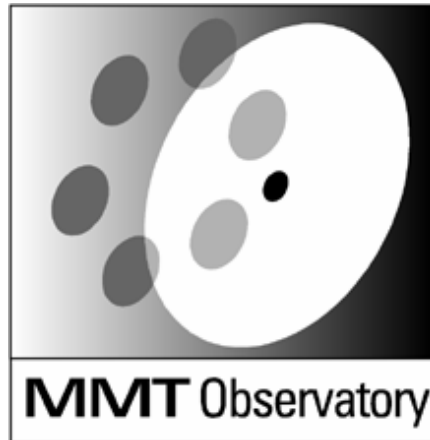


MMTO Internal Technical Memorandum #09-2



Smithsonian Institution &
The University of Arizona®

Elevation Tracking for the 3rd Trimester of 2008 (September – December, 2008)

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Introduction

The MMTO MySQL database was queried for routine tracking and weather data for the final trimester of 2008 (Sept-Dec). These data are presented with discussion of data sources, their distribution over various dimensions of the data, and appropriate statistics are shown for the purposes of evaluation of the tracking performance of the latest iteration of the elevation servo (e.g. the version released after Summer 2008 Shutdown).

The database query returned 5064 entries from the tracking performance MySQL table¹. The tracking performance table contains entries for the timestamp, source filename from the mount tracking logging software, position, RMS error, peak-to-peak error, and tracking rate. In addition, a Python application was written by Tom Trebisky to acquire the wind sensor data from the database that matched the tracking data entries with similar (or the same) timestamps for study of the wind influence on tracking performance. All of the figures that follow are available via the web at <http://tinyurl.com/cop6v8> if closer study is desired.

Data Collection

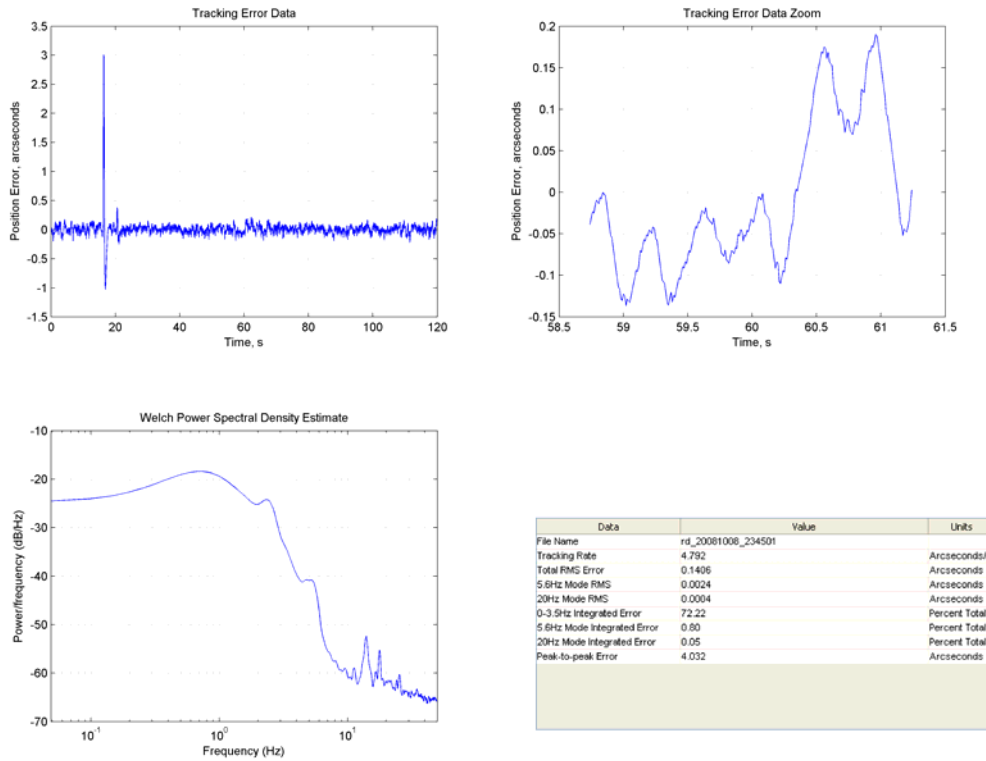
The mount computer automatically collects data from the servo controller at the end of every slew to an object. This was improved in December 2008 to add automated collection of tracking data every 10 minutes. Tracking data can also be captured at will by MMT operators via the mount control GUI. This data is returned over the network to the MMTO data archive on a daily basis; backend software reduces this data for statistics collection. A web page provides a graphical interface to the data-reduction software for routine examination by MMTO staff. Interested readers are directed to the URL: <http://hacksaw.mmt0.arizona.edu/plots/tracking/plots.php>. The web page shows the time series of the tracking error, its frequency content, relevant statistics of the error, and wind conditions for each tracking data file.

