Active Optical Control with Machine Learning: A Proof of Concept for the Vera C. Rubin Observatory

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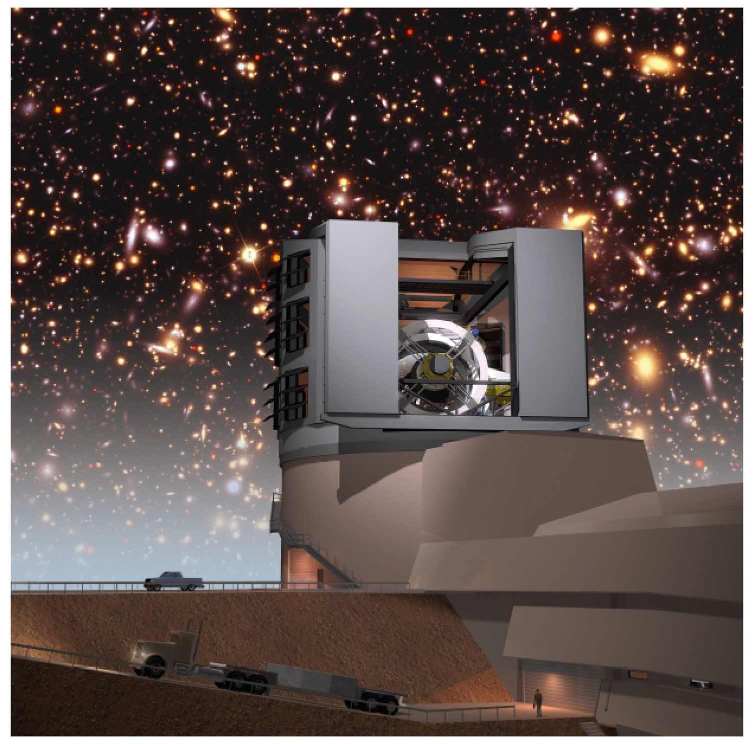
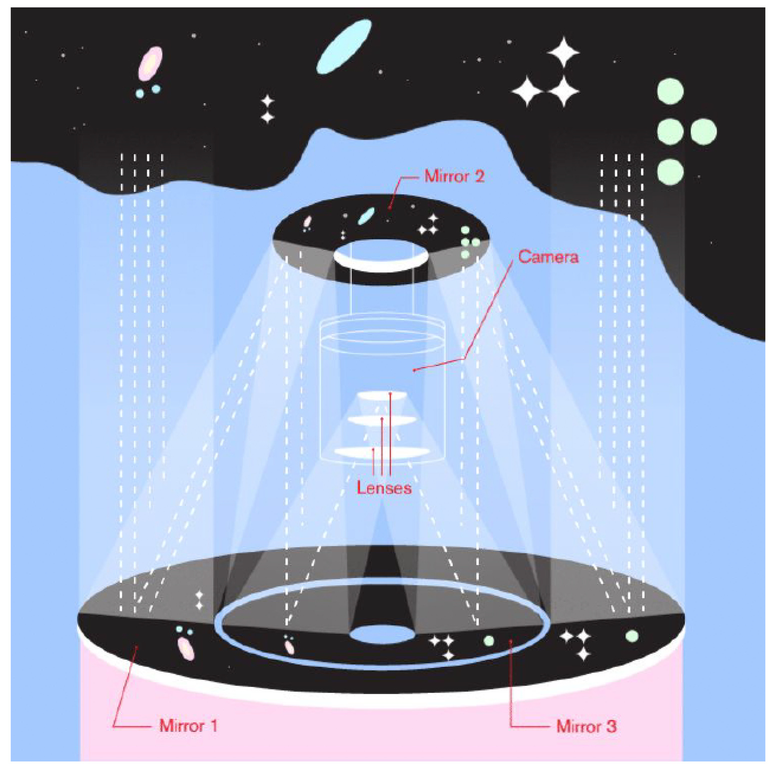
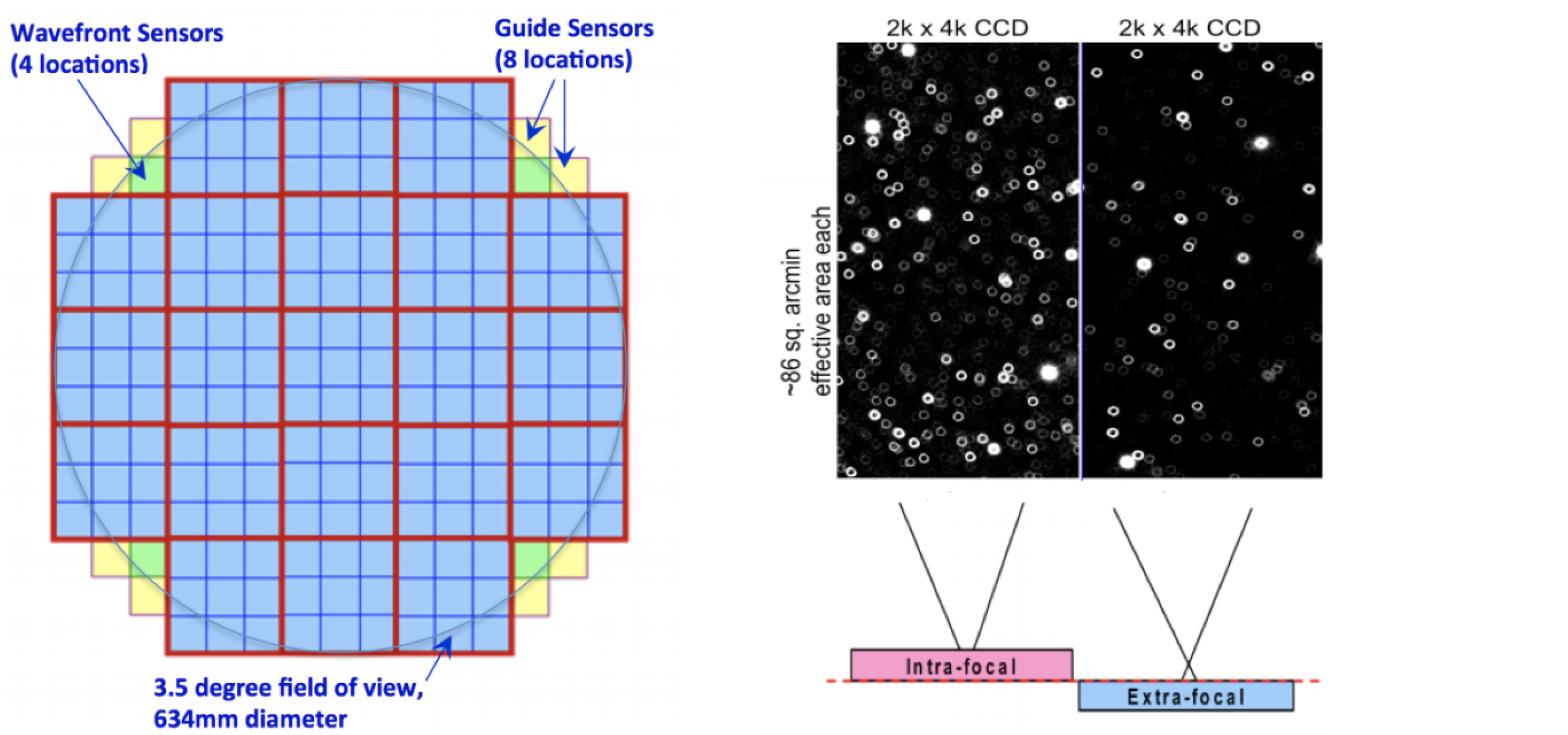
Vera C. Rubin Observatory (Rubin)





