



# OPTIMIZING A COMPRESSIVE IMAGER FOR MACHINE LEARNING TASKS

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## Task-specific optical systems

The final data product is a decision not a high resolution image

Is this a cat?

Yes

No

2 → 2

9 → 9

0 → 0

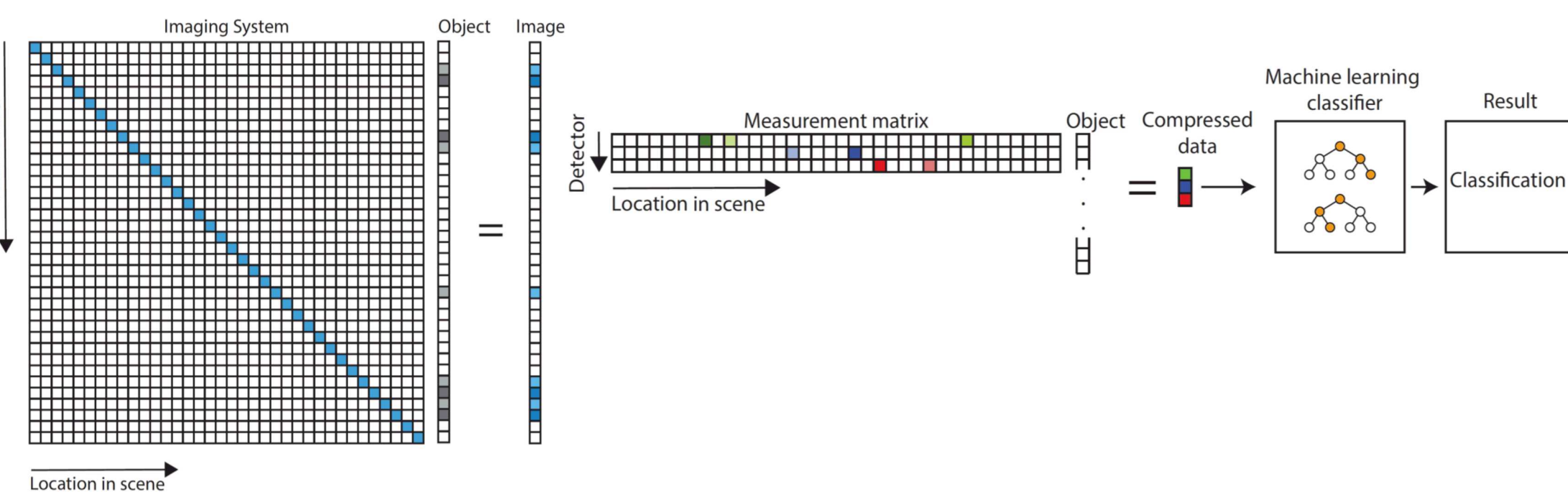
5 → 5

MNIST dataset for this project



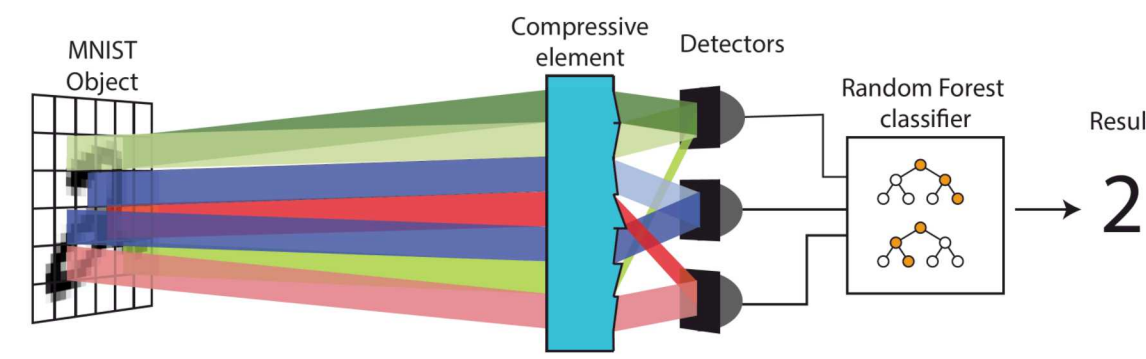
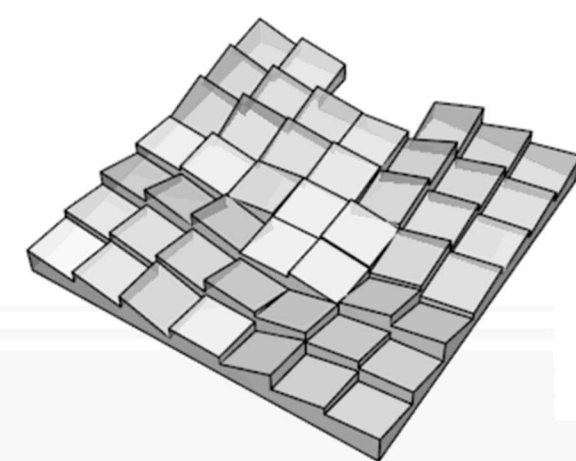
## Compressive Classification

