



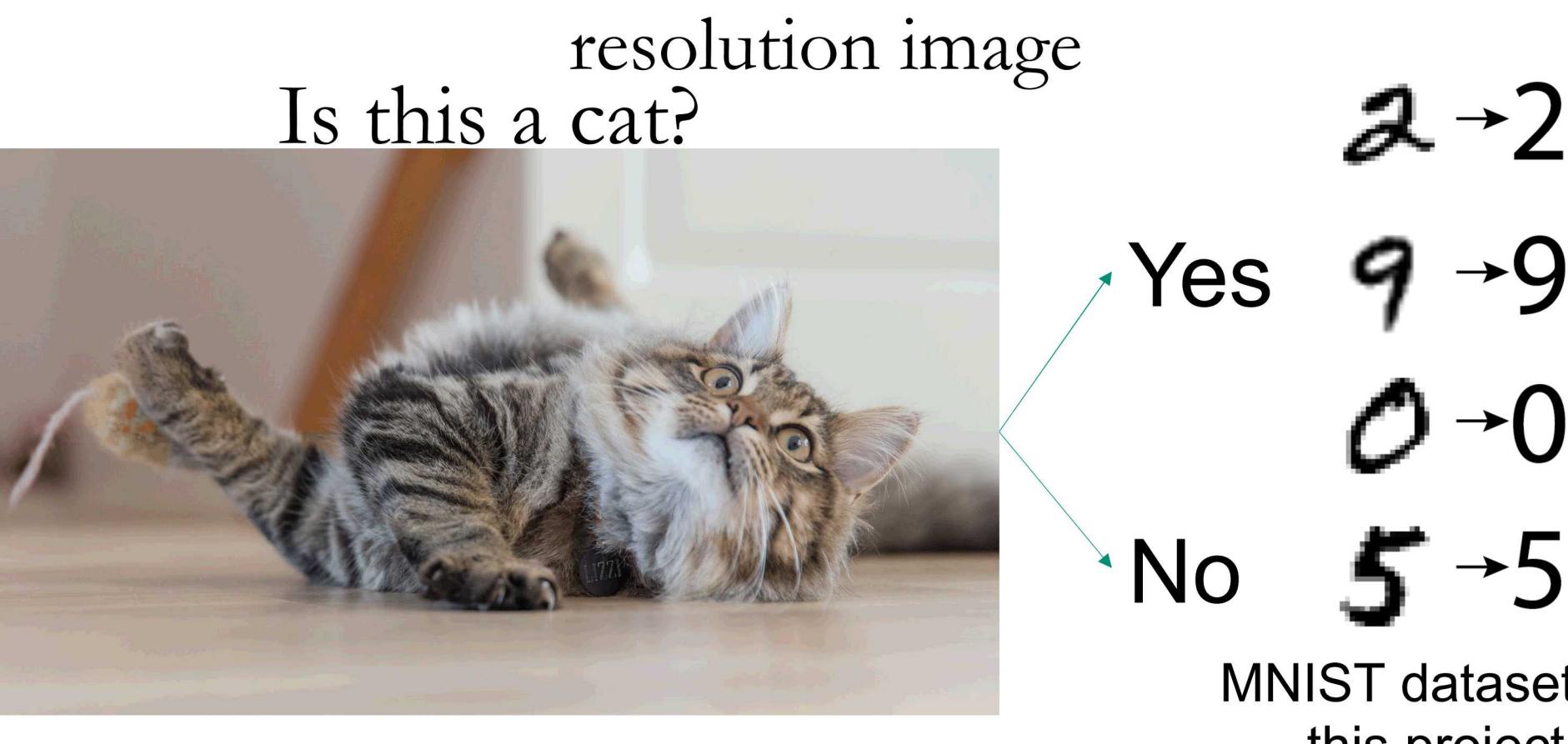
# OPTIMIZING A COMPRESSIVE IMAGER FOR MACHINE LEARNING TASKS