Optical design of Rubin

Active Optics Systems (AOS)



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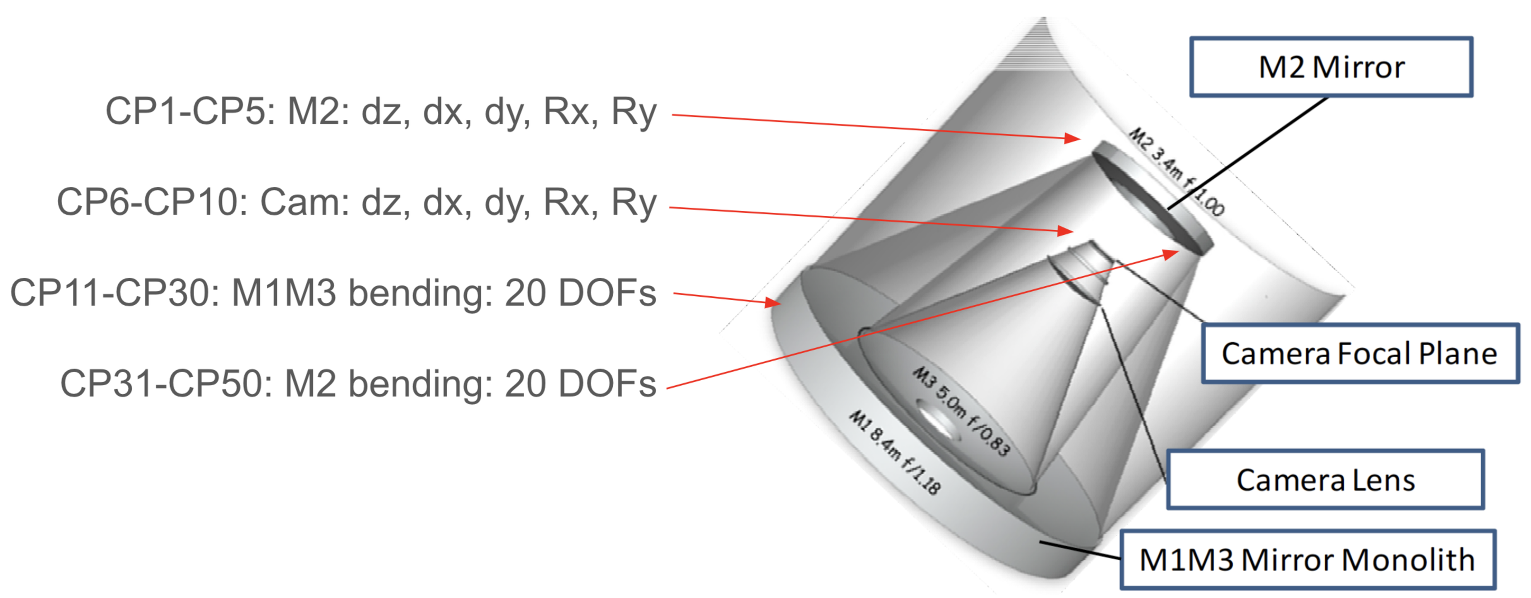
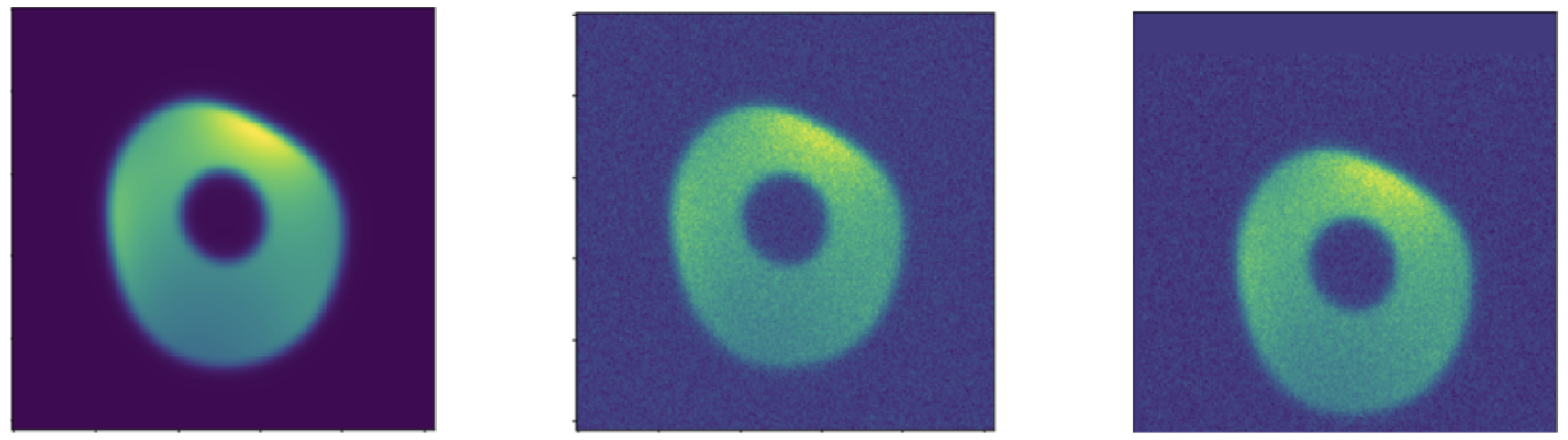
The Vera C. Rubin Observatory focal plane and the schematic operation of the split wavefront sensors

