
Astronomical Image Quality Prediction based on Environmental and Telescope Operating Conditions

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Abstract

Intelligent scheduling of the sequence of scientific exposures taken at ground-based astronomical observatories is massively challenging. Observing time is over-subscribed and atmospheric conditions are constantly changing. We propose to guide observatory scheduling using machine learning. Leveraging a 15-year archive of exposures, environmental, and operating conditions logged by the Canada France Hawaii Telescope, we construct a probabilistic data-driven model that accurately predicts image quality. We demonstrate that, by optimizing the opening and closing of twelve vents placed on the dome of the telescope, we can reduce dome-induced turbulence and improve telescope image quality by (0.05-0.2 arc-seconds). This translates to a reduction in exposure time (and hence cost) of $\sim 10 - 15\%$. Our study is the first step toward data-based optimization of the multi-million dollar operations of current and next-generation telescopes.

1 Introduction

We describe initial steps towards the first-ever machine-learning driven approach for real-time scheduling of astronomical observations at the Canada France Hawaii Telescope (CFHT). Situated at

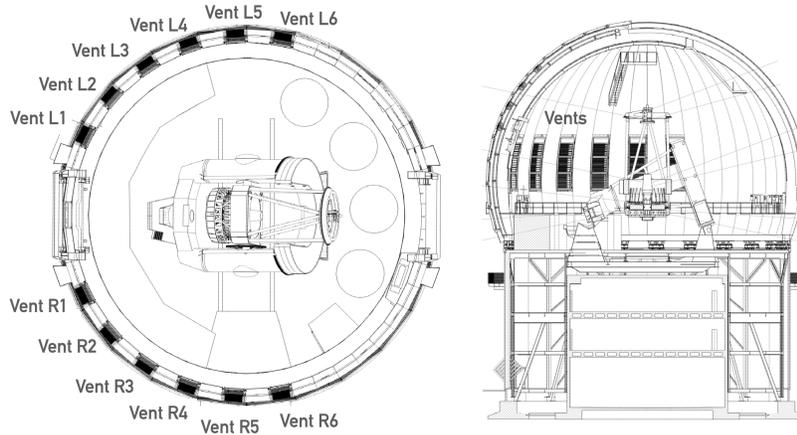


Figure 1: A schematic of CFHT. The twelve actuatable dome vents are marked.

the summit of the 4,200m volcano of Mauna Kea on the island of Hawai’i, CFHT is one of the world’s most productive ground-based observatories [1]. CFHT has gathered decades-worth of observational data since it saw first light in 1979 [2]. We train a deep neural network on this data archive to predict the “image quality” (IQ) of each candidate scientific exposure as a function of environmental and observatory dome operating parameters. Our long-term goal is to leverage such predictors to schedule observations and dome controls to maximize IQ. Real-time scheduling is key since (i) observing time at CFHT is oversubscribed with science proposals by ~ 3 fold, and (ii) CFHT costs around USD 25,000 to operate per night (a tenth of what next generation 30m-class telescopes will cost). Improving the efficiency of operations will yield more science, and will pave the way for the more complicated scheduling tasks of next-generation telescopes.

IQ measures the blurring of a point-like star and relates directly to signal-to-noise ratio (SNR). IQ degradation from the theoretical maximum results from turbulent mixing both in the atmosphere and from local effects near the ground and the observatory. The summit of Mauna Kea is a prime site for an observatory as free atmosphere is minimal due to the smooth flow of the prevailing trade winds and the height of the summit. In such conditions local degradation of IQ is significant and despite continual improvements to CFHT since 1979, including the 2012 introduction of vents to assist in flushing mixed air from the dome (see Fig. 1), as with all major ground-based observatories, IQ rarely reaches what the site can theoretically deliver.

Through the implementation of a probabilistic DNN, we demonstrate that ancillary environmental and operating parameter data are sufficient to predict IQ accurately. We illustrate that, keeping all other setting constant, there exist optimal configurations of dome vents that can substantially improve IQ. Our successes here lay the foundation for developing automated control and scheduling approaches.

