

Introductions

Antennas are an inherent part of the wireless reception and transmission of electromagnetic (EM) signals. Here, we propose and demonstrate that in scenarios dealing with targets which belong to the same category, a neural network (machine) is capable of learning certain features of those targets from the prior antenna measurements collected from different targets. Upon completion of training, the machine will be able to predict the shape of unseen targets merely based on the antenna measurements acquired at a few sampling points in space.

As a proof-of-concept, we made use of an 8-by-8 array of independently-controlled square patches designed to operate at 10 GHz on a PCB board to form the target shape. Certain patches can be toggled into their active (radiating) state using electronic switching, which in essence allows us to control the shape of the bright target at a high speed. The 17 antennas used as receivers far away from the target in combination with the trained predictor machine are referred here as Artificially Intelligent Antennas (AIA).

Methods

The predictor machine and the antenna measurements are the two key components here. Each of the square patches on the 8-by-8 array serves as a "Microwave pixel" which could be either radiating (on) or not radiating (off) [Fig. 1].

A random-number generator is used to shuffle the on/off states of each of the 64 pixels to generate thousands of distinct bright patterns on the PCB as the target. We then made use of EM simulations [Ref. 2] to generate the corresponding antenna measurements at the 17 sampling points located 10 feet away from the target [Fig. 2].

A U-shaped Neural Network Architecture known as UCNN [Ref. 1] is utilized as the predictor machine. The UCNN topology is adjusted to the number of the receiver antennas (17), the number of sampled frequencies (4) and the number of microwave pixels (64) [Fig. 3]. The UCNN is designed to generate the overall on/off state of the bright target in the form of a 64-digit binary number as output when fed with the antenna measurements.

