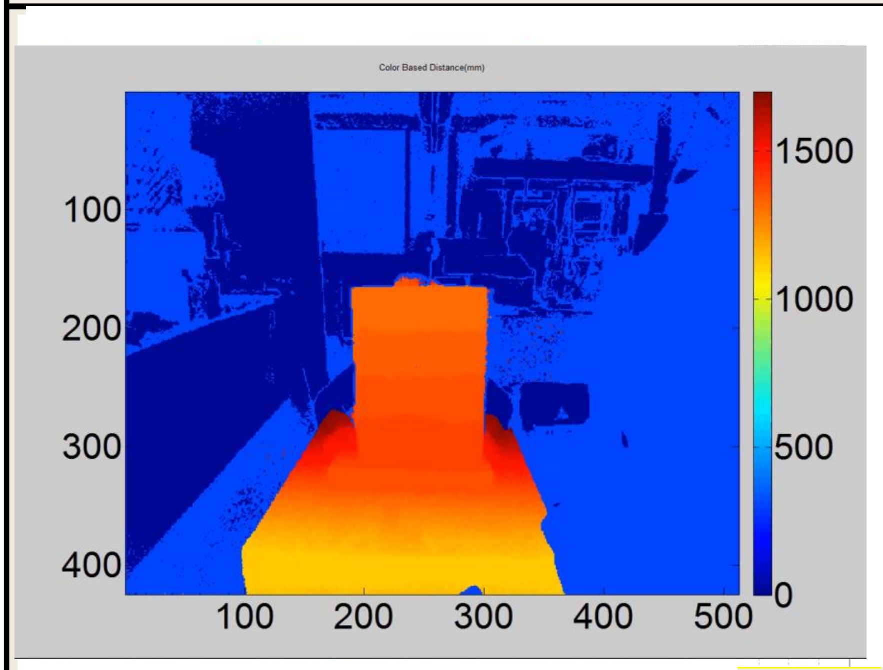

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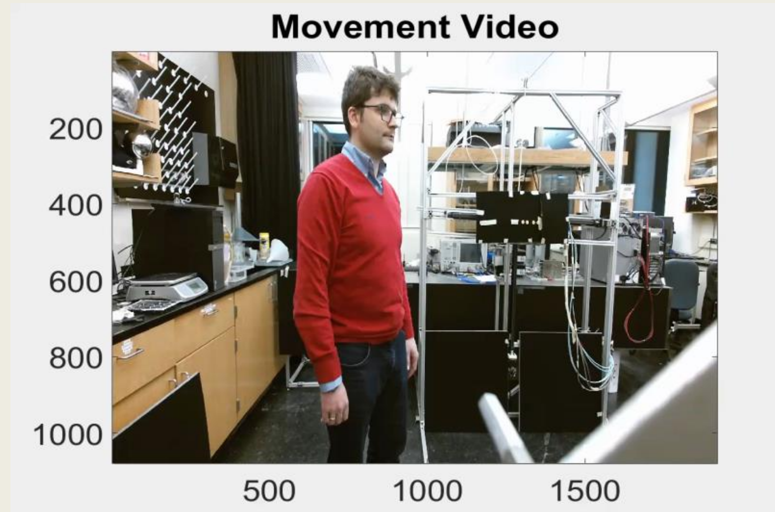

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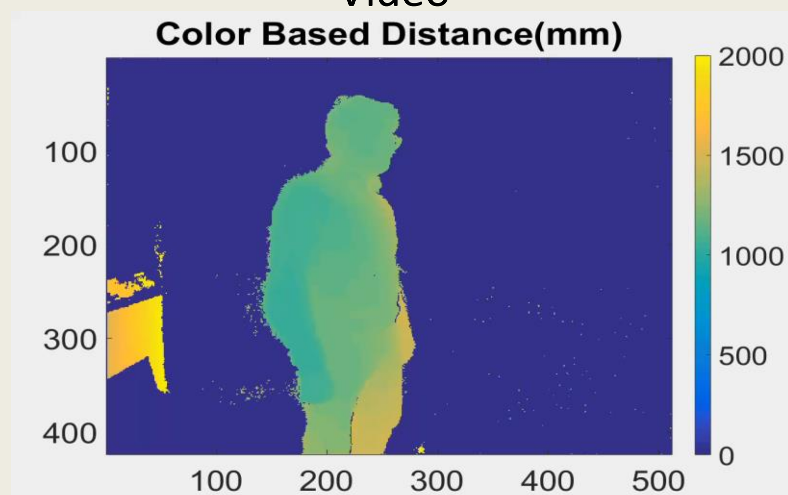

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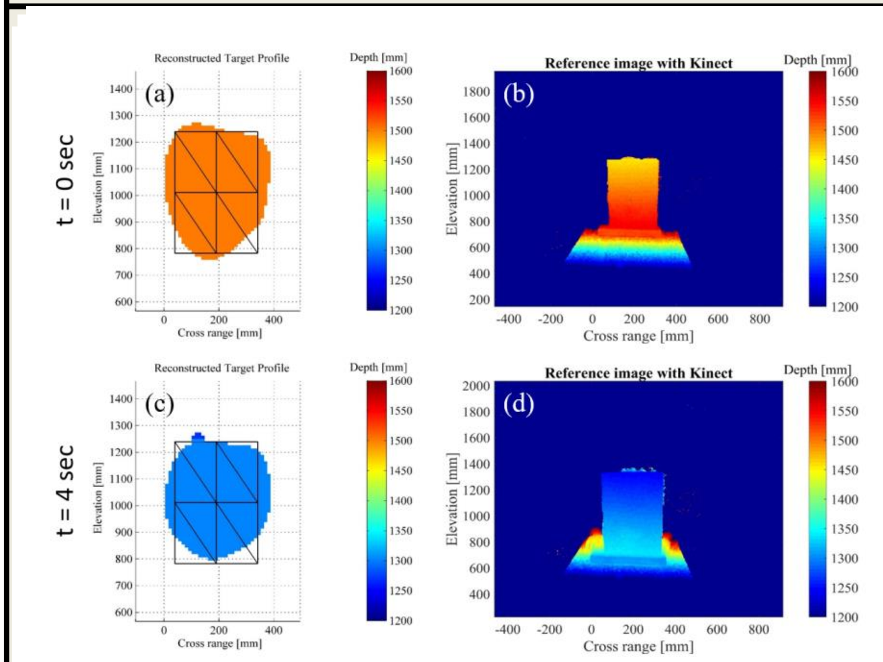