Control Parameters and Wavefront Generation



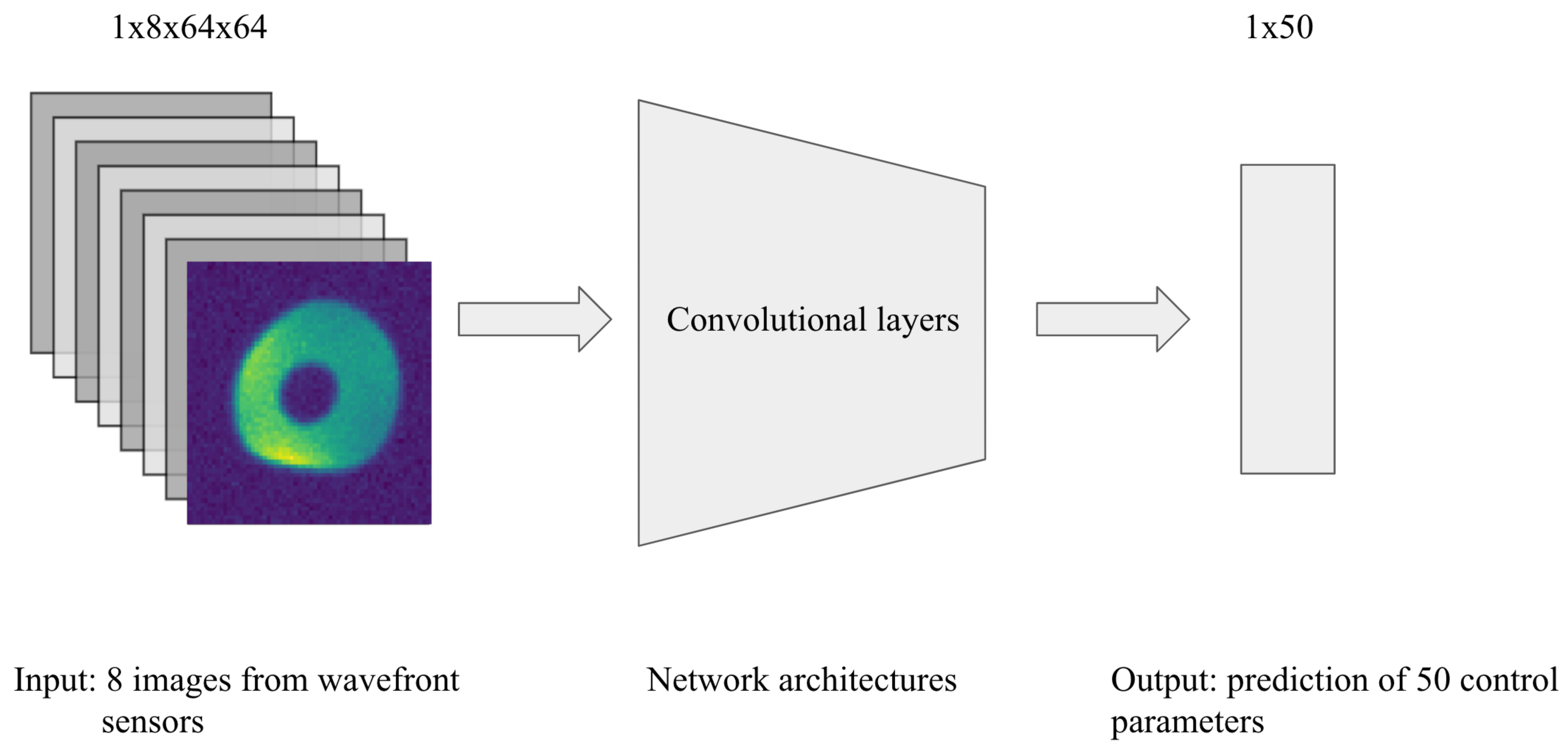
Donut generation



No noise and no shift | With noise but no shift | With noise and shift

Donut images were produced using the *makedonut* code provided by A. Roodman.