Unconstrained by imaging



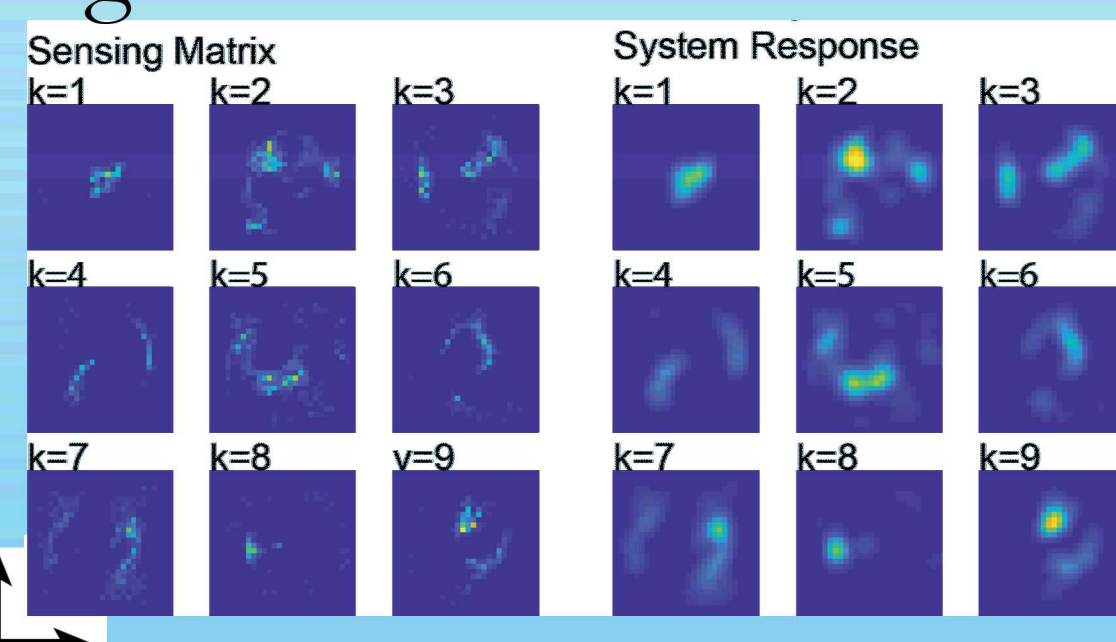
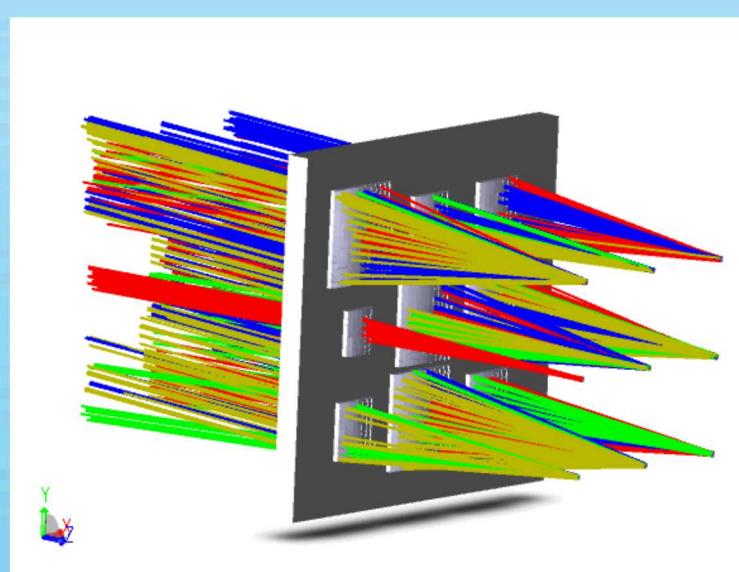
## Prism arrays