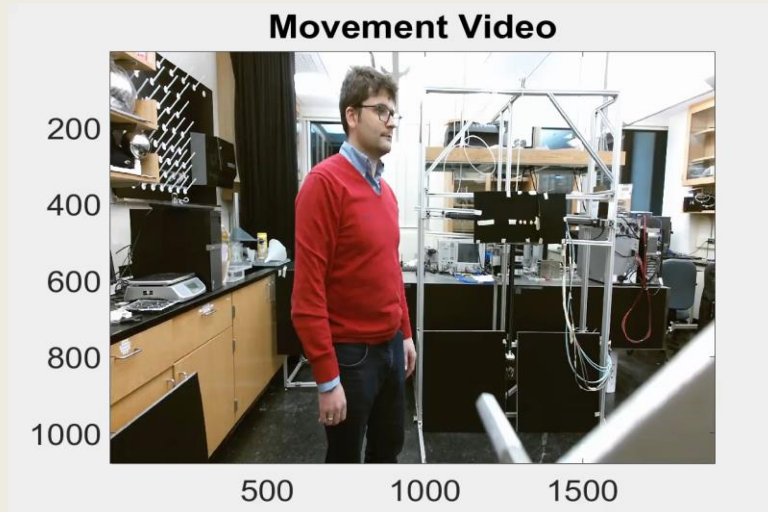

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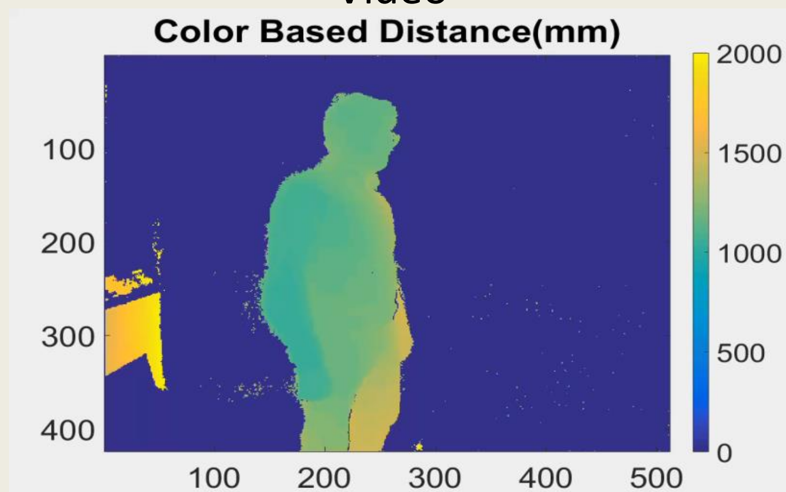

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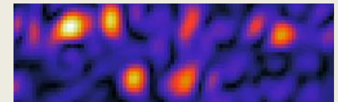

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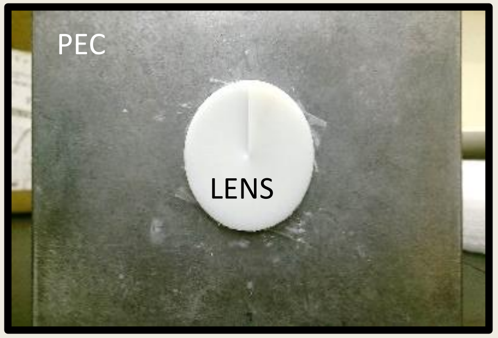

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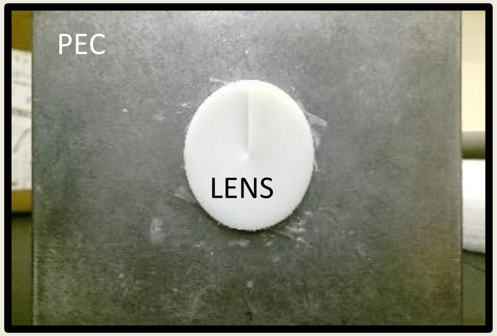

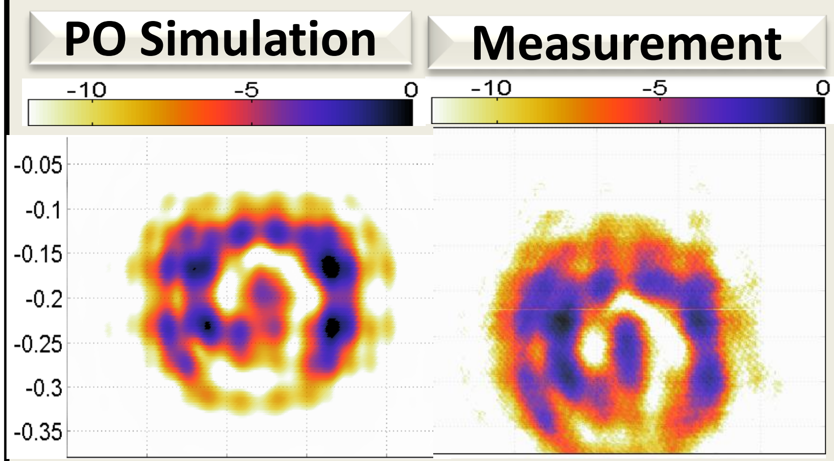

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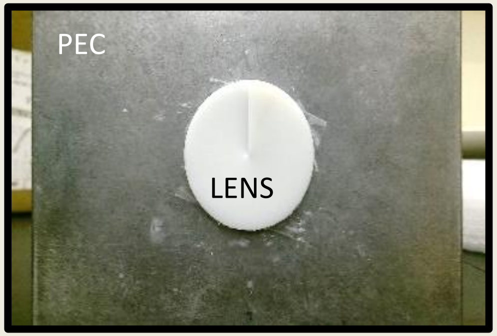
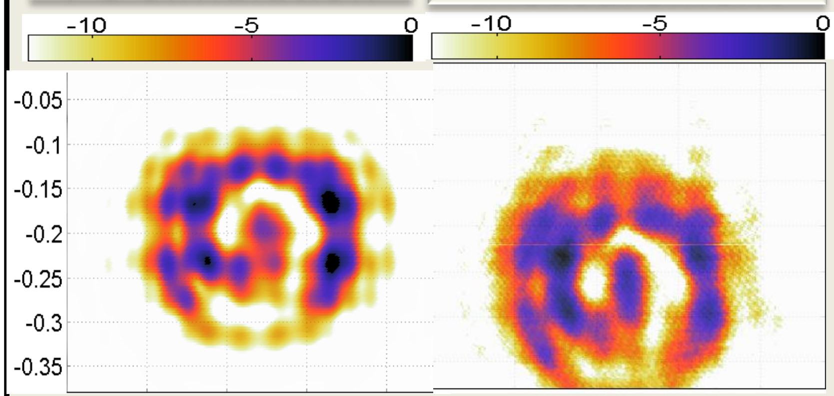
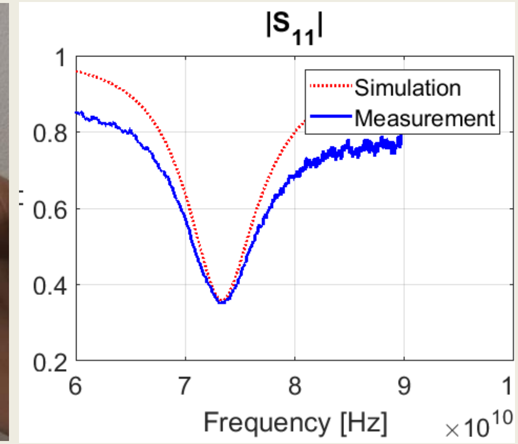


