HALcoll: Neural Network-based Optical Collimation and Alignment at the MMT Observatory

The MMT Observatory
A joint facility of
The Smithsonian Institution & The University of Arizona

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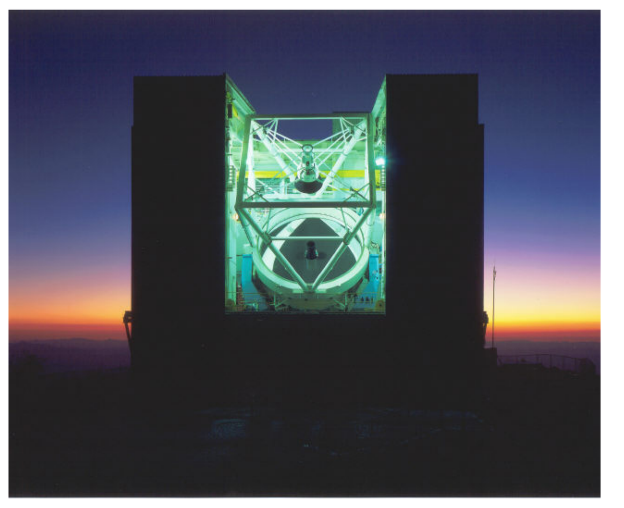


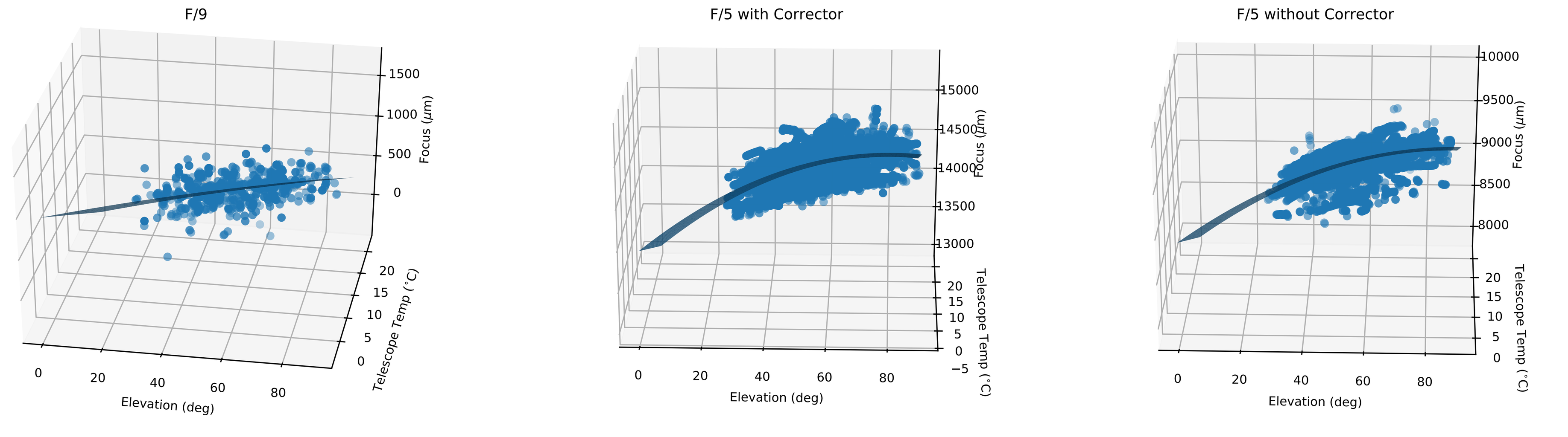
Abstract

Since its recommissioning as a 6.5-meter telescope, the MMT Observatory (MMTO) has used a suite of Shack-Hartmann wavefront sensors (WFS's)[1] to do fine adjustments of focus, collimation, and primary mirror optical figure. Coarse adjustments are made using open-loop models to get initial pointing, collimation, and focus within the capture range of the WFS's. These models are also used to maintain focus and collimation in between WFS measurements. HALcoll is an attempt to improve the performance and predictive accuracy of these models using neural networks.

Background

The MMTO's very fast f/1.25 primary mirror places very stringent requirements on the positioning of the secondary mirror to maintain acceptable image quality. With the excellent seeing that is achievable at the site, even 10 micron focus errors produce noticeable degradation.