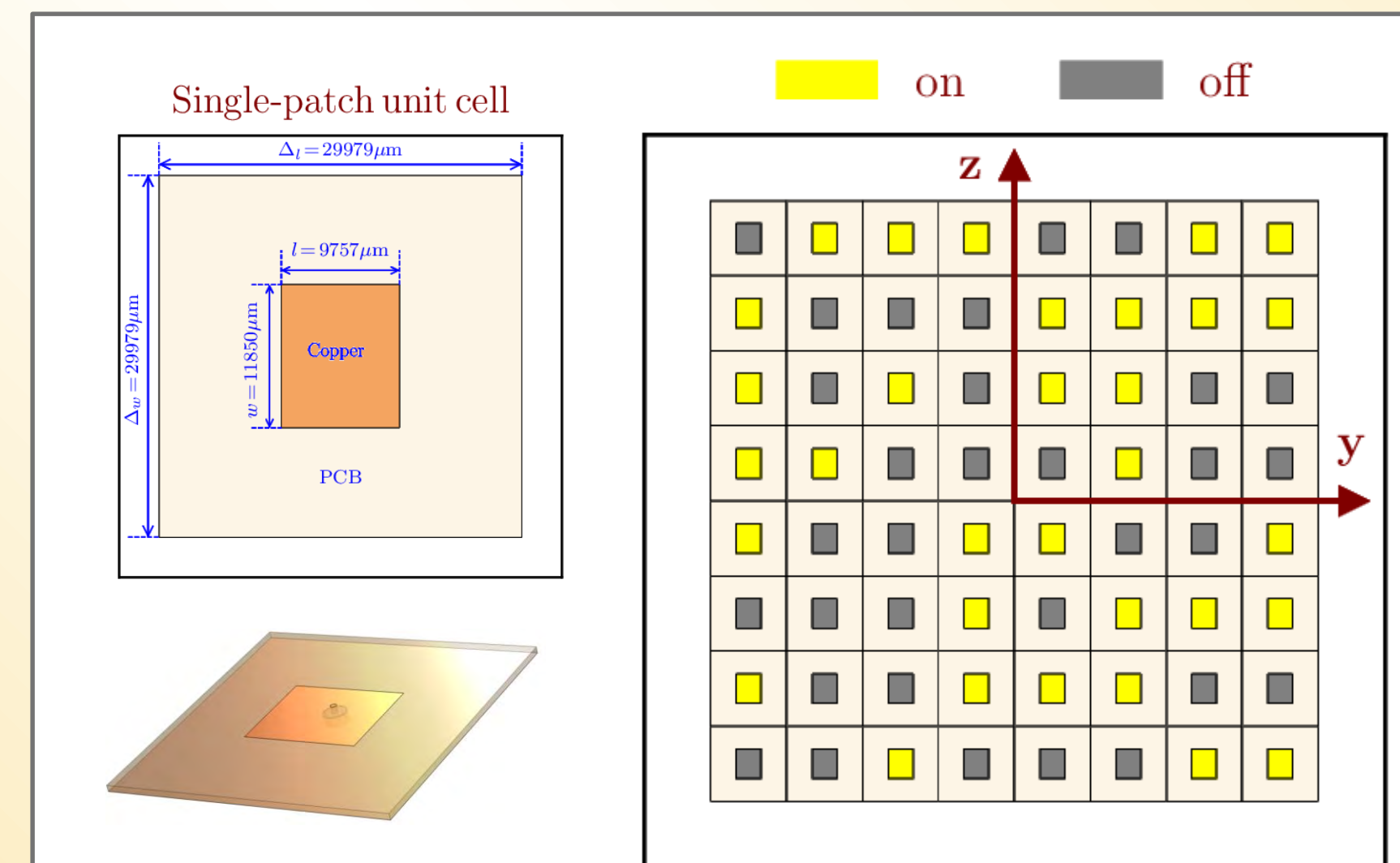


Figure 1. A single patch (top-left and bottom-left) and 64 patches in their on/off states (right).