PO Simulation **Measurement**





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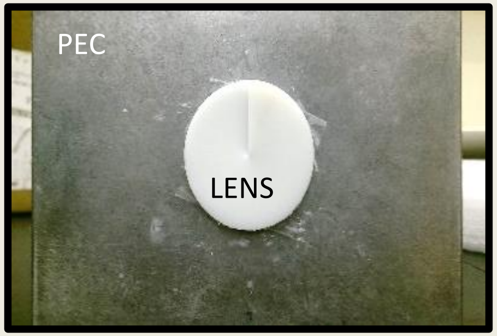
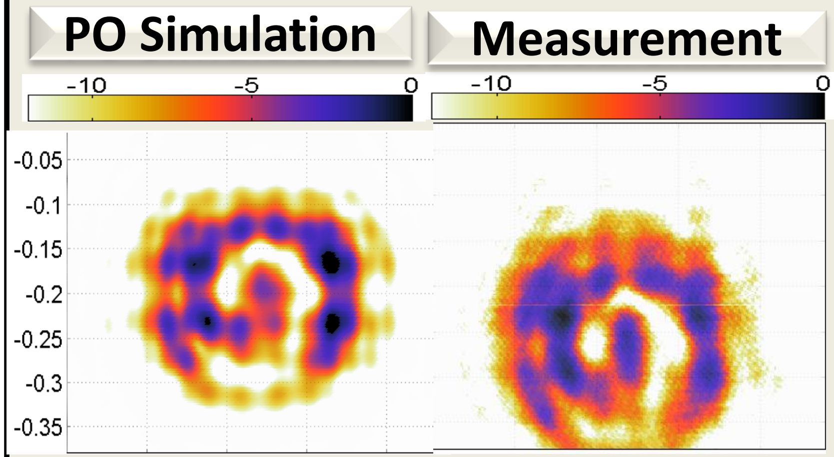
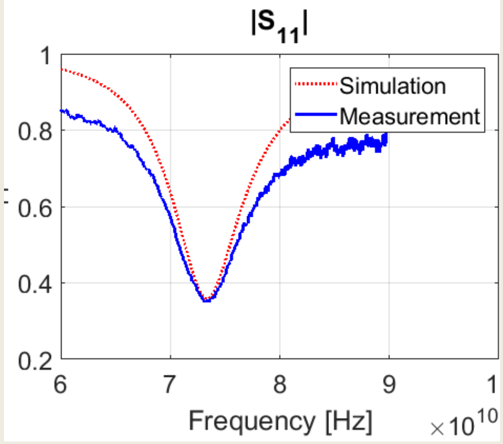
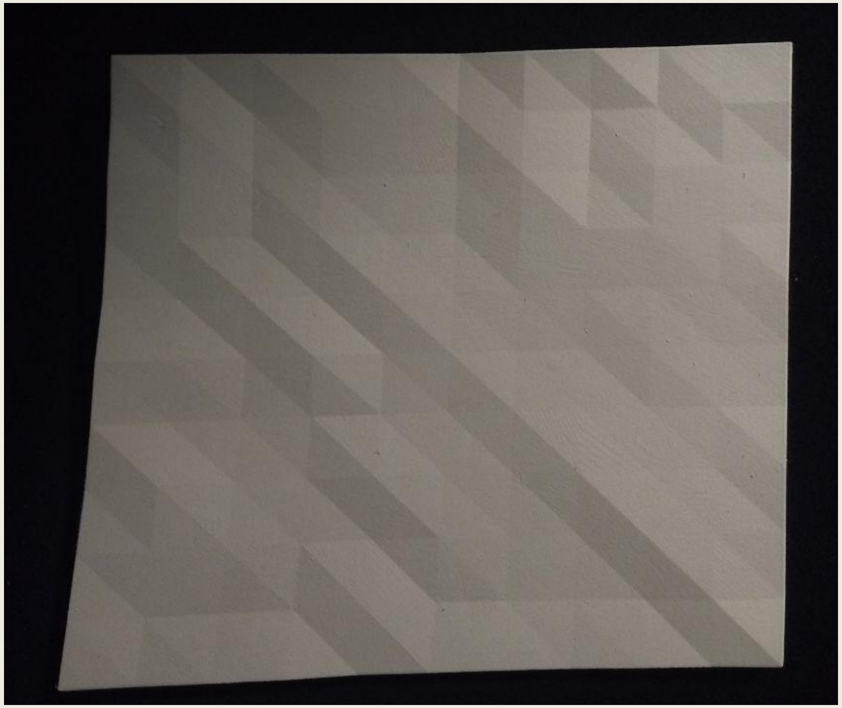




G. Ghazi, A. Ghanbarzadeh, A. Molaei, L. Tirado, A. Bisulco, J. Heredia Juesas and J. A. Martinez-Lorenzo. High Frequency Modeling of Large Composite Scatterers of Arbitrary Shape: Vortex-Lens Validation. CD Proc., EuCAP 2016—IX European Conference on Antennas and Propagation, Davos, Switzerland, April, 2016.





