Pointing the South Pole Telescope with Machine Learning

Paul M. Chichura (1, 2), Thomas M. Crawford (2, 3), and Alexandra Rahlin (2, 4)

(1) Department of Physics, University of Chicago, Chicago, IL, 60637
(2) Kavli Institute for Cosmological Physics, University of Chicago, Chicago, IL, 60637
(3) Department of Astronomy and Astrophysics, University of Chicago, Chicago, IL, 60637
(4) Fermi National Accelerator Laboratory, Batavia, IL, 60510

***Abstract*—The South Pole Telescope (SPT) is a millimeter/sub-millimeter telescope primarily used to characterize the cosmic microwave background. The SPT's ability to point accurately at the sky depends on its structural imperfections, which are impacted by the South Pole's harsh weather. Pointing errors are particularly detrimental to SPT participation in Event Horizon Telescope observations, which require stricter pointing accuracy than typical SPT observations. Here, we present our efforts to improve the SPT's real-time pointing accuracy by using machine learning. We train two XGBoost models on data compiled from archival observations made during standard operation. The models learn a mapping from current weather conditions to two telescope drive control arguments that correct for errors in azimuth (az) and elevation (el), respectively. Our models achieve root mean squared errors on test data of 3.01″ in az times cosine el and 3.57″ in el, well below our goals of 5″. We deploy our models on the telescope and perform additional testing. Our models result in significantly reduced pointing errors: for sources where the models are best trained, average total error improved 33%, from 15.9″ to 10.6″. These improvements, while significant, fall shy of our goal yet serve as proof of concept for further development.**

Keywords—pointing accuracy; pointing error; machine learning

I. Introduction

In order to make observations, telescopes must be able to point towards a desired location on the sky and to do so accurately. Errors in pointing, often called "pointing offsets," occur when the telescope is not aligned as instructed. Pointing offsets can be caused by a telescope's structural deformations, most of which can be accounted for by analytically modeling their effects on pointing. Such "pointing models" will relate some desired location to a different location instructed to the telescope, such that the telescope will point at the desired location after deforming in an expected way. Determining the ideal values of pointing model parameters is a critical task for any telescope.

The South Pole Telescope (SPT) is a 10-m millimeter/sub-millimeter telescope located near the geographic South Pole and used primarily to make high angular resolution measurements of temperature and polarization anisotropies in the cosmic microwave background (CMB) [1]. The SPT has been outfitted with a series of three cameras, the most recent of which is the SPT-3G camera [2]. To make the desired measurements of the CMB, the SPT is used to make "maps" of the same region of the sky repeatedly over many years.

The SPT's building specifications required high pointing accuracy: repeatedly within 4″ error, which is much smaller than the SPT-3G's beam sizes of order 1′. Although the SPT met these requirements when it was test built in Texas prior to deployment, the specifications did not hold in the harsh Antarctic climate, which, although stable, is windy and incredibly cold. These conditions, in conjunction with a heated control room, cause a thermal gradient throughout the telescope's support structure. As the weather changes, the thermal gradients induce thermal deformations which induce pointing errors as large tens of arcseconds in azimuth (az) and elevation (el). During typical CMB observations, these errors are forgivable: any one observation's pointing offsets can be corrected afterwards by shifting the map so that sources appear at their known, expected locations.

However, there are some uses of the SPT for which pointing offsets are not as forgivable. The SPT is part of the Event Horizon Telescope (EHT), a very-long baseline interferometry experiment consisting of telescopes across the world [3]. The EHT receiver on the SPT consists of a single detector that must consistently point directly at the astronomical source of interest [4]. Because EHT observations do not make maps of the sky like typical SPT observations, we cannot correct for pointing offsets after the fact.

To meet the stricter requirements for EHT observations, we must correct for variations in the pointing model parameters caused by changing weather in real time. Simple modeling based on physical intuition fails to capture the complexity of the data, so we require more complex modeling. We train two machine learning (ML) models which can correct the SPT's pointing in real time. We train the models to take information about a target location, the current state of the telescope, and weather conditions, then estimate the ideal pointing model parameters which yield accurate pointing. Here, we present the development, integration, and evaluation of these ML models.

II. Model Development

A. Target and Feature Variables

The components of the SPT's structure most susceptible to weather-induced thermal deformations are the yoke arms, which hold up the primary mirror and receiver cabin. The yoke arms are expected to deform in two primary modes which map directly to two pointing model parameters. These parameters affect pointing accuracy in az and el, respectively. Our goal is to estimate those parameters in real time to update instructions to the telescope control system.

To make these estimations, we use the following inputs: We include the target az and el, as we know the pointing model depends on a source's position. We include "linear sensors" that measure changes in the height of the yoke arms relative to a stiff reference frame. We include 33 thermometers located throughout the telescope structure. We include ambient air temperature, wind direction, and wind speed as measured by a weathervane on a nearby roof. All these input features can be monitored in real time by the telescope control software.