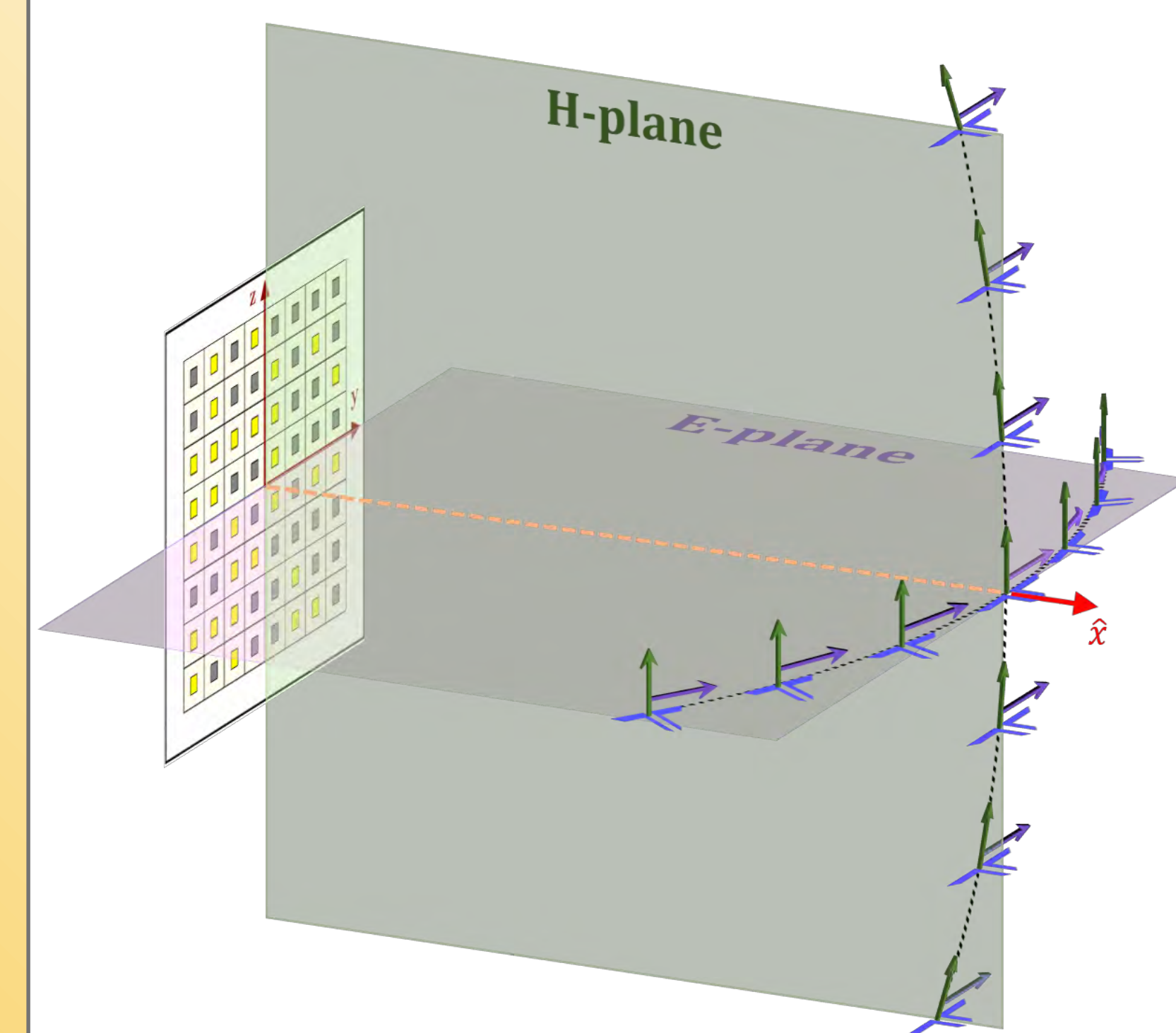


Figure 2. The placement of the receiver antennas relative to the patch array. For graphical clarity, only 13 antennas out of 17 are shown here.