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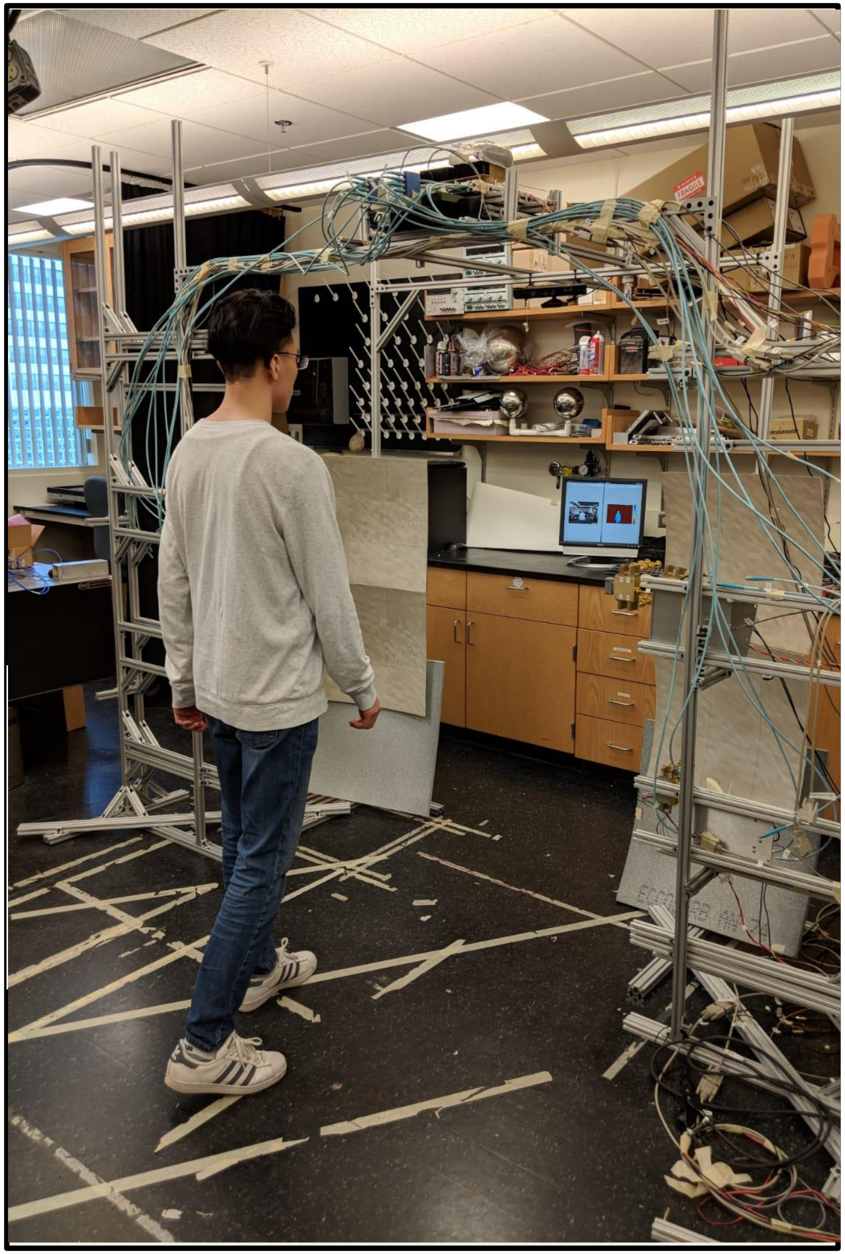