Monolithic hardware to realize compressive sensing matrix

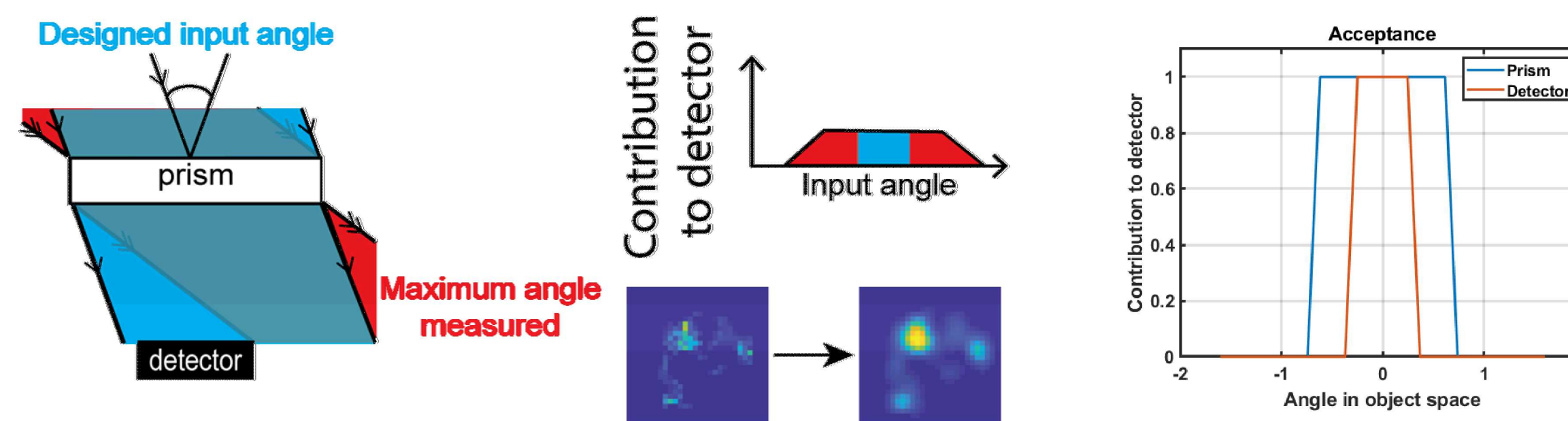


## Simulations of hardware

Non-sequential ray tracing