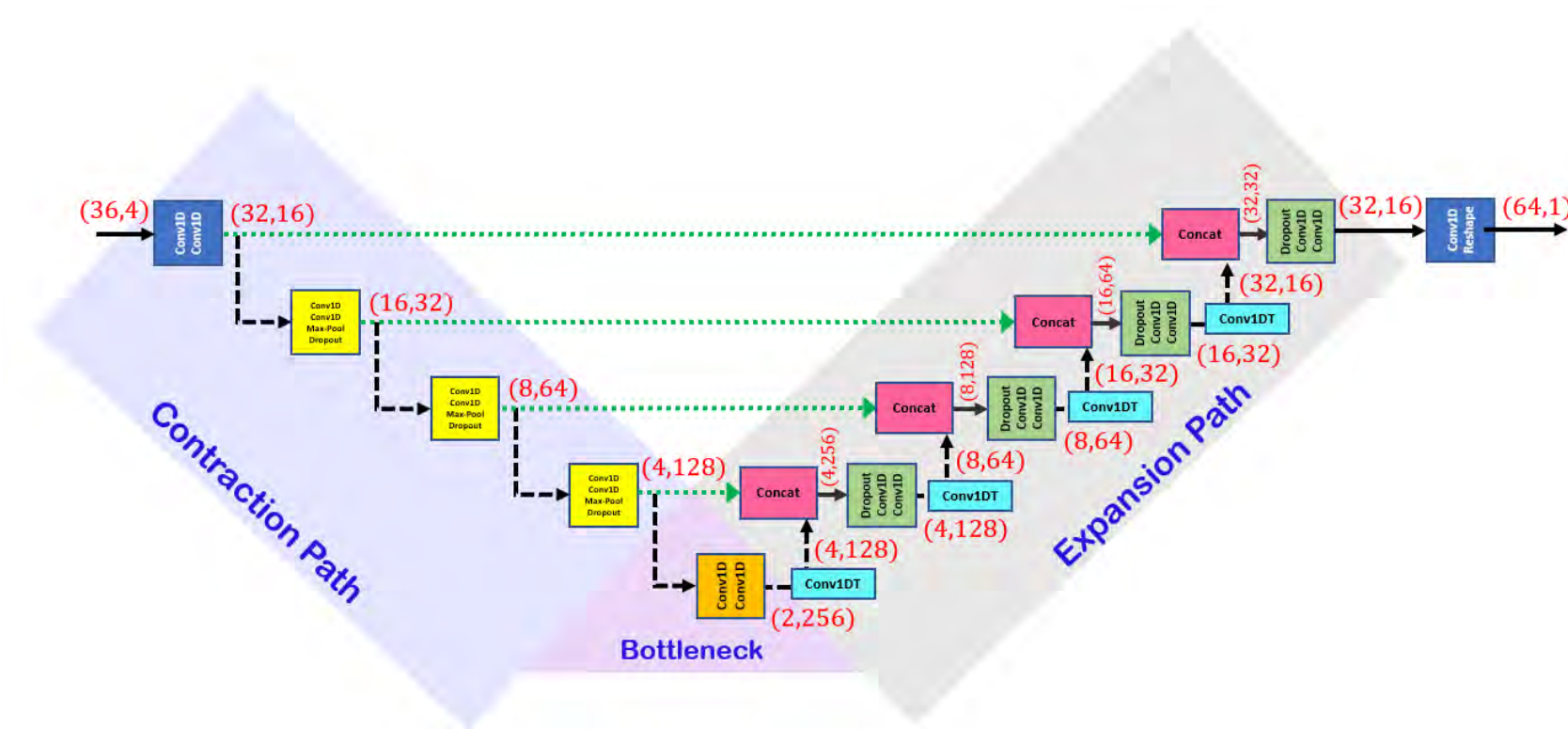


Figure 3. Our designed topology of the UCNN used as the predictor machine.

Preliminary Results

After trained on 900K samples, the UCNN was put to the test by reconstructing the images of unseen bright targets merely from the receiver antenna measurements. The accuracy of the predictions can be assessed by comparing the reconstructed (predicted) images with their actual counterparts.