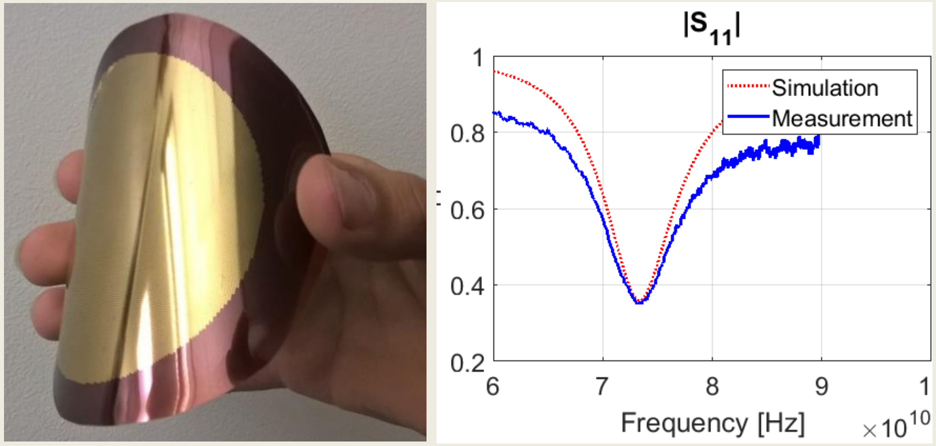

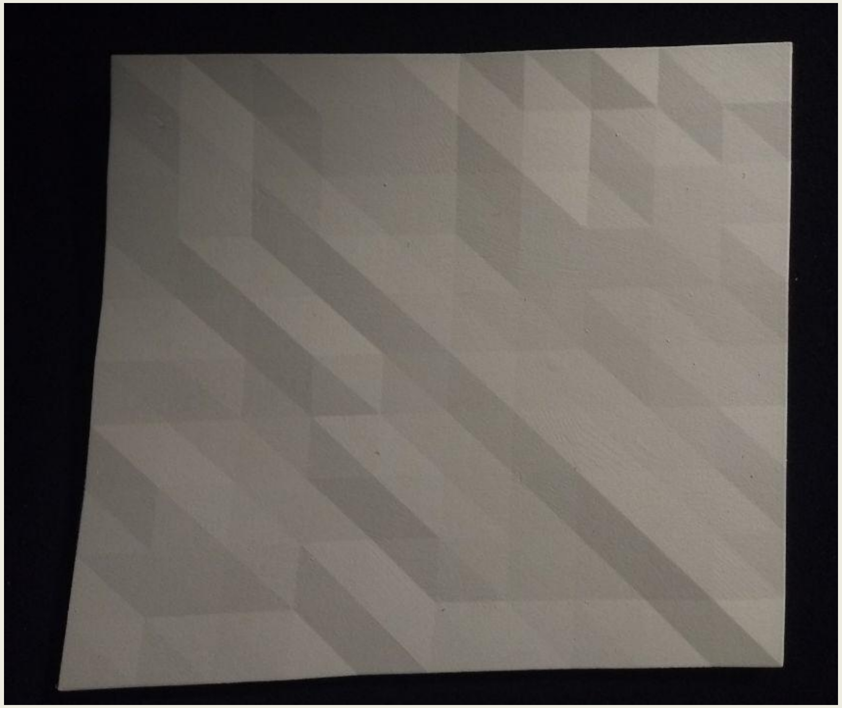

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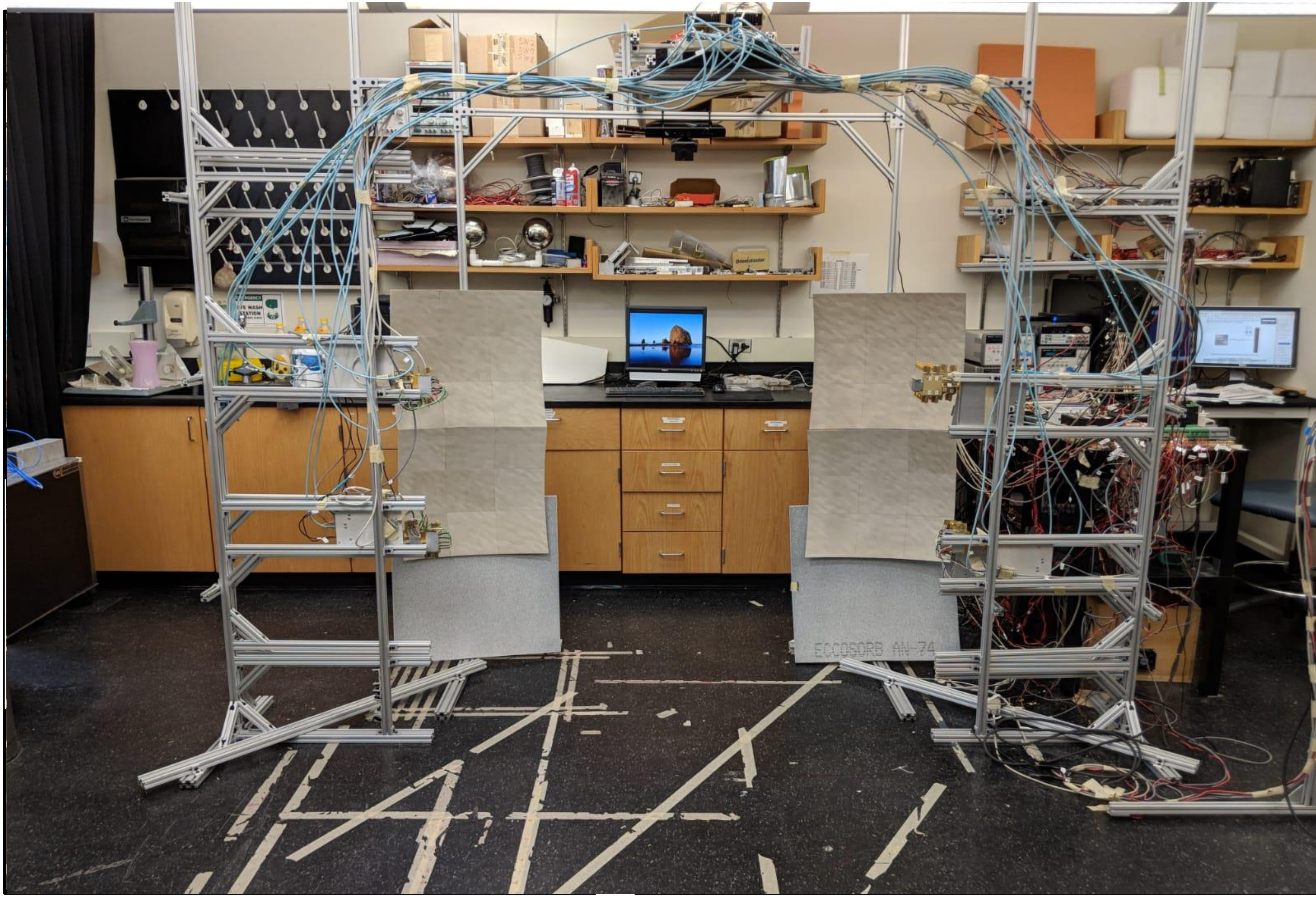
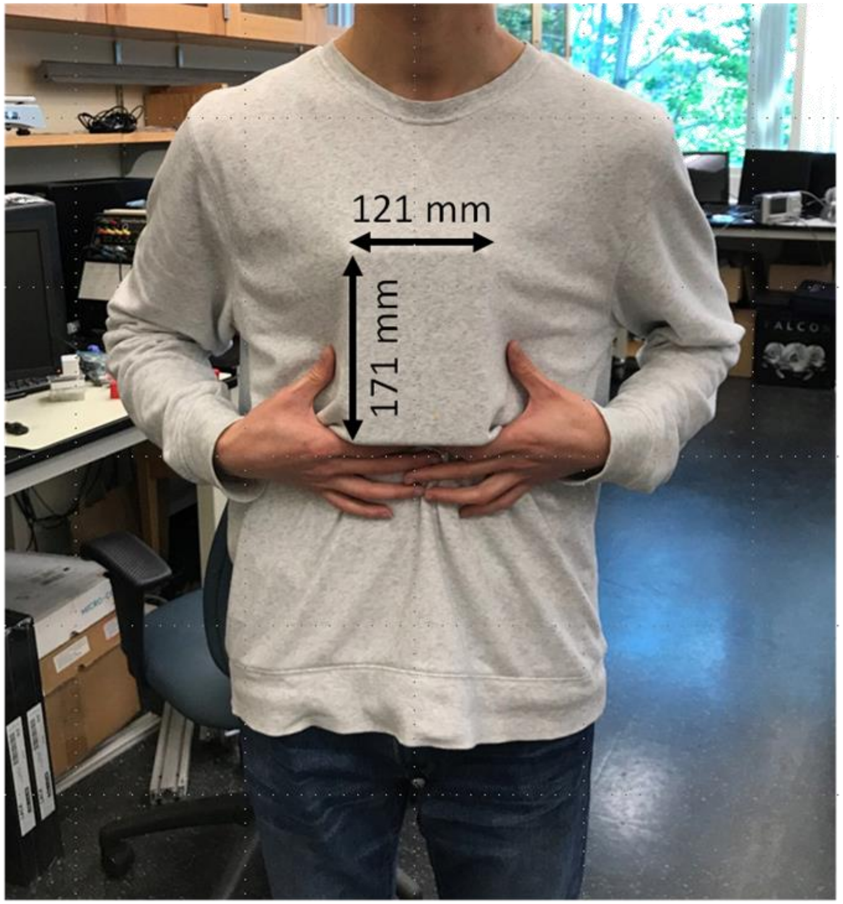
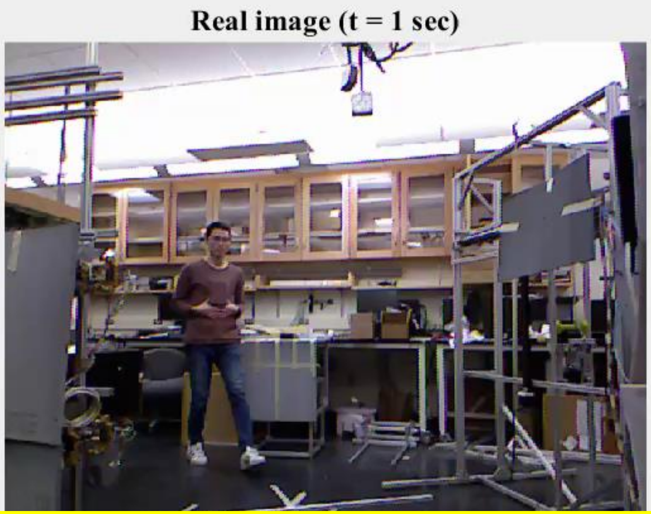
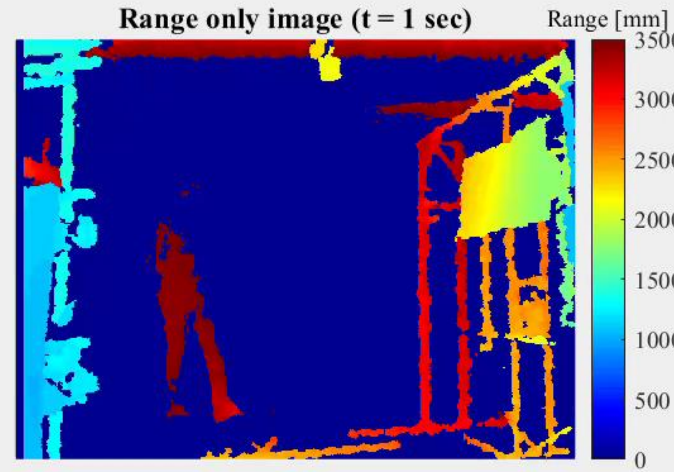