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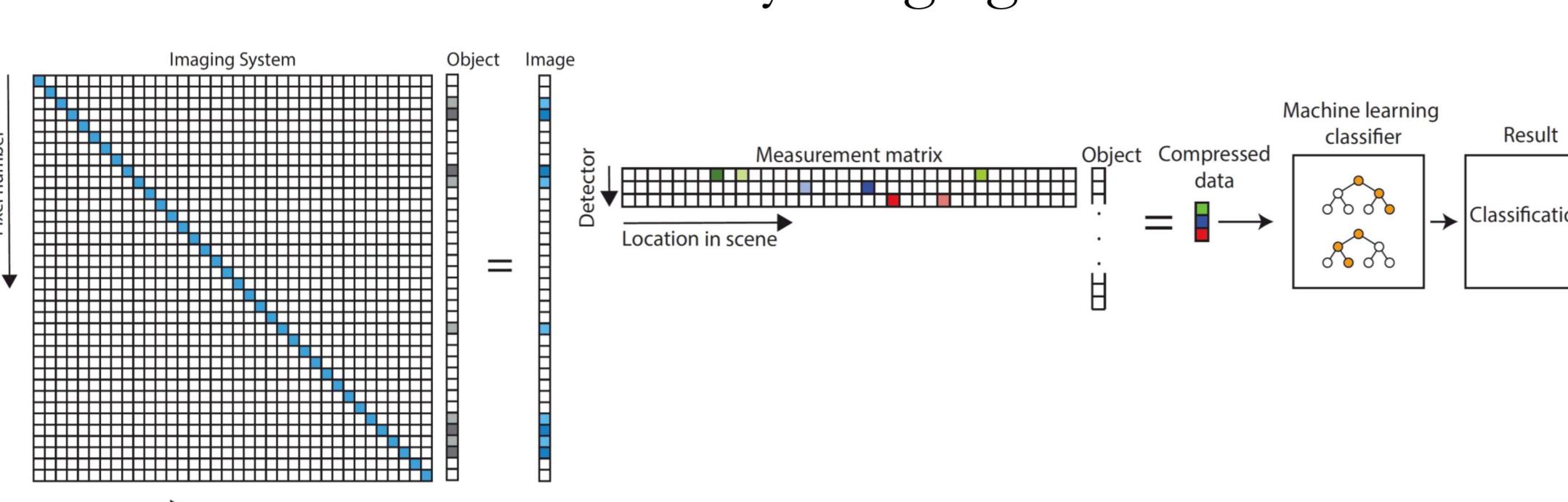
## Task-specific optical systems