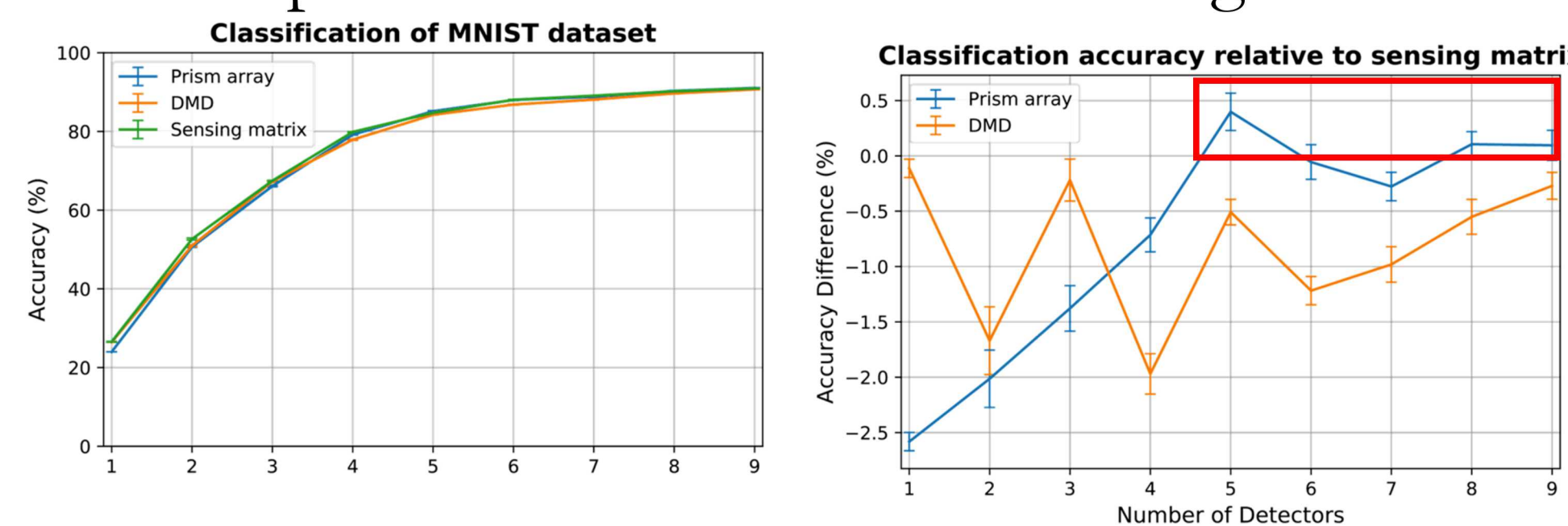


Width of prism sets cone of light accepted



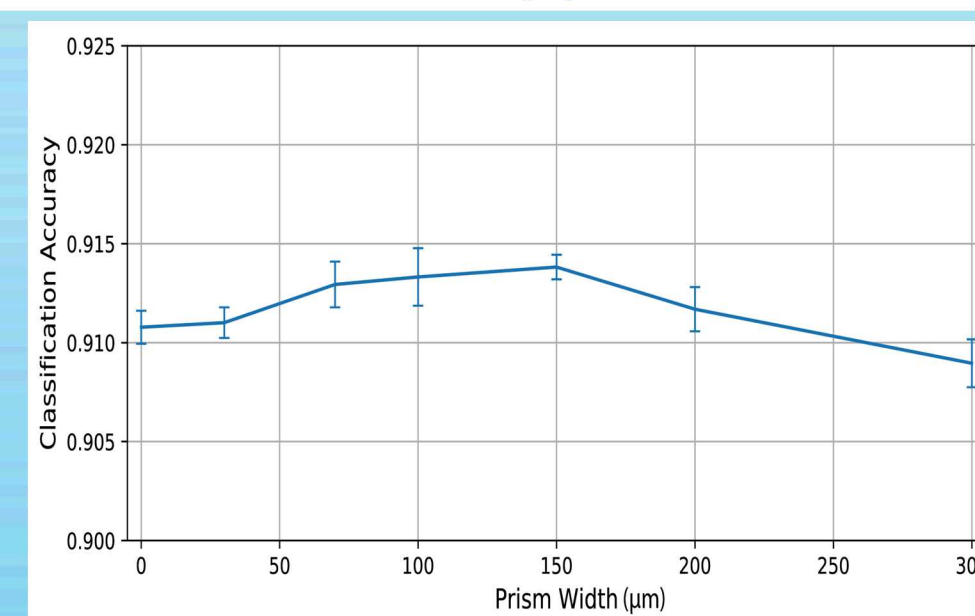
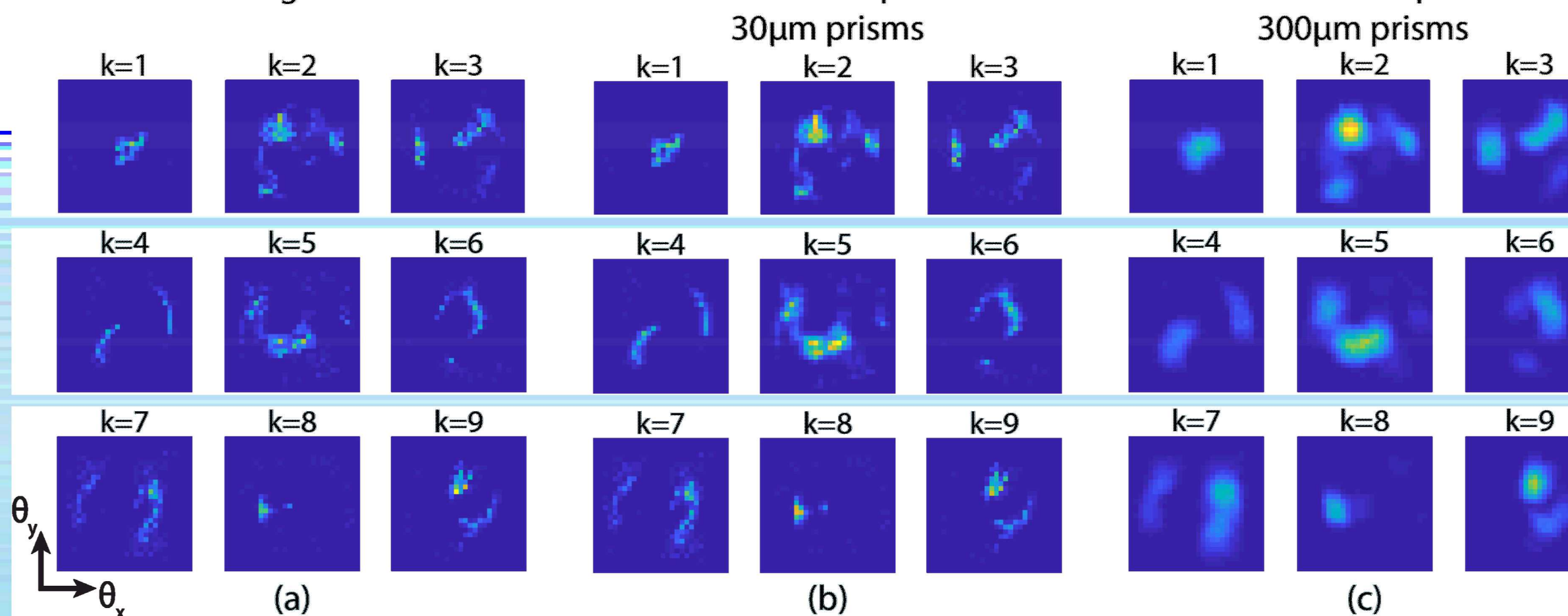
## Classification Accuracy