2. Imaging of a metallic target

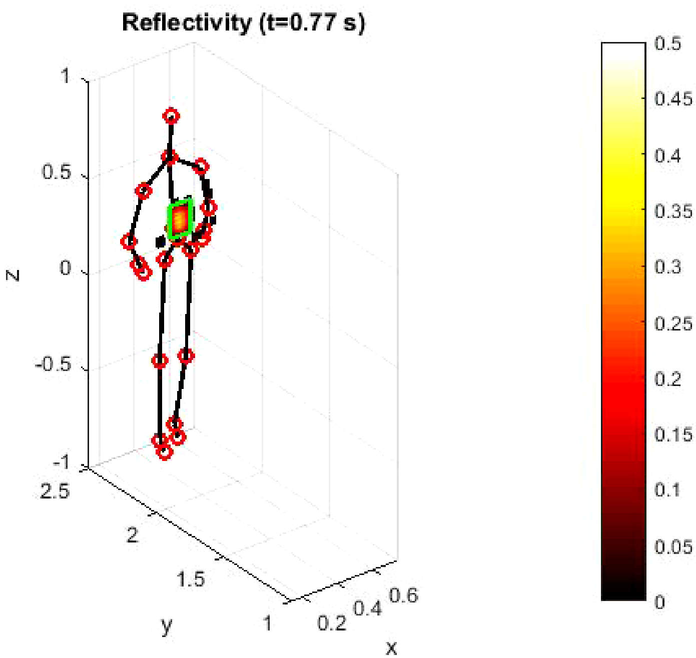


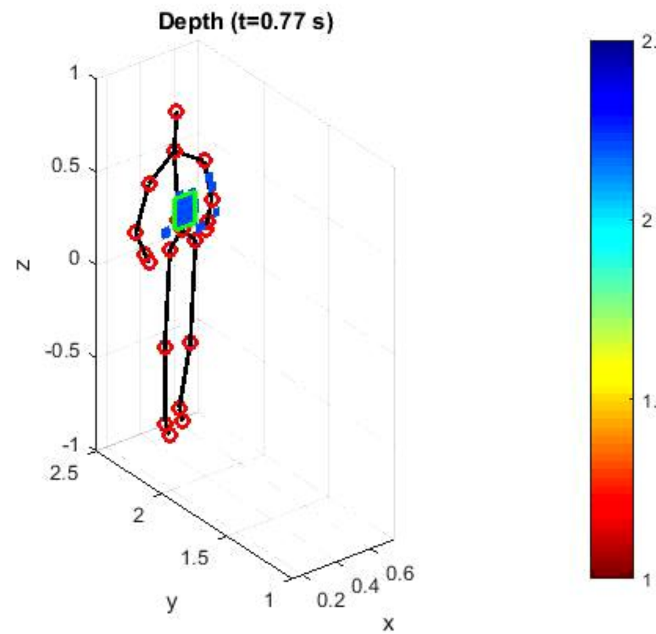




Real video

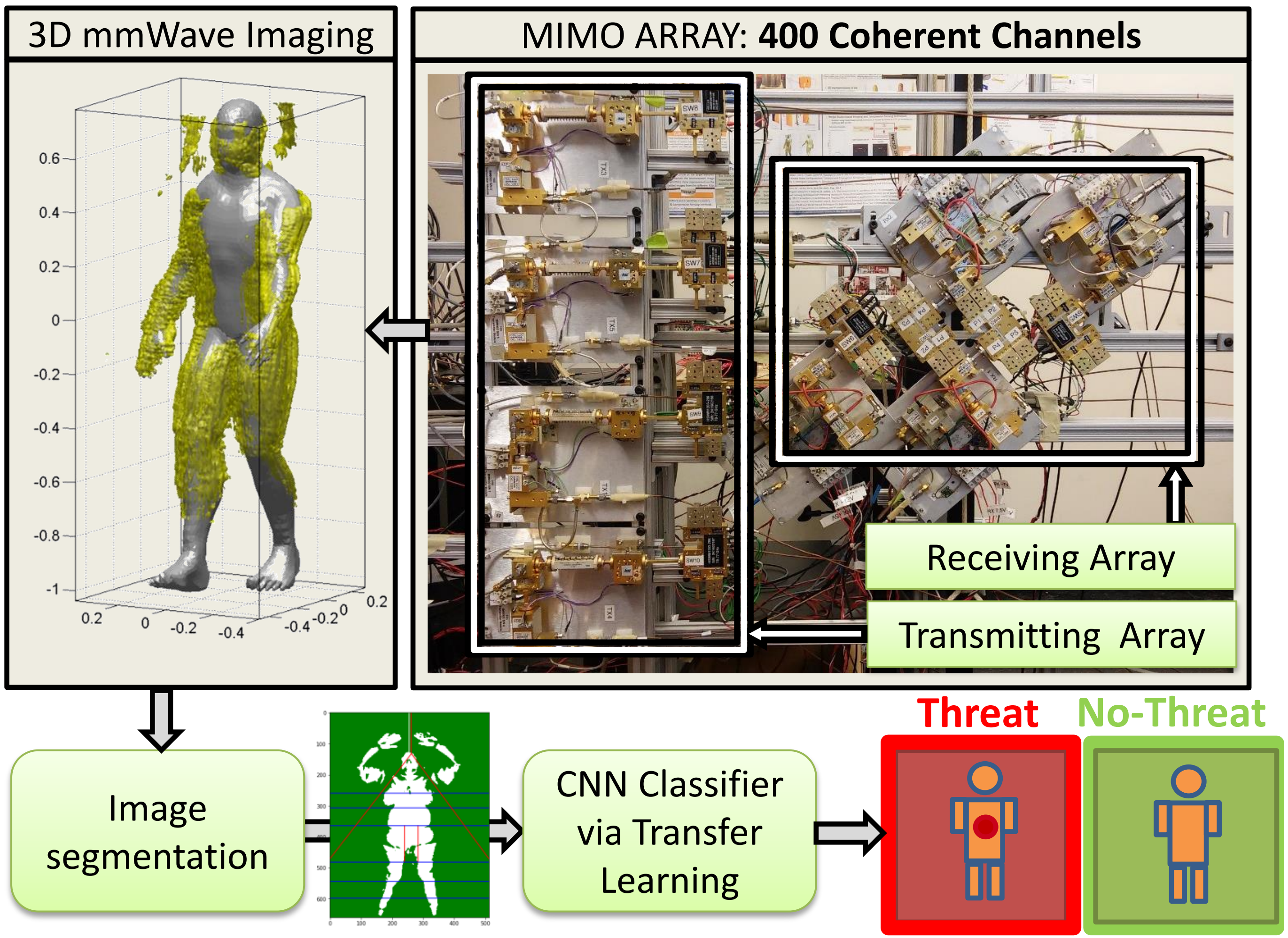
3D Stereo camera + joint detection





Experimental mm-wave Image (1 CRA) + joint 3D video

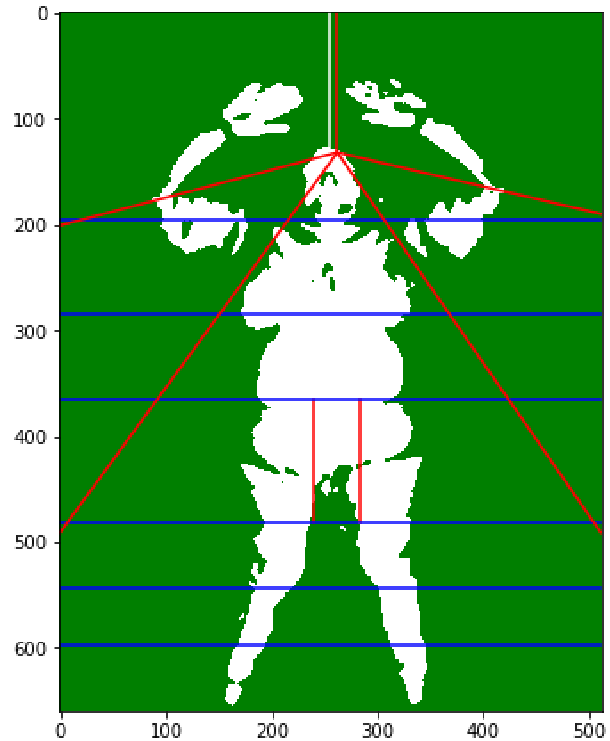
3. Overview Deep Learning for threat detection



[1] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

3. Deep Learning: segmentation & transfer learning

- ***3D Data*** dataset is projected into 16 views.
- Reflectivity and junctions are used to segment the image into several regions: this presentation will focus on the chest.