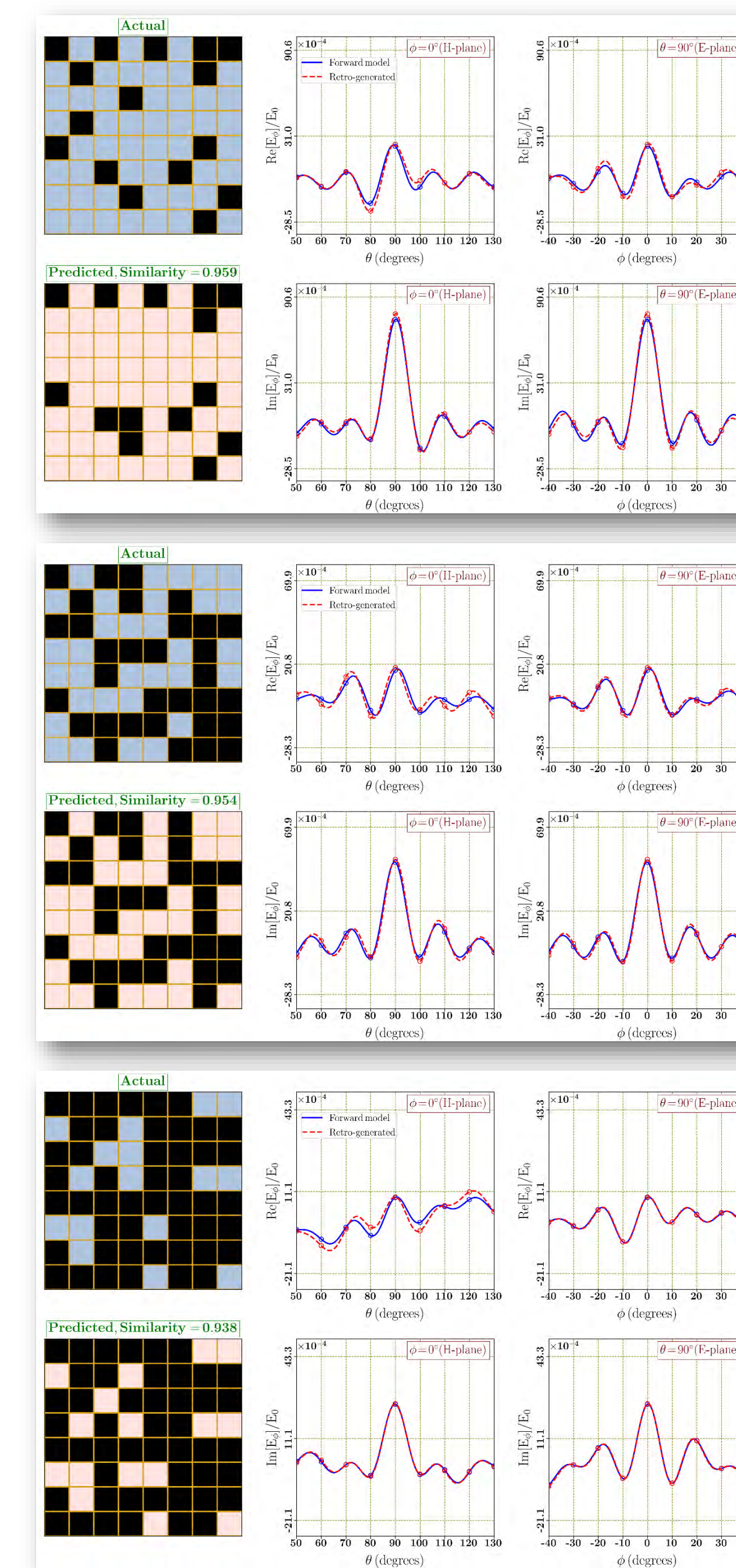


Figure 4. Comparison between the reconstructed and actual target images for an average target brightness of 0.75 (top), 0.50 (center), and 0.25 (bottom). The cosine similarity (CS) measure is used to quantify the accuracy of the image reconstructions, with CS=0 and CS=1 indicating fully dissimilar and identical, respectively. To see how similar the actual and predicted target shapes "look" from the point of view of the receiver antennas, the signals retro-generated from the reconstructed targets are compared with the signals generated from the actual target shapes.

Conclusion

We demonstrated that previously-acquired antenna measurements can be utilized to train UCNN. Trained UCNN will then be capable of making reasonably accurate predictions about the unseen targets. Since the receiver antennas, when coupled to a trained AI-based predictor, return more details about the target compared to the case where no trained predictor is present, we refer to them as Artificially Intelligent Antennas [Fig. 5].