B. Dataset

We compile a dataset from years of archival data taken with the SPT-3G and EHT cameras. These data consist of observations of bright astronomical sources with known positions. The SPT data come from typical CMB observations of the target science field. The EHT observations come from test observations during setup for yearly EHT observing campaigns. For each source observation, we record the measured, incorrect source position, then fit for the pointing model parameter values which would have minimized their offsets. In addition, the archival data include sensor data logged multiple times a second, from which we can recover values of the feature variables at the time of each observation. We scrub five years of archival data for a total of 121,369 source observations. 97% of the data were acquired with the SPT-3G camera, which presents an interesting domain generalization challenge for use during EHT observations.

C. Training and Evaluation

Our stated problem is a supervised regression problem with tabular data and two target variables. We choose XGBoost architecture, which performs particularly well on tabular data [5]. We tuned the XGBoost hyperparameters through five-fold cross validation. The trained models achieve root mean squared error (RMSE) of 3.01″ in az times cosine el and 3.57″ in el, well below our goals of 5″.

The SPT is an expensive instrument, so model fidelity is critical. We perform several stress tests before deployment. We interpret feature importance to investigate how the model makes decisions and whether those decisions follow physical intuition. We extrapolate the models to feature values beyond the ranges of training data to check for reasonable behavior, as EHT observing may deviate from the training regimes. We check model performance on just the EHT sources in test data to explore whether deployment might encounter a domain shift; in this test, the models perform worse than for all sources but still near goals.

III. Deployment and Testing

We integrate the models into the control software for use during the EHT observing campaign in April 2024. When the telescope is instructed to point at a source, it slews to the source's location, pauses for ten seconds to average input feature variables, feeds the features into the ML models, then updates the instructed pointing model parameters to those values estimated by the ML models. After setup was complete, we spent the remainder of the 2024 EHT observing campaign either performing the scheduled EHT observations or conducting test pointing observations with ML corrections active. We acquired 966 source observations which we use as *in situ* validation of our trained ML models.

For all sources, using the ML adjustments resulted in a 22% reduction in the average error measured along a great circle, from 15.6″ to 12.2″. These data include many observations of planets that appeared at el much lower than the training data, so we did not expect the models to extrapolate well to these el ranges. For sources within el ranges where the models are best trained, using the ML corrections resulted in a 33% reduction in the average error measured along a great circle, from 15.9″ to 10.6″. For these sources, errors in az time cosine el improved from $-3.8 \pm 11.6''$ to $1.8 \pm 6.4''$. Errors in el improved from $0.9 \pm 12.5''$ to $0.1 \pm 9.3''$. These errors fall short of our stated goals of 5″ RMSE along az times cosine el and along el, but these data demonstrate significant progress towards our goals.

A closer look at these data suggest a few curiosities. For instance, some of the pointing sources already meet our goals, while others do not. Similarly, the az model performed better than the el model. Furthermore, the ML models perform worse on EHT datapoints in withheld test data and in *in situ* test observations. These curiosities could be explained by potential domain shifts between the SPT-3G and EHT cameras, and we can address many of these concerns in the future as we gather more training data.

IV. Conclusion

We demonstrate that ML can be used to improve the real-time pointing accuracy of the SPT. Our trained ML models generalize well to withheld test data. As a proof of concept, they improved our pointing accuracy when deployed and active on the telescope. Upcoming datasets like the SPT Wide Field and further EHT observations will improve future models. This work demonstrates a significant improvement in the SPT's pointing accuracy. It will enable the expansion of science possible with the SPT as part of the EHT collaboration.

References

[1] J. E. Carlstrom *et al.*, "The 10 meter South Pole telescope," *Publications of the Astronomical Society of the Pacific*, vol. 123, no. 903, pp. 568–581, May 2011, doi: 10.1086/659879.

[2] J. A. Sobrin *et al.*, "The design and integrated performance of SPT-3G," *The Astrophysical Journal Supplement Series*, vol. 258, no. 2, p. 42, Feb. 2022, doi: 10.3847/1538-4365/ac374f.

[3] S. Doeleman *et al.*, "Imaging an event Horizon: SubMm-VLBI of a super massive black hole," *arXiv (Cornell University)*, Jan. 2009, doi: 10.48550/arxiv.0906.3899.

[4] J. Kim *et al.*, "A VLBI receiving system for the South Pole Telescope," *Proceedings of the SPIE*, Jul. 2018, doi: 10.1117/12.2301005.

[5] T. Chen and C. Guestrin, "XGBoost," *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Aug. 2016, doi: 10.1145/2939672.2939785.