Thank you, Professor Torlak.

Thank you all for joining today’s presentation. We are excited to update you on our progress over the past several months.

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In this presentation, we will overview a brief review of the mail inspection scanner application, discuss in detail the SAR imaging pipeline with our proposed machine learning methods, and our synergy with the THz imaging team.

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As mentioned previously, we are working on a mail inspection scanner as a potential application of a high-resolution THz imager such as the one the larger team is developing.

We have put our system-level experience to work in designing a two-dimensional downward-facing scanner to simulate the conveyor belt mail scanning scenario.

Since our current SAR scanners are vertically oriented, we built a new versatile system that can operate in either horizontal or vertical orientation.

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The dual-mode scanner which we have built is shown here. Currently, it operates with a TI 77 GHz mmWave radar, but soon we are excited to use the entire system with the THz chip.

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We have collected some images of various items inside envelops for an early investigation on the mail scanning scenario, as shown here.

As expected, hard metal objects, such as the metal cutout shown on the left, are easily identifiable as they have high reflectivity, even when hidden inside an envelope.

We also captured an image of several metal nuts inside of an envelope. While some of the nuts are clearly resolved, the weak reflection obscures the shapes somewhat.

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Since our goal is to identify and predict harmful contents on a smaller scale than even these metal nuts, we need higher resolution to achieve both better detection performance and image quality.

One way to achieve this is by increasing carrier frequency, so we expect higher resolution with the THz board than this 77 GHz radar. However, another promising solution which we have been pursuing in the meantime is the use of machine learning.

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Improving the resolution of SAR images is highly valuable to a host of sensing and tracking problems. Due to the inherent limitations on the device itself, limited bandwidth, finite aperture, and non-linearities, the resulting SAR images tend to have blurry and distorted characteristics.

The image shown here was generated by placing the 4 points as you can see on the left. Each point is simulated as an ideal point reflector, but we can see the distortion that results from the imaging nonidealities on the right.

We propose that the resolution of the recovered image, can be improved by leveraging machine learning algorithms.

While this type of image enhancement is similar to denoising, we are not removing an additive noise or deconvolving a linear filter. As the figure on the right demonstrates, the distortion introduced in the radar image is highly spatially variant and non-linear.

Thus, a nonlinear solution such as machine learning could offer an elegant solution.

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For simplicity’s sake, we will first consider 2D SAR images captured from a one-dimensional linear scan.

We will generate synthetic images in simulation by virtually scanning a mmWave radar across an aperture and assume the target is in the near field.

To recover the synthetic image, we perform the range migration algorithm (or RMA), which is a near field beam-former that effectively introduces an efficient backpropagation matched filter algorithm.

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Due to the inherently spatial nature of this problem, we propose a convolution neural network approach for image enhancement. More details on the implementation will come shortly.

Here, we show some early results using a simple multilayer CNN.

As with any machine learning problem, access to meaningful and plentiful data is crucial to training a robust and generalizable model.

Since capturing a large quantity of labeled data is infeasible for this imaging problem, we synthetically generate radar images for training the network.

For each radar image, we generate a set of randomly places point reflectors and simulate the resulting image, shown on the left. Since we know the exact location of the ideal points, we also construct a ground-truth image, shown on the right.

Each radar image will have a corresponding ideal image without distortion. The goal of the machine learning algorithm will be to learn to transform the image on the left to the image on the right.

The distorted radar images will be our training features and the ideal images will be the training labels.

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During the training phase, the CNN will converge as it learns to remove the distortion of the radar images.

It is important to emphasize that this blur of the SAR images does not follow a known mathematical relationship and while other methods exist for improving the image resolution, machine learning has shown to be superior on many similar tasks in the literature.

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After training the network, we test on images that it has never seen. The image on the top is the distorted radar image.

On the bottom left is the output of the network, the enhanced image.

For comparison, we have also included the ideal, ground-truth image corresponding to the input image on the bottom right. Compared to the radar image, we see a significant improvement in resolution of the points and removal of undesirable sidelobes.