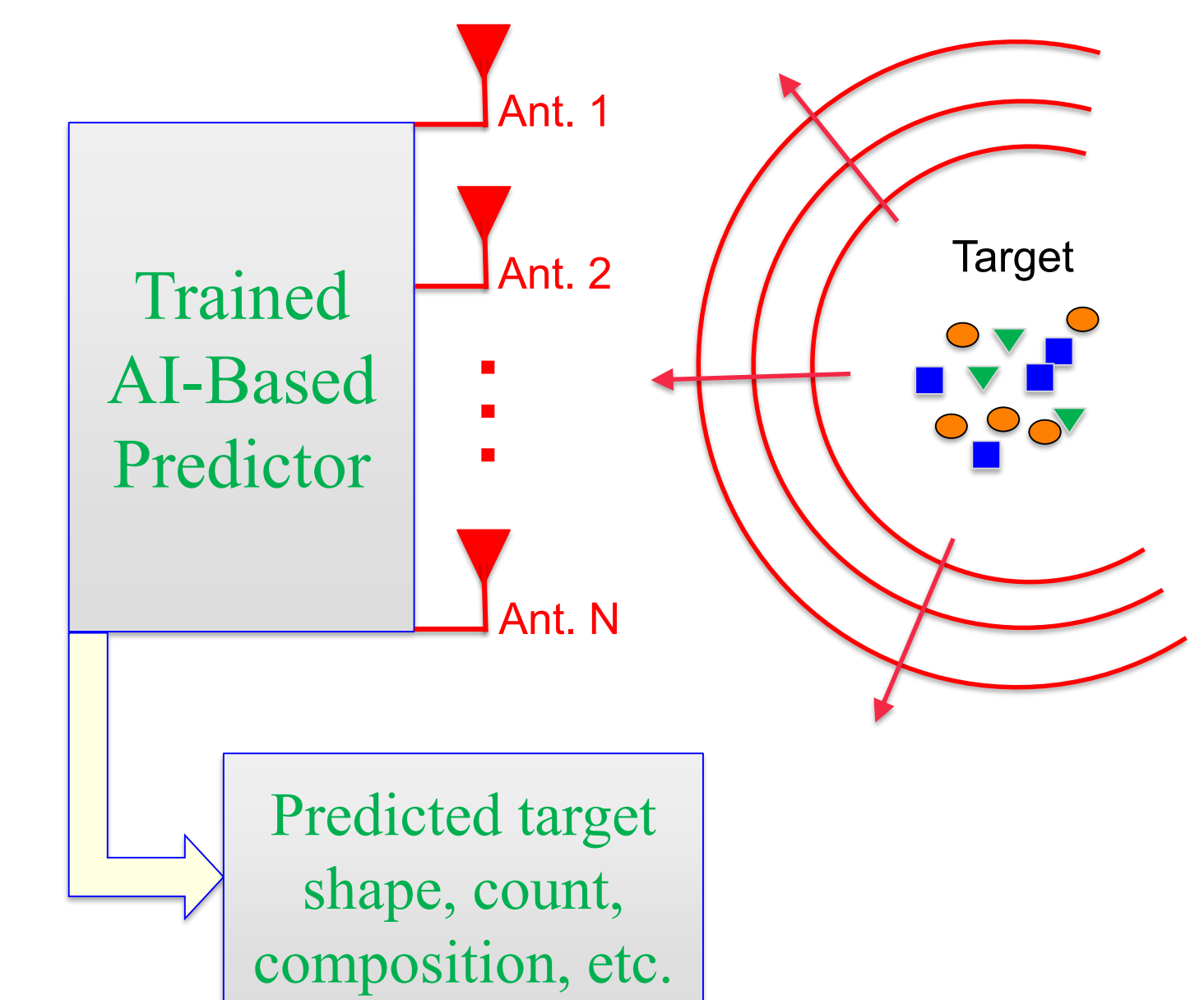


Figure 5. Depiction of the concept of Artificially Intelligent Antennas (AIA).

Ongoing and future efforts

We are currently in the process of the design and fabrication of the patch array PCB and switching matrices required to acquire training/testing samples in an anechoic chamber as a controlled environment. Additionally, parameters such as number and the placement of the receiver antennas will be optimized numerically to achieve predictions of reasonable accuracy at the lowest cost (fewer antennas in a more compact space!) The long-term goal is to implement the concept of AIA in microwave medical imaging to overcome the barrier of low resolution, which is inherent to this imaging technique compared to X-ray or MRI. With that objective in mind, training/testing samples will be generated for multiple receiver distances to unravel the dependence of the prediction accuracy on the target-receiver distance. This provides a systematic approach in exploring the possibility of overcoming the diffraction limit through the implementation of AIA as a continuation of our past efforts [Ref. 3].

References

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- [2] Balanis, C. (2012). "Antenna theory: analysis and design," Wiley.
- [3] M. Sabbaghi, J. Zhang and G. W. Hanson, "Machine Learning Target Count Prediction in Electromagnetics Using Neural Networks," in IEEE Transactions on Antennas and Propagation, vol. 70, no. 8, pp. 6171-6183, Aug. 2022, doi: 10.1109/TAP.2021.3118799

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To see animated results, visit, <https://youtu.be/JY3SIBQBxFo>