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



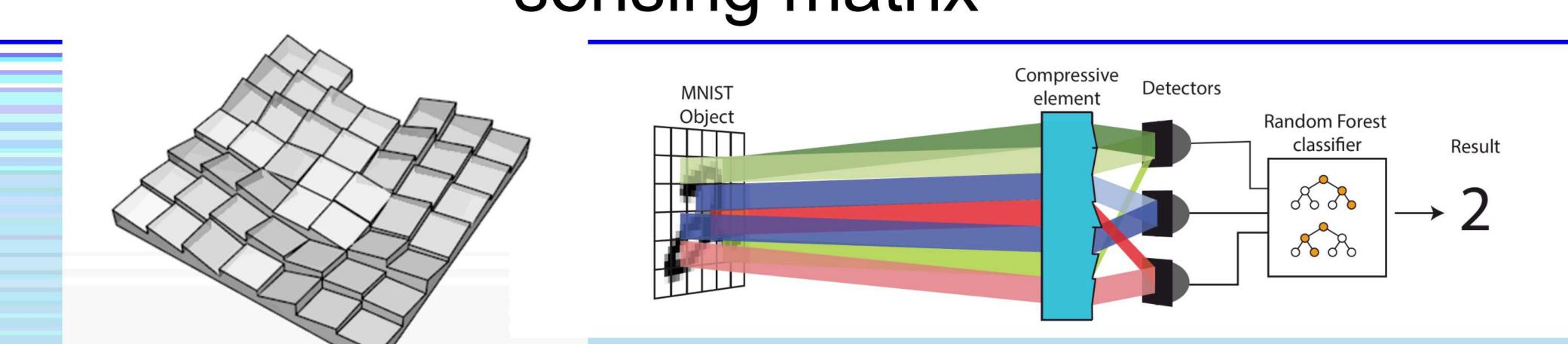
## Compressive Classification

Unconstrained by imaging



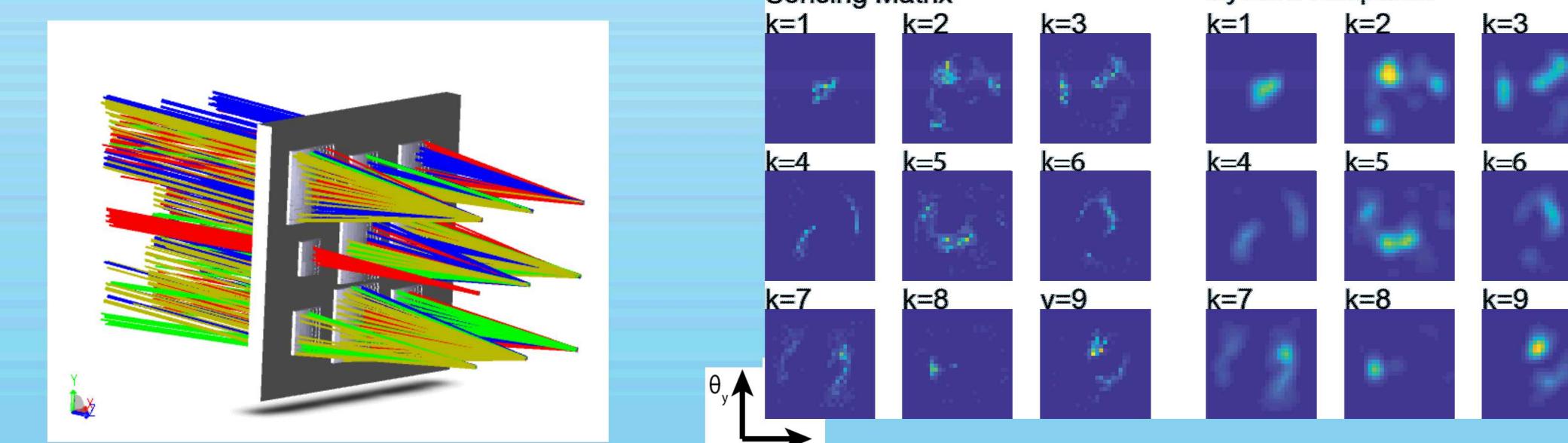