However, at some points, circled in red, we observe some distortion compared to the ground-truth image. This is room for improvement.

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When we input an image containing many point reflectors, the output image on the bottom left has some major differences compared to the ground-truth image.

Namely, the regions where the point reflectors are densely located are difficult for the model to resolve. That being said, the image quality is improved over the raw image at the top of the page.

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We see similar results for non-randomly placed points such as this diamond shape.

On the left is the raw radar image and on the right is the enhanced image, the output of the CNN.

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Of course, the more challenging and realistic problem is 3D SAR image resolution improvement.

In this case, the sensor is scanned across two dimensions and the target scene is allowed to be 3D in space. We will use x and y as the cross-range axis and z as the range dimension.

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After training a similar machine learning algorithm as before, this time on 3D images, we see promising results.

On the left is the distorted radar image and on the right is the enhanced image after the CNN.

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The enhanced image is now on the left and we compare it to the ideal ground-truth image on the right-hand side.

Again, we observe distortion to some points. But the enhanced image is strikingly close to the ground-truth image and has a significant resolution improvement over the original radar image.

In the 3D case in the real world, even in the presence of many targets, there is a considerable tendency towards sparsity due to the higher dimensionality. This will result in better machine learning performance. As in the 2D scenario, when the points are less densely located, the algorithm is able to remove the distortion more effectively.

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Looking at the point spread function, we see a very nice result where the sidelobes of the enhanced image on the right have been considerably reduced compared to the radar image, on the left.

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Looking at slices of the ideal point spread function along each of the three dimensions, we compare the performance to that of the state of the art algorithms, the range migration algorithm and back projection algorithm for radar image formation.

Our enhanced image is in the yellow and outperforms the existing methods significantly in terms of main beam width and sidelobe reduction.

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Again, we see very nice performance on non-random point targets as well.

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For the 3D case, we consider solid targets as well such as this triangle shape and the network performs nicely, reducing the sidelobes that look like ghosting in the z-dimension here on the left.

Up until this point, we have seen quite promising and results, but all in simulation.

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Let’s now take a look at a real example. We have captured a radar image of the knife shown on the left. Notice the shape of the blade and the three metal inlays in the handle.

On the right is the distorted radar image, thresholded at 5 dB to remove the low power ambient noise. However, this thresholding process does lose some information about the knife such as the handle inlays.

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On the left, we show the reconstructed image at various thresholding values.

When we apply the CNN to the image with a 25 dB threshold, we get a much improved image, shown on the right.

Not only is the knife blade more resolved and its width in the z-dimension is much more accurate to the real knife, but also two of the metal dots on the knife handle are visible in the image.

This demonstrates the power of such a machine learning algorithm for image enhancement.

Additionally, even though the network was trained on exclusively synthetic data, it generalizes well on real radar data.

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As we transition to the THz domain, we again need to generate large synthetic datasets for training machine learning models.

To streamline this process, we developed a MATLAB user interface for the entire THz image simulation pipeline, which we are in the process of publishing.

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The interface allows for complete control over the waveform, MIMO array, scanning pattern, and target scene.

Additionally, it can efficiently generate large training datasets of diverse targets.

Here we show the setup for quickly simulating the THz image of the two strips of copper tape discussed earlier.

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As a side note, from our past work on SAR scanners, we have observed some system nonidealities, such as position ambiguity of the array as it is scanned across time. We have incorporated this into the simulator to produce data that will be most similar to real radar data and thus improve the machine learning model.

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We observe that will some position error, the shape of solid objects is lost. It remains to be seen if machine learning can offer a solution to this problem, but our results thus far are promising.

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On simple 2D images with position error, the machine learning algorithm is able to produce a nearly ideal image, shown in the middle, from the distorted image on the left.

Our study on machine learning for resolution improvement shows serious promise to offer considerable improvements to the existing techniques and we are excited to extend this work to the THz domain and continue our synergy between teams.

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Lastly, we have collected a large set of radar images to supplement the training set with some real images of known targets.

These can be best used in an unsupervised learning approach, which we may consider down the road.