2 Data

Almost two decades of panoramic images with metadata from CFHT’s MegaCam [3] are publicly available in the CFHT-CADC archive [4]. Prior to their use in our network, we needed to clean the metadata substantially: pertinent variables were spread across multiple data sets, records were missing or incorrect, and IQ values were recalculated to a common reference with respect to wavelength and airmass/zenith to make them easier to compare. The data we use in this study are publicly available.¹

Each input record contains three distinct types of predictive variables: (1) *Dome operating parameters*: These include the configurations of the twelve dome vents (open or closed), and the windscreen setting (degrees open). These are examples of the variables that we can adjust and optimize the settings of in real time. In this initial study we focus on the dome vents. (2) *Environmental parameters*: These include exposure-averaged wind speed, wind direction, barometric pressure, and temperature values at various points both inside and outside the observatory. (3) *Ancillary parameters*: These include,

¹http://www.cfht.hawaii.edu/~billy/cfht_site_seeing/results2020/

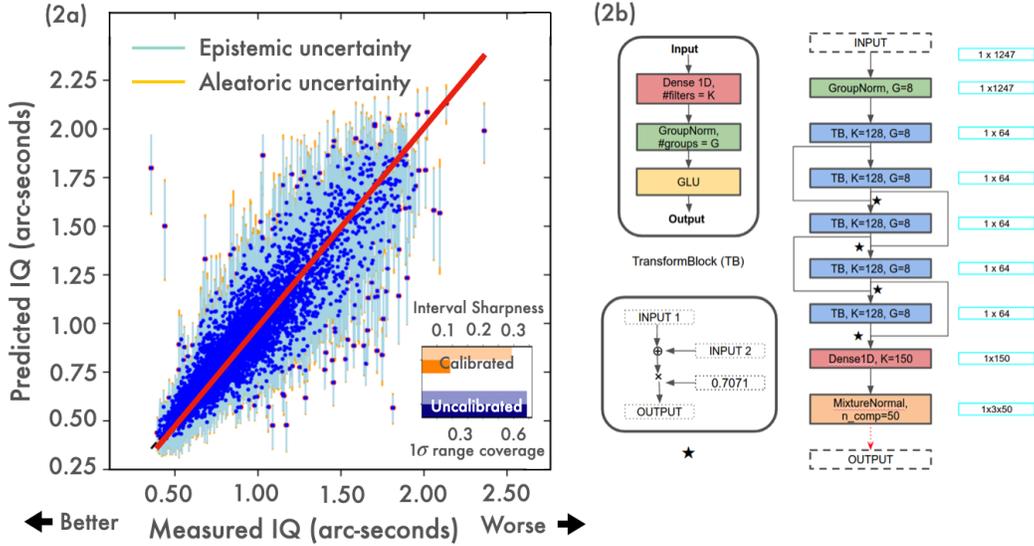


Figure 2: **(2a)**: Telescope IQ can be predicted to, on average, 0.07 arc-sec based on configurable telescope parameters (e.g., vent configuration) and environmental conditions (e.g., wind speed, bolometric pressure). The inset shows the "sharpness" of the prediction and the range covered by the predicted one-sigma uncertainty. This demonstrates that the CRUDE calibration improves the robustness of the probabilistic outputs. **(2b)**: The network architecture used in this study: a dense feed-forward network with skip connections and GLU activations.

for each observation, the telescope altitude and azimuth (which correspond to the astronomical object being observed), the central wavelength for the filter, and the integration time of the observation. In total, there are 86 variables (including IQ) provided with each exposure. We engineer these as follows: the vent status are binarized as 0 and 1, and every temperature variable is subtracted from every other temperature variable to enable ease capture of secondary effects. Variables with $> 50\%$ missing or errant values are dropped, followed by samples with any missing values. The final dataset thus obtained has 1,247 variables and 69,846 records, spanning observations made from May 2005 to March 2020.

3 Method

We implement a feed-forward neural network (see Fig. (2b)) with 5 dense layers, 64 neurons per layer, skip connections, and generalized linear units [5]. We wrap the network as part of a mixture density network (MDN) [6] to provide probabilistic output of the image quality, comprised of a mixture of a weighted sum of 50 Beta distributions. The network is optimized using adaptive gradient descent and the negative log likelihood loss function.