Blurred system response matrix had higher accuracy than compression matrix that it was designed from



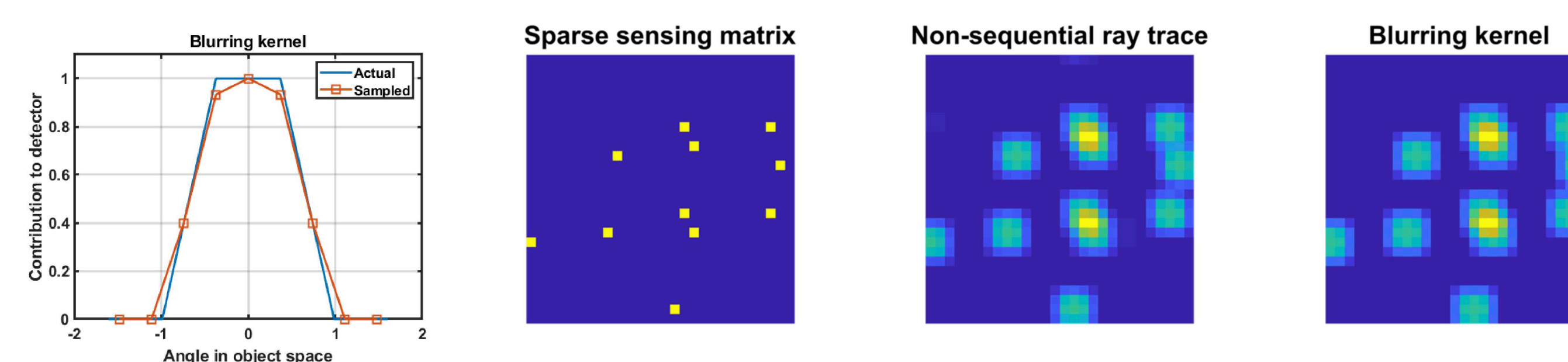
## Changing Prism size

Simulations changing size of prism without re-optimizing



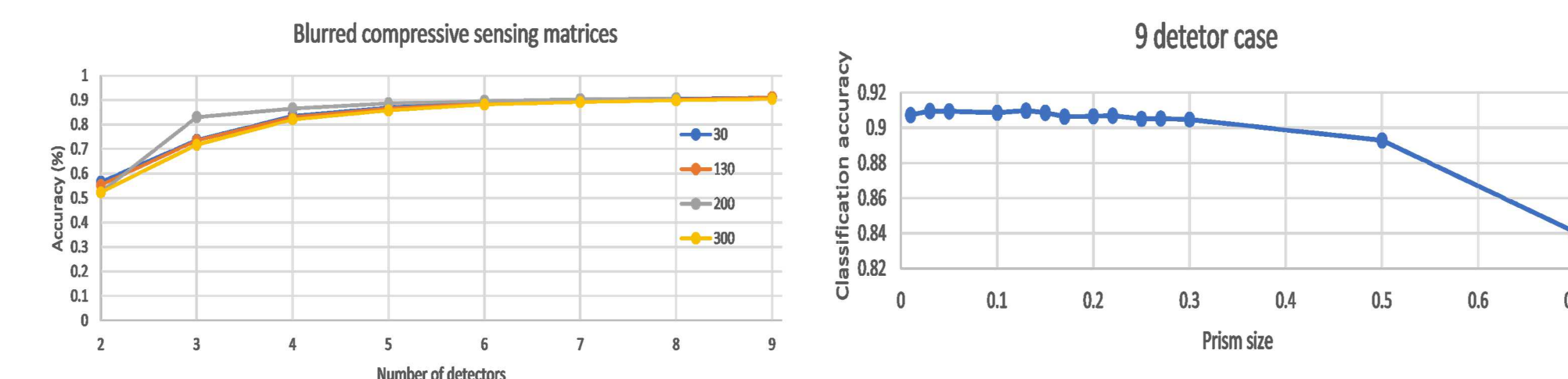
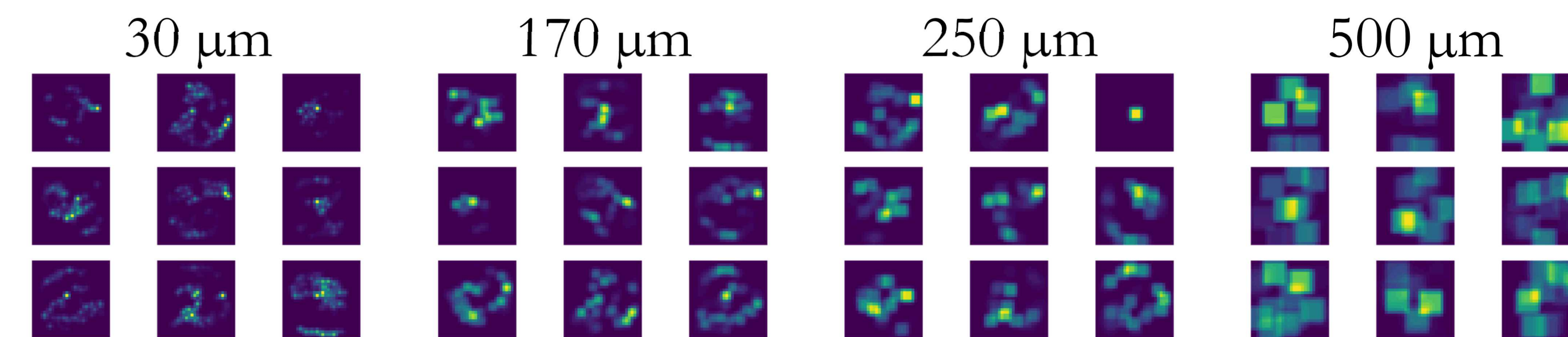
## Simulating blurring

Blurring kernel faster than non-sequential ray trace