## Prism arrays

Monolithic hardware to realize compressive sensing matrix

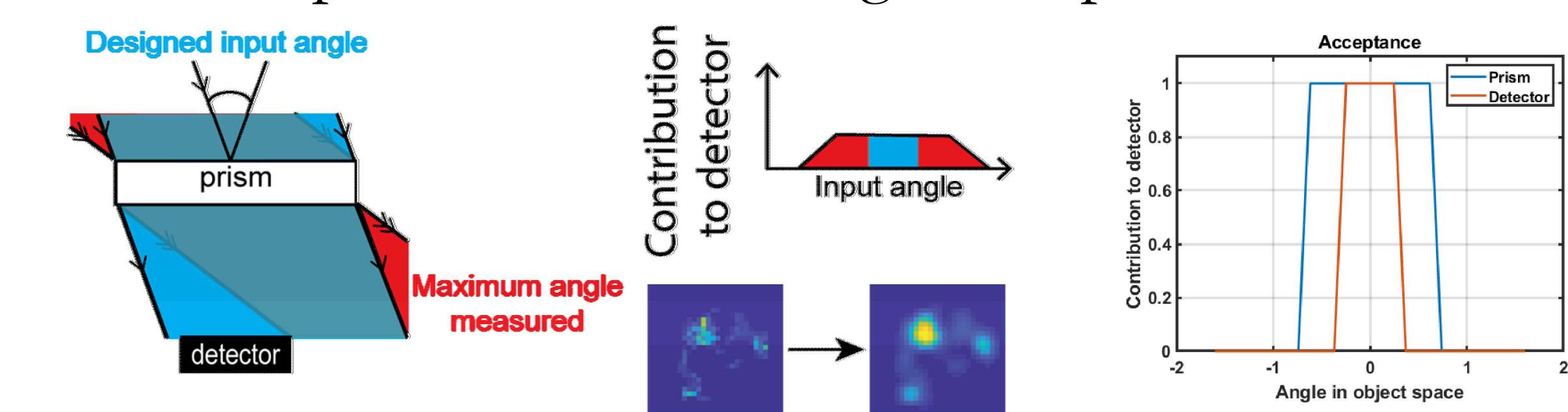


## Simulations of hardware

Non-sequential ray tracing

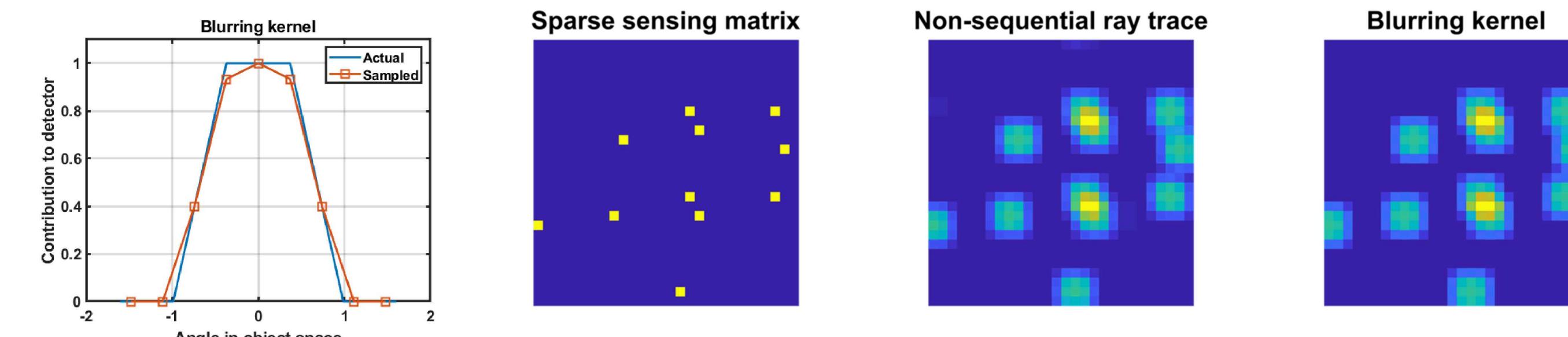


Width of prism sets cone of light accepted