The nature of the MDN allows us to predict a PDF of IQ for each sample. For data sample i and mixture model component j , let $\mu_{i,j}$, $\sigma_{i,j}^2$, and $\omega_{i,j}$ respectively denote the mean, variance, and normalized weight in the mixture model. We obtain the predicted IQ value as the weighted mean of the individual modes, $\mu_i = \sum_{j=0}^{m-1} \omega_{i,j} \mu_{i,j}$. Aleatoric uncertainty (or "irreducible uncertainty") [7, 8] quantifies the inherent stochasticity of the inputs. We use a weighted average of the mixture model variances $\sigma_{i,a}^2 = \sum_{j=0}^{m-1} \omega_{i,j} \sigma_{i,j}^2$ as its estimator [9]. Epistemic uncertainty (or "reducible uncertainty") [7, 8] quantifies the model's uncertainty in parts of the parameter space sparsely populated by the training samples. We use the weighed variance of the mixture model means, $\sigma_{i,e}^2 = \sum_{j=0}^{m-1} \omega_{i,j} \mu_{i,j}^2 - \mu_i^2$ [9]. Total uncertainty is computed by adding these in quadrature.

Noting that, in practice, most uncertainty estimates are over-confident when estimating the prediction uncertainty [10–12], we use the CRUDE method [12] to re-calibrate our model's predictions *post-hoc*. CRUDE ensures that not only are the post-processed predictions calibrated, but that they are also

sharp [13]. Sharpness refers to the concentration of the predictions. The more peaked (the sharper) the predictions are, the better (provided it is not at the expense of calibration).

We split the total input data into training and test sets in a ratio of 9-to-1. The training data is the subdivided into training and validation subsets via cross-validation in a ratio of 9-to-1. During each of the 10 iterations, model predictions on the 9 validation splits are concatenated and used to calibrate the predictions on the held-out test set. Finally, both uncalibrated and calibrated predictions on the 10 test sets are concatenated.

4 Results

In Fig. (2a), we compare the predicted IQ as a function of the IQ measured on the astronomical images. Error bars show both the epistemic and aleatoric parts of the prediction error obtained by the MDN. The figure shows that IQ can be predicted without bias and with reasonable accuracy using only measured environmental conditions and dome operating parameters as inputs. The mean absolute error is 0.07 arc-seconds (or arc-sec, for simplicity). The inset demonstrates the benefit of *post-hoc* calibration with CRUDE: for samples in our test set, the predicted $1\text{-}\sigma$ uncertainties much better capture the expected 68% of the true IQ values, and are also small enough so that the resulting probability distribution functions are sharply peaked.

As already mentioned, the dome vents (see Fig. 1) were installed in 2012 to accelerate thermal equilibrium between the telescope structure and ambient air, and to flush pockets of settled thermal anisotropy from the air within the dome.[14–16]. In Fig. 3 we investigate the effect of these vents in some detail. By discovering relationships between vent configurations and environmental conditions we show that there exist optimal vent configurations (Fig. (3b)) that could improve observed IQ (Fig. (3c)). Fig. (3a) visualizes the “nominal” vent configuration in effect when data was collected for a randomized sample of 250 exposures. The red/blue horizontal lines indicate the configuration of the 12 vents with red denoting closed and blue denoting open. The figure shows that vents have historically been mostly all closed or all open. However, our model can make predictions across all possible 2^{12} vent configurations. We can therefore ask which of the possible vent configurations would result in the best (the lowest) IQ. The (predicted) IQ-minimizing vent configuration for each of the 250 exposures is shown in Fig. (3b). The difference between the nominal and optimal vent configurations is immediately apparent. The latter are often a mixture of open and close vents. For historical reasons the dome vents at CFHT have been operated using small number of fixed configurations

The improvement (decrease) in predicted IQ is shown in Fig. (3c). When nominal IQ is excellent (< 0.5 arc-sec), we see that the possible improvement in IQ is marginal. In this regime atmospheric turbulence, over which we have no control, dominates IQ. However, when IQ is middling or degrades (> 0.5 arc-sec), by optimizing vent configuration we can substantially improve the (predicted) IQ. The improvement ranges from about 0.05 arc-sec for a nominal IQ of 0.5-1.0 arc-sec, to about 0.1 arc-sec for a nominal IQ of 1.0-1.5 arc-sec, and to 0.2 arc-sec for a nominal IQ > 1.5 arc-sec. This range of IQ captures most observations; it is rare to have nominal IQ < 0.5 arc-sec. Using the CFHT exposure time calculator², we find that these IQ improvements correspond to a 10 – 15% reduction in exposure time (and hence cost). The result is largely independent of the nominal IQ, target SNR, and source brightness