- Pre-trained ***CNN Alex Net*** (1000 classes) used for **transfer learning**.
- Re-train Alex Net using five new layers (2 classes).



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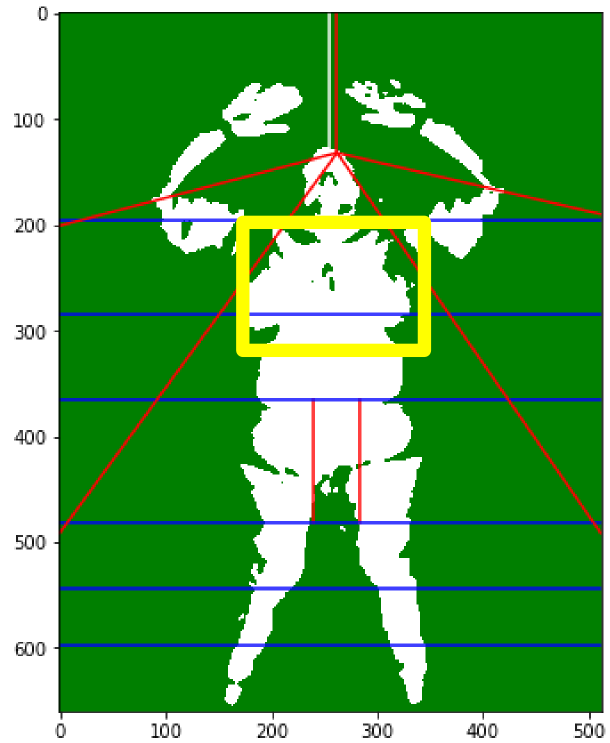

3. Deep Learning: Cross-validation

- **Training:** 150 images (75 from each class) are randomly selected
- **Cross-validation:** 30 images (15 from each class and different from the training ones) are randomly selected for testing.

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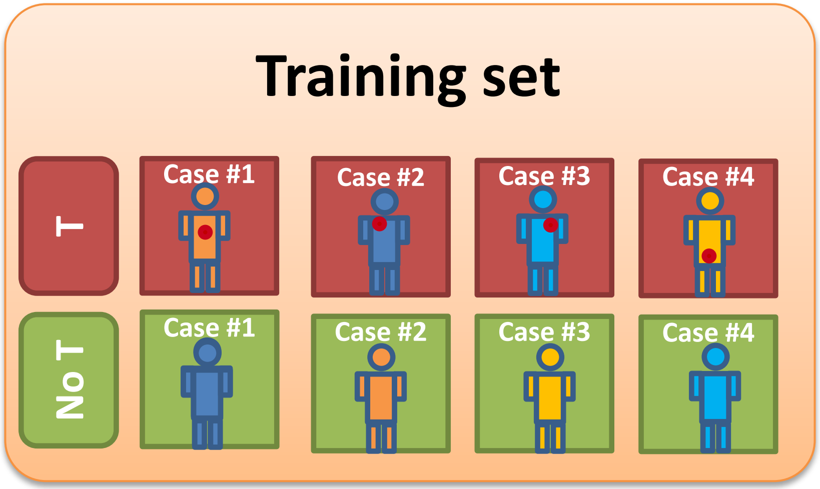

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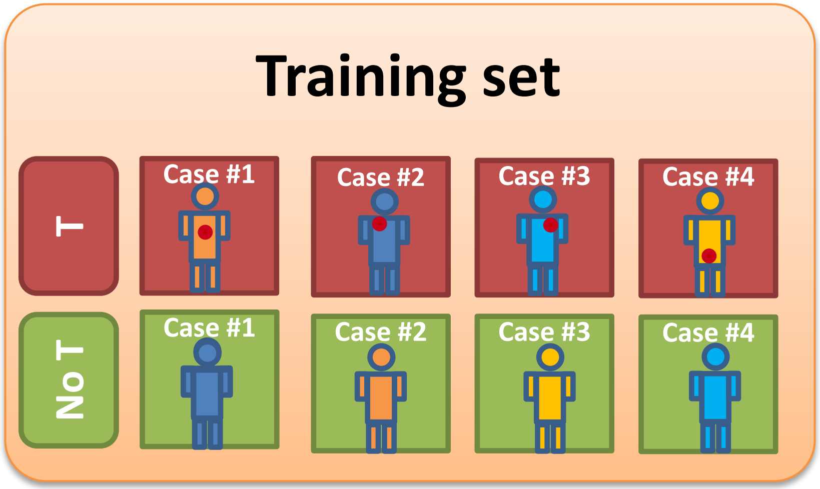