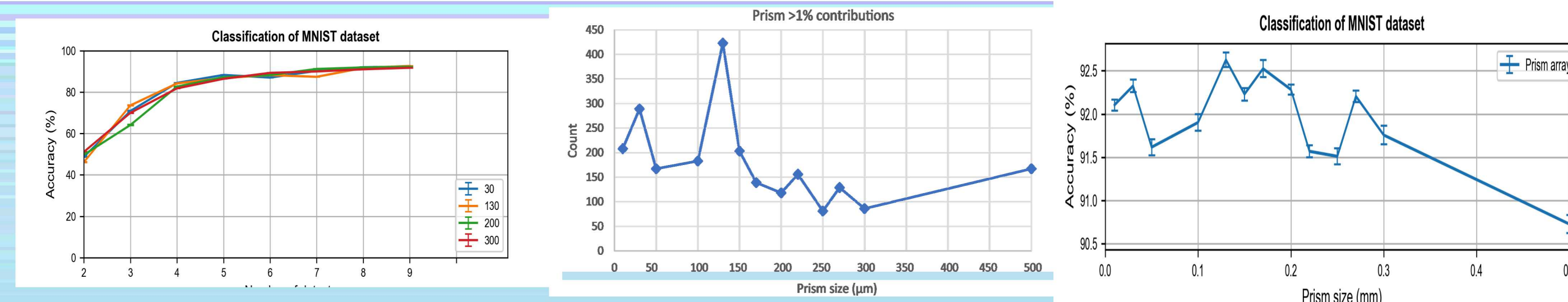


## Optimizing prism size

Neural network optimizes compressive sensing matrix based on the prism width



Removed prism <1% contribution



## Conclusion

Concurrently optimizing the sensing matrix and the hardware design has the potential to both improve performance and increase sparsity.