5 Discussion and Future Directions

This study applies a probabilistic network to fifteen years of data collected by the Canadian-France-Hawaii Telescope. We demonstrate that on average image quality can be predicted to 0.07 arc-sec accuracy based on environmental conditions and telescope operating parameters. By varying the configuration of the dome vents in response to extant environmental conditions, we show that IQ can be improved by about 10% across all regimes, with larger gains when the nominal IQ value is large. Assuming an SNR-driven observing model, this translates to a reduction in observation time and costs of up to 10-15% (about 1M USD a year). Overall, this study is an important first step towards active and automated optimization of telescope IQ, and eventually real-time scheduling with dynamic vent configuration.

²<http://etc.cfht.hawaii.edu/mp/>. We assumed point sources of 20-23 mag in the r-band filter.

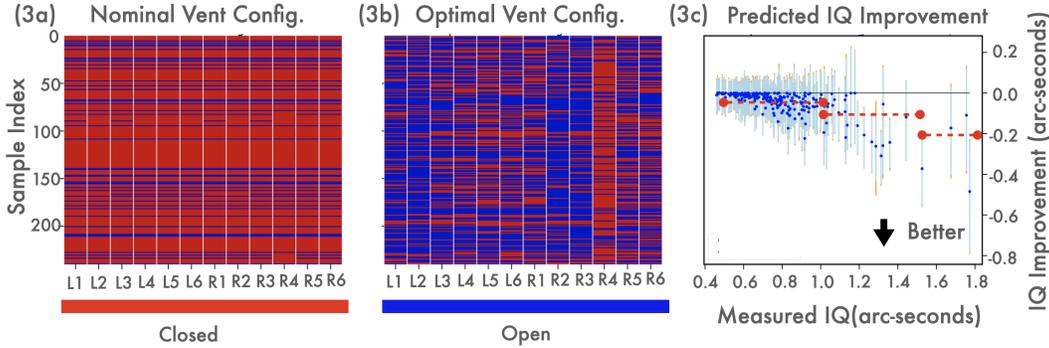


Figure 3: Optimizing the vent configuration can dramatically improve the image quality of the telescope. (3a) shows the nominal vent configurations, and (3b) the (predicted) optimal vent configuration that leads to the IQ improvements shown in (3c). The red dashed lines in (3c) delineate the assumed improvements for the exposure time calculation.

We will pursue several avenues of further inquiry. The improved IQs we present here are predicted by extrapolating over hypothetical vent configurations. While the uncertainties output by our model suggests that these marginal “out-of-distribution” predictions are most likely robust, they must be verified in real-life. We also treat the input data as independent and thus do not leverage various temporal relationships. Correlations between adjacent time stamps contains implicit information that we plan to exploit using specialized architectures such as LSTMs [17] to predict IQ in real-time – some 5 to 10s of minutes out – to enable adaptive reorganization of the nominal observation schedule. Finally, in future work we will explore use of variational encoders for feature imputation [18], since it is known that dropping samples negatively impacts a model’s predictive ability [19].

Broader Impact

This study leverages deep learning to exploit existing data catalogs at the Canada France Hawaii Telescope to improve telescope operations. Time is a fundamental limitation of world-class telescopes, which are heavily over-subscribed and crucial for furthering our understanding of the universe and of ourselves. Exponentially larger and more expensive telescopes with identical time limitations suggest a corresponding trend of scarcity. By capitalizing on data in hand we can do more with the same amount of time, gain novel insights, and develop techniques for advancing the scientific agendas of observatories worldwide. We note that application of data sciences to improve observatory operations is a nascent field. One recent work, somewhat paralleling our motivations, develops turbulence “nowcasting” for the Paranal Observatory in Chile [20]. A second from the Mauna Kea Weather Center develops a model to forecast and quantify optical turbulence on the summit of Mauna Kea [21]. We anticipate this budding field will grow substantially and will make impactful contributions to the operations of future telescopes. We do not foresee any ethical concerns arising from this work.

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