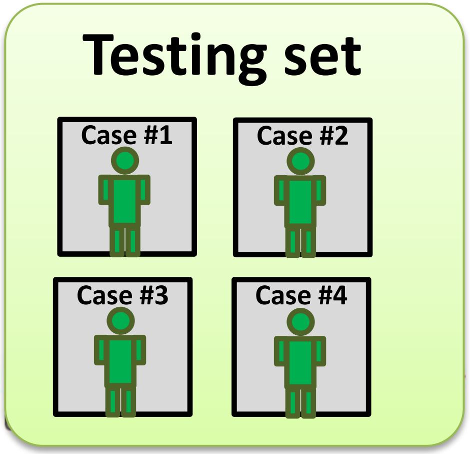

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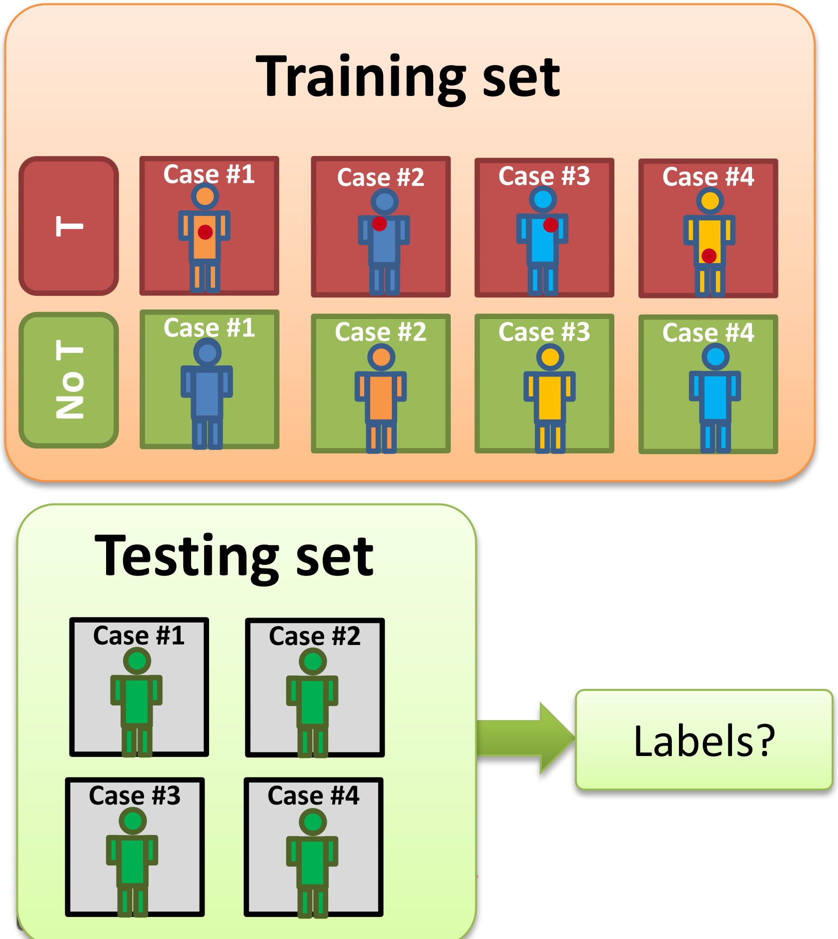

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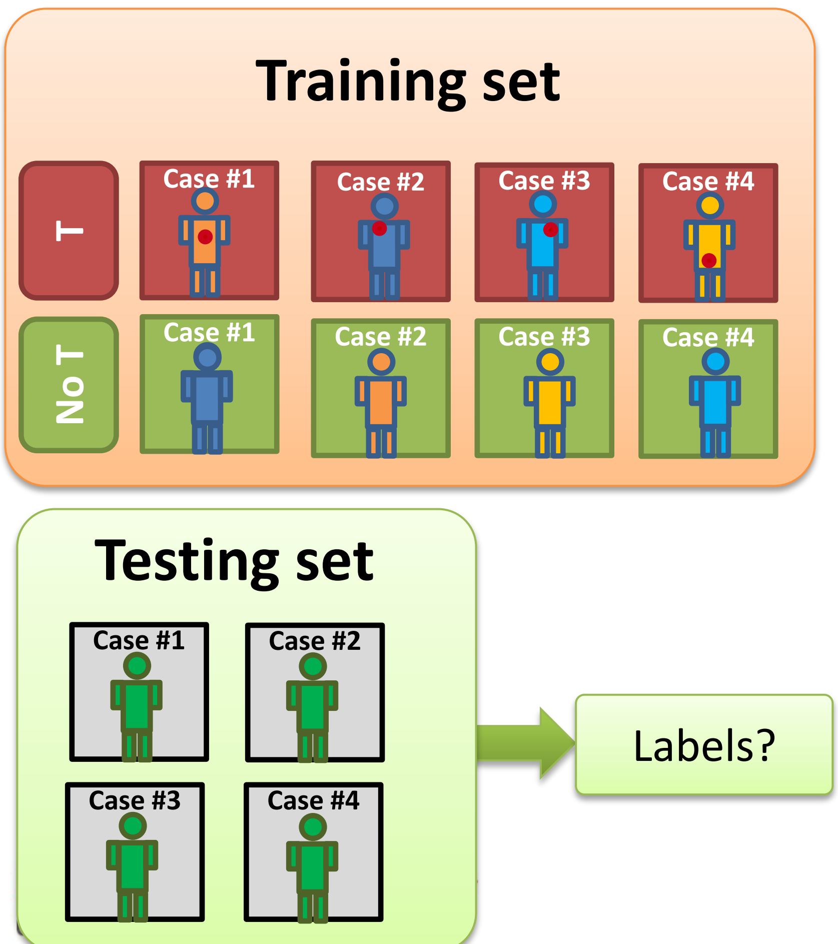

Running	Accuracy	Log loss
#1	90.00 %	0.2130
#2	96.67 %	0.1861
#3	76.67 %	0.3873
#4	86.67 %	0.3609
#5	96.67 %	0.1693
#6	83.33 %	0.3971
#7	90.00 %	0.2522
#8	83.33 %	0.3561
#9	100.00 %	0.1253
#10	90.00 %	0.2523
Mean / std	90.00 % / 7.27 %	0.2558 / 0.0933

4. Conclusions

- ***High sensing capacity*** imaging using compression at the physical layer
  - Using CRAs, Vortex meta-lenses, MMA, random cavities.
- Fused ***3D stereo cameras*** and ***mm-wave images.***
  - Fast **compressive sensing**.
  - **Norm-1** regularized imaging using distributed **ADMM**.
- ***Deep Learning*** for threat detection
  - Deep learning directly applied to the mm-wave image.
  - Training is done using available datasets
  - Additional datasets will be collected in the SICA-LAB
- The ***proposed system***, imaging algorithms, and DL detection can be ***easily deployed*** in the field.
- The ***performance*** of the system can be ***tuned*** based on the following:
  - Speed of the target
  - Resolution
  - Cost
- ***Secondary inspection*** may require additional ***video analytics*** (Prof. Octavia Camps - ALERT) for tracking a target after flagging.