Gravity-induced flexure and expansion/contraction due to temperature changes are the predominant effects that must be counteracted to maintain focus/collimation. A simple baseline model is a 2D surface that is linear with telescope temperature and second-order with pointing elevation. The models can then be fit to archived WFS data. The results for each of the three optical configurations show significant scatter:



The RMS scatter is 130-160 microns in each case. Only the focus axis is shown here, but similar behavior is seen for the other axes of secondary mirror motion. Fitting the models to data from 2017-2018 and checking against data from 2019 yields similar results, but slightly worse scatter, 140-180 microns.

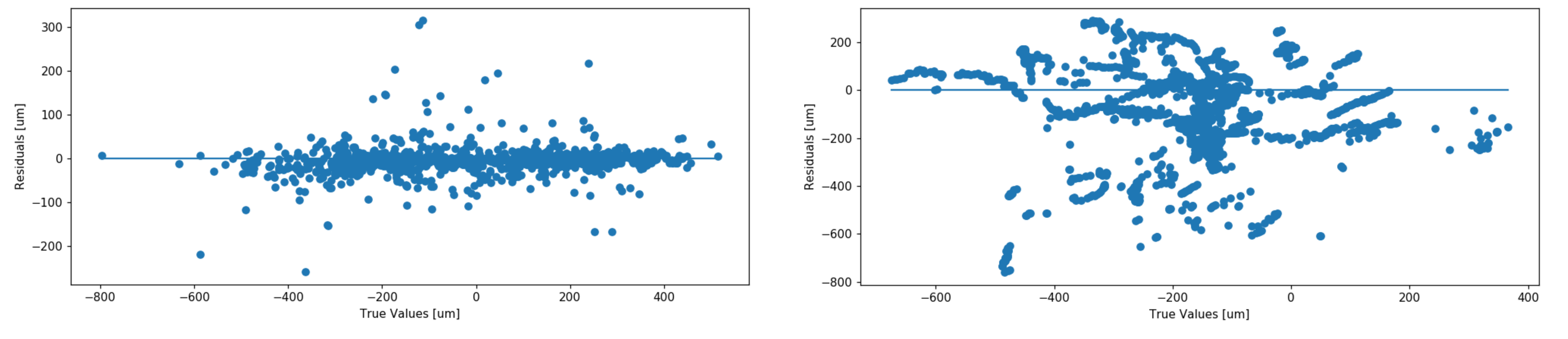
Neural Network Models

The rich array of telemetry and large amount of training data (>40000 suitable WFS observations in total) makes this problem well-suited to modern machine learning techniques. Their use makes it much easier to incorporate more telemetry more directly and provides the ability to automatically learn relations between different telemetry measurements.

As a first attempt, we use TensorFlow[2] to set up a regression problem where the training data is "fit" to a neural network model consisting of multiple densely connected layers. The Keras[3] API provides a very straightforward way of defining such models and manipulating them. We build `Sequential()` models with lists of `Dense()` layers and perform the fitting using the `RMSprop()` optimizer along with a mean squared error loss function. Models were trained for each of the five relevant axes of secondary mirror motion. The input data included all of the individual temperature readings on the telescope structure, ambient temperature, time of night, telescope pointing, and date of observation.

Results

We used models with 2 layers of width 16 for the F/9 configuration, which has less training data, and 2 layers of width 32 for the others. Using the entire dataset for training and verification with a 75/25 random split yielded promising results with, e.g., focus predicted to 20-30 microns RMS. However, using the 2017-2018 data for training did a very poor job predicting the 2019 data. These plots show the focus results for F/5 w/ no corrector. Left is the 2017-2018 data verified against itself, Right is the same model verified against the 2019 data.



The neural network model turns out to be, alas, no more predictive than the simple 4-parameter model.

Work is still ongoing to see if a better model can be produced or if the limit truly is unpredictable "flop" within the telescope structure. There is also a lot more telemetry that could be incorporated into the training, most notably data from the primary and secondary mirror support cells.

References

1. Timothy E. Pickering, Steven C. West, & Daniel G. Fabricant, "Active optics and wavefront sensing at the upgraded 6.5-meter MMT", in *Ground-based Telescopes. Edited by Oschmann, Jacobus M., Jr. Proceedings of the SPIE*, Volume 5489, pp. 1041-1051, 2004
2. Martín Abadi, et al., *Tensorflow: Large-scale Machine Learning on Heterogeneous Systems*, 2015. Software available from tensorflow.org.
3. François Chollet, et al., *Keras*, 2015. Software available at keras.io.

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