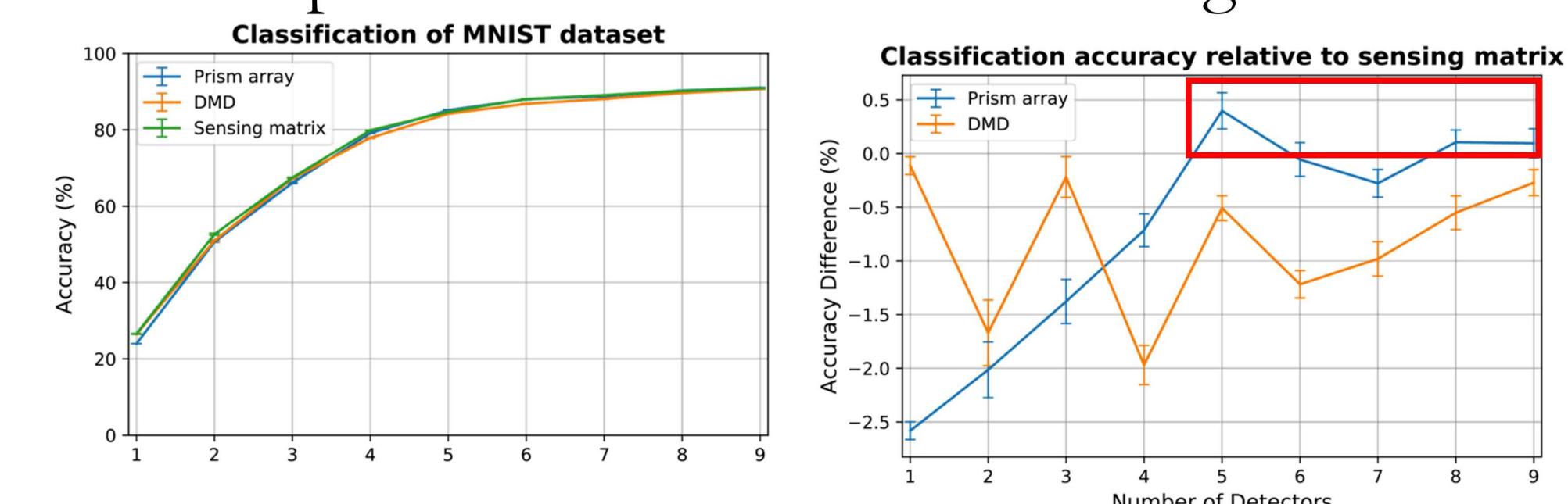
## Simulating blurring

Blurring kernel faster than non-sequential ray trace



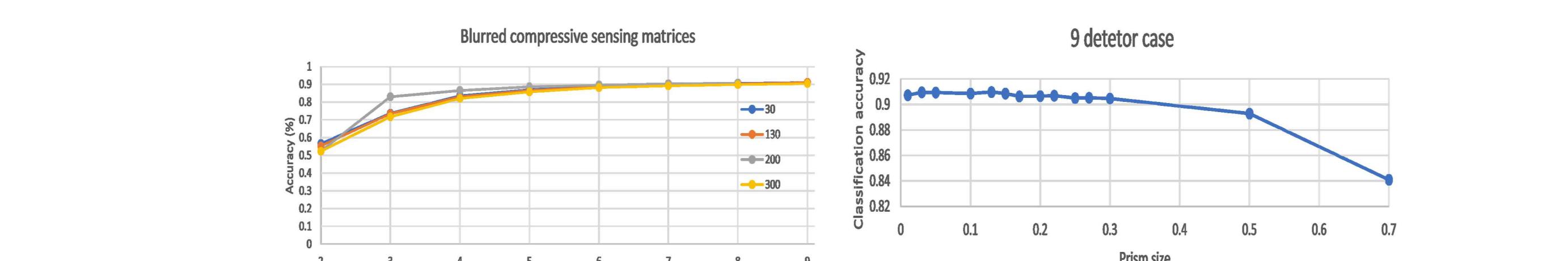
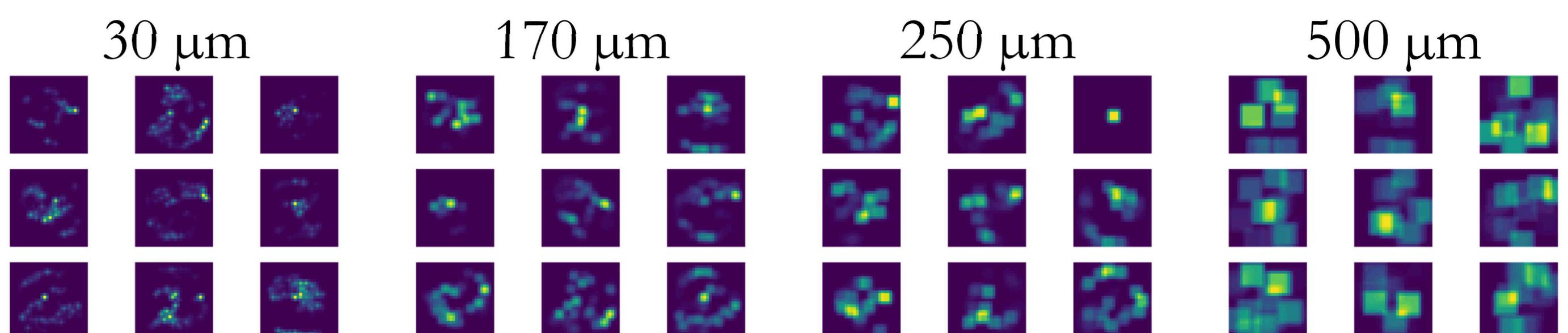
## Classification Accuracy