Algorithm

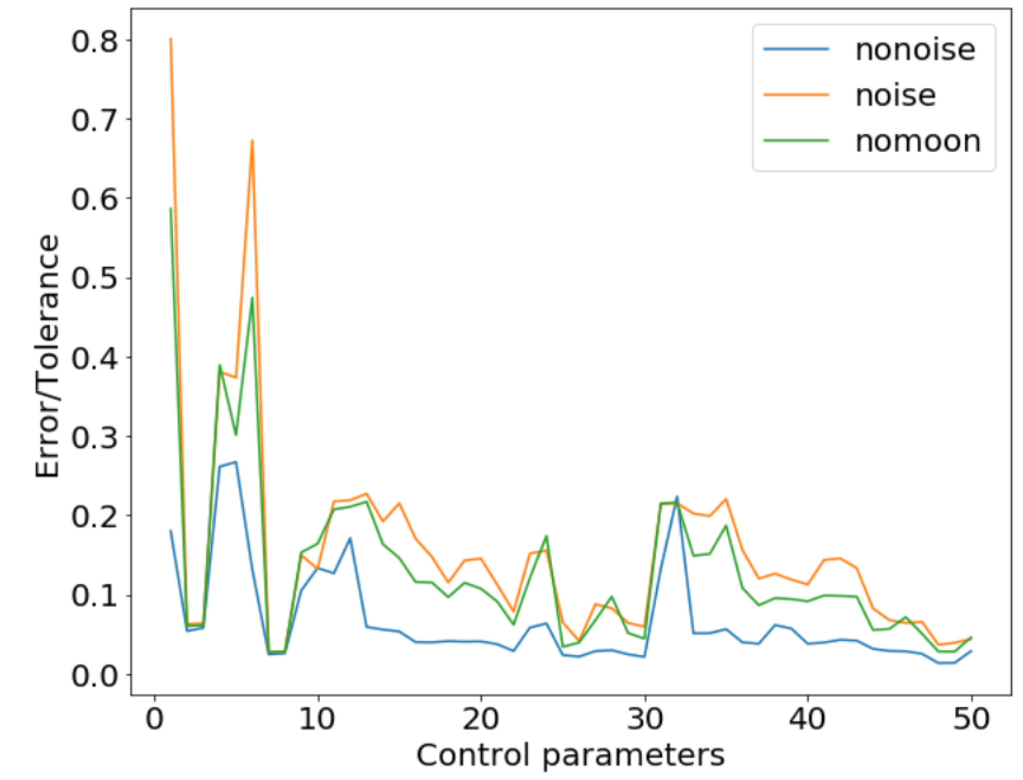


Loss function

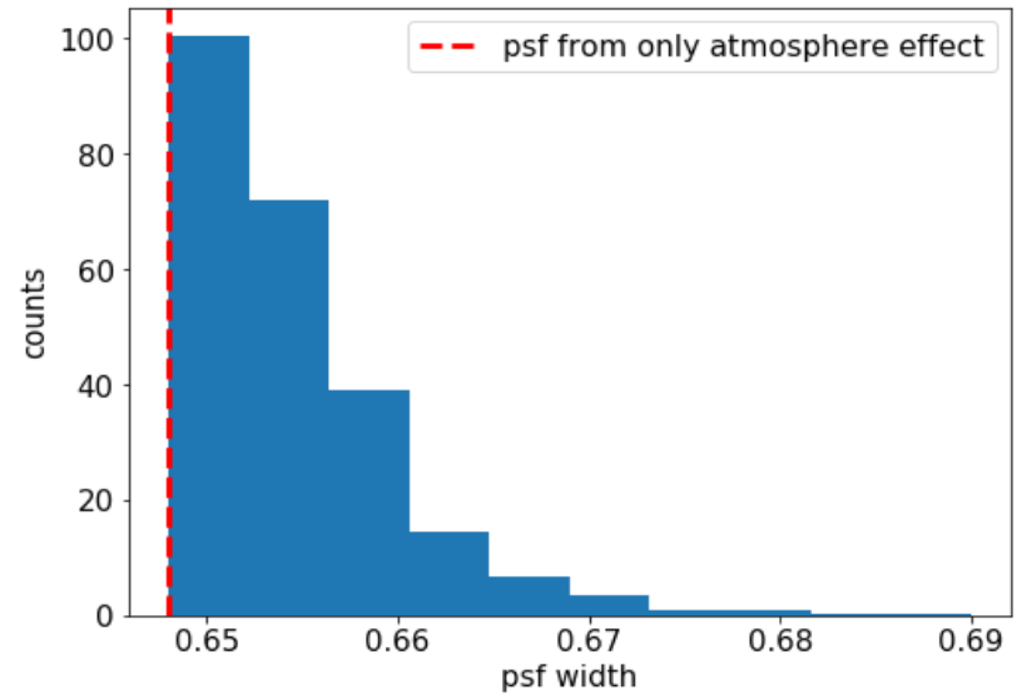
$$L(\mathbf{y}, \mathbf{y}^*) = \sum_j \alpha_j L_2(y_j, y_j^*) + \beta f(\mathbf{y}^* - \mathbf{y})$$

- scaled L2 loss;
- addition of a PSF term to the loss function;
- anti-aliasing pooling;
- self-attention

Results



Prediction RMSE over error tolerance for the 50 control parameters. The RMSE ofeach CP output by the neural network is within the tolerance.



Selecting the 10% worst casesbased on PSF, we construct the PSF for typical seeing of ~0.65arcsec, measure its FWHM, and find that the prediction error of the CPs makes only a small contribution to the FWHM.

Summary

- Using the scaled L2 loss and adding a PSF term to the loss function enhances performancesubstantially;
- Including anti-aliasing pooling, and augmenting the training data to include randomly shifteddonuts, the resulting model performance is insensitive to image shift;
- Including self-attention modules in the CNN led to modest changes in performance;
- Significant up-front computational expense is rewarded with fast and accurate evaluation