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



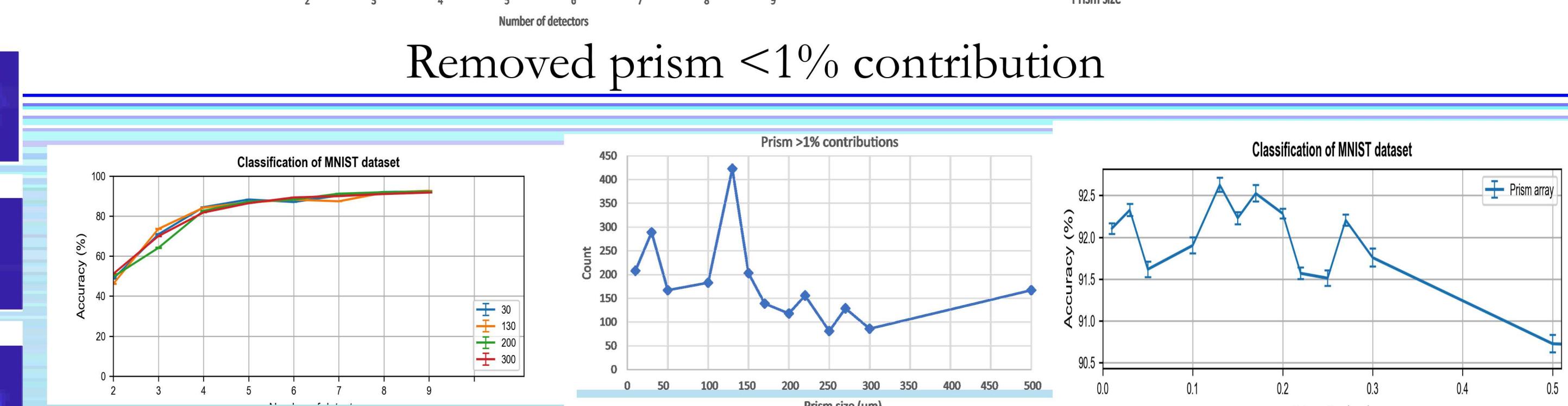
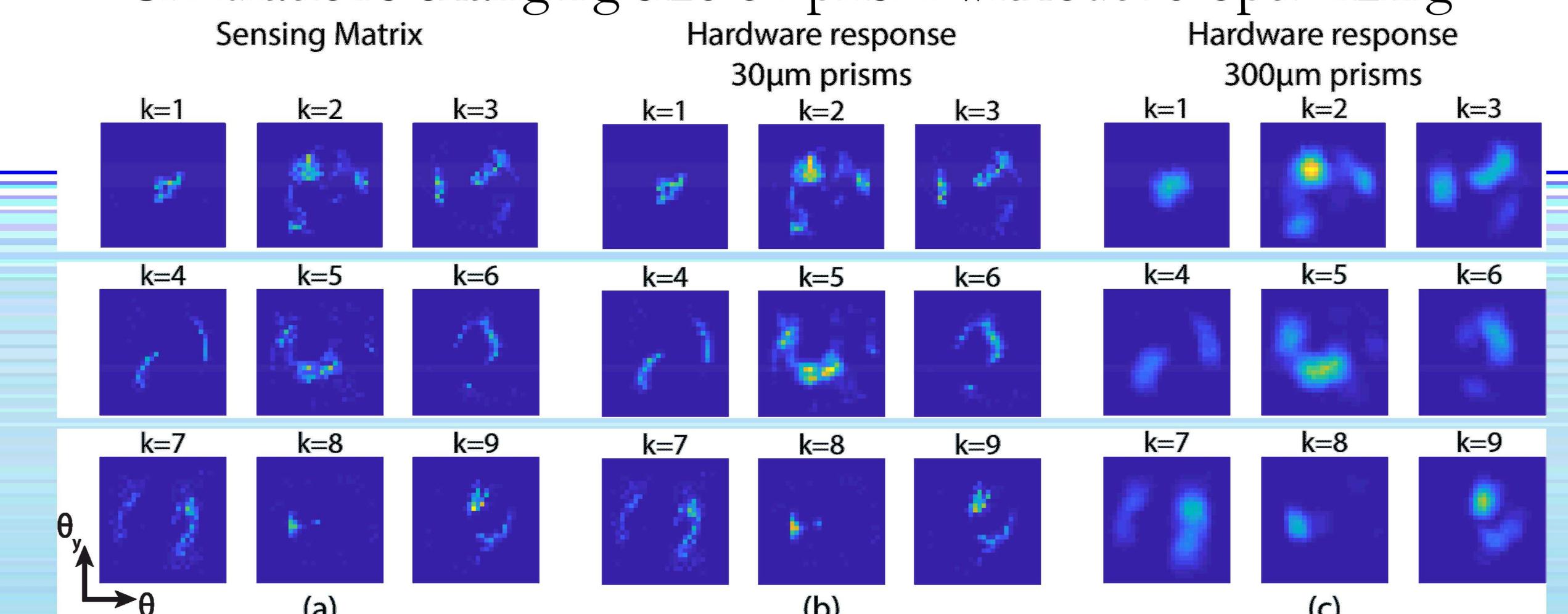
## Optimizing prism size

Neural network optimizes compressive sensing matrix based on the prism width



## Changing Prism size

Simulations changing size of prism without re-optimizing



## Conclusion

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