The primary data collection files contain data sampled at 100Hz for 120 seconds. Each file contains the azimuth, elevation, and rotator positions and their respective position errors. This report focuses only on the elevation axis performance to help evaluate the performance of the recent upgrades to the elevation-axis servo controller. A separate report is planned for the azimuth axis performance.

A known problem with the tracking error data collection is that it collects tracking data for each new object acquired just after completing the slew to the object; applications of offsets or other pointing corrections (e.g. guider inputs) to the mount are also often captured in the logging data. This means that large step responses in the error signal can be present in the data. Early versions of the logging software would often trigger the data collection before the slew completed, contaminating the data output – indeed, this was a good part of the motivation for addition of the automatic data collection at 10-minute intervals.

¹ See the appendix portion, “SQL Query and Python Data Collection” for details.

This defect in the data-collection system can tend to overstate the RMS tracking error. Consider as an example this typical tracking data file from October 2008:



This file reports a peak-to-peak error of just over 4 arcseconds, due to the offset step response at ~18s. The RMS error seen in this file is reported as 0.14", yet if only the data from 20s to the end is processed, the RMS error becomes 0.067" – a much more reasonable result, given the obviously smaller amplitude in the majority of the time history.

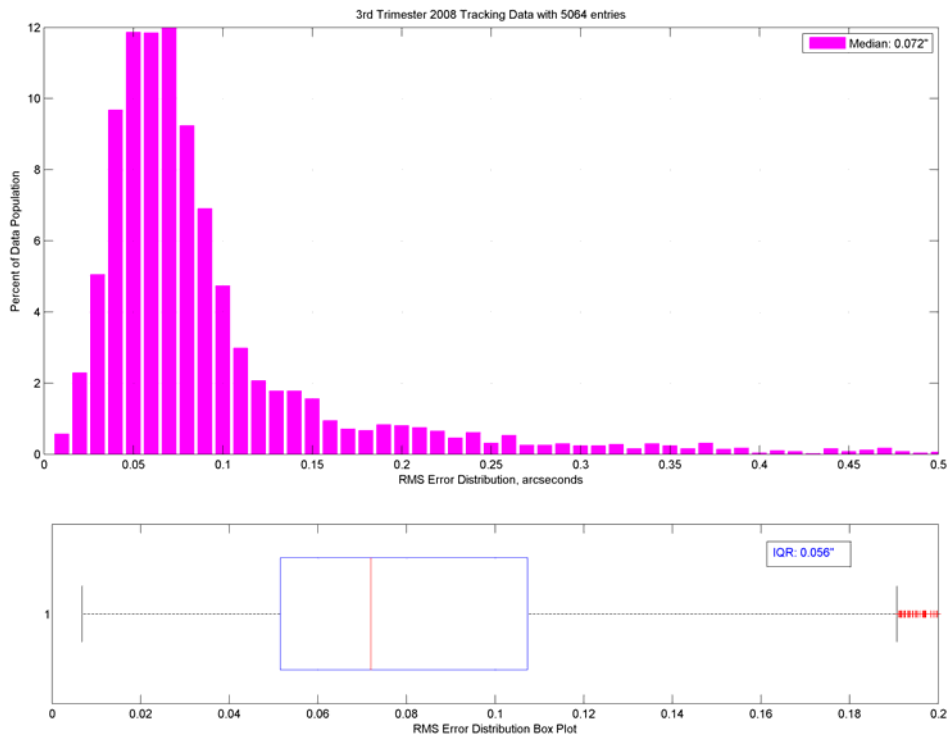
RMS Tracking Error

The RMS error statistics in arcseconds for the whole data population are:

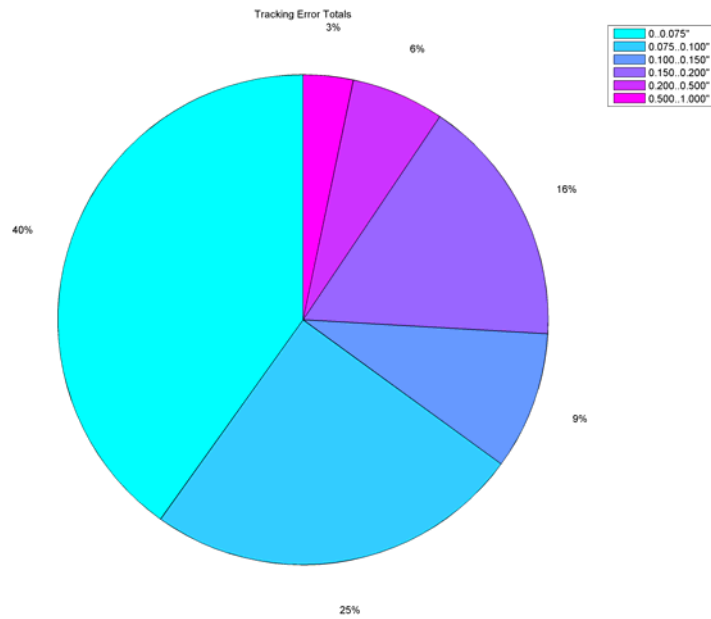
Min	Max	Median	Inter-quartile Range
0.007	1.76	0.072	0.056

The inter-quartile range (IQR) measures the width of the 50% of the data that lies between the 25th and 75th percentiles, and gives a better estimate of the spread of the data than the standard deviation (std), which can be sensitive to outliers.

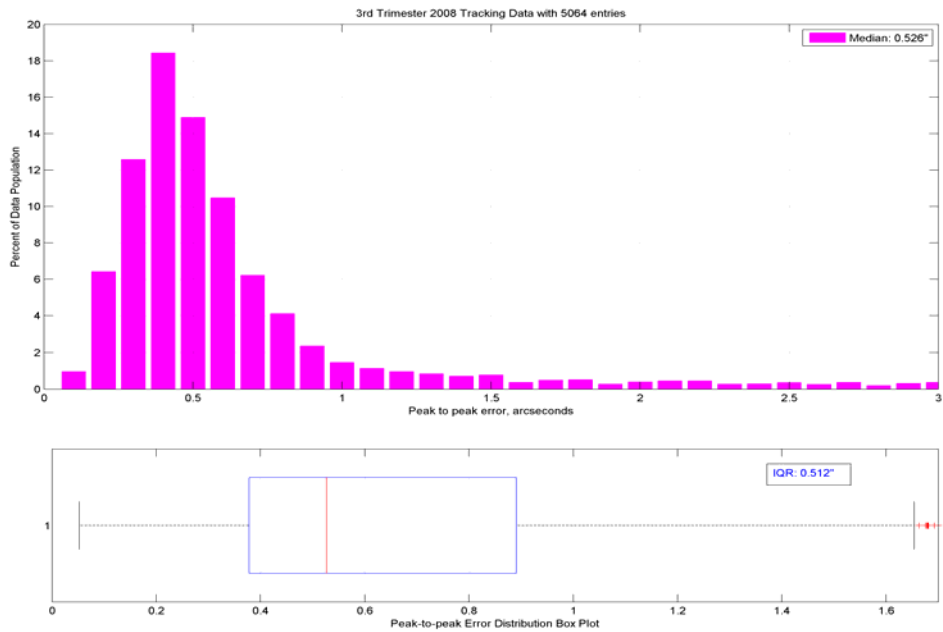
Below we have a histogram of the RMS error data (top), and a box plot of the RMS error zoomed over the range of interest. The histogram contains all of the data, binned into 0.01'' sections, or ~1 encoder count. The box plot shows the IQR range as a blue box, with a red line inside at the median value of the data. The left-hand black line is the smallest data entry, while the right black line is set to 1.5 times the IQR value away from the median value box by the Matlab `boxplot` routine. Values outside this are marked with red crosses and are considered outliers by `boxplot`. The `boxplot` routine returned 654 entries in the data as outliers (out of the 5064 total). With this, we see that 50% of the RMS error in the data lies between 0.05 and 0.107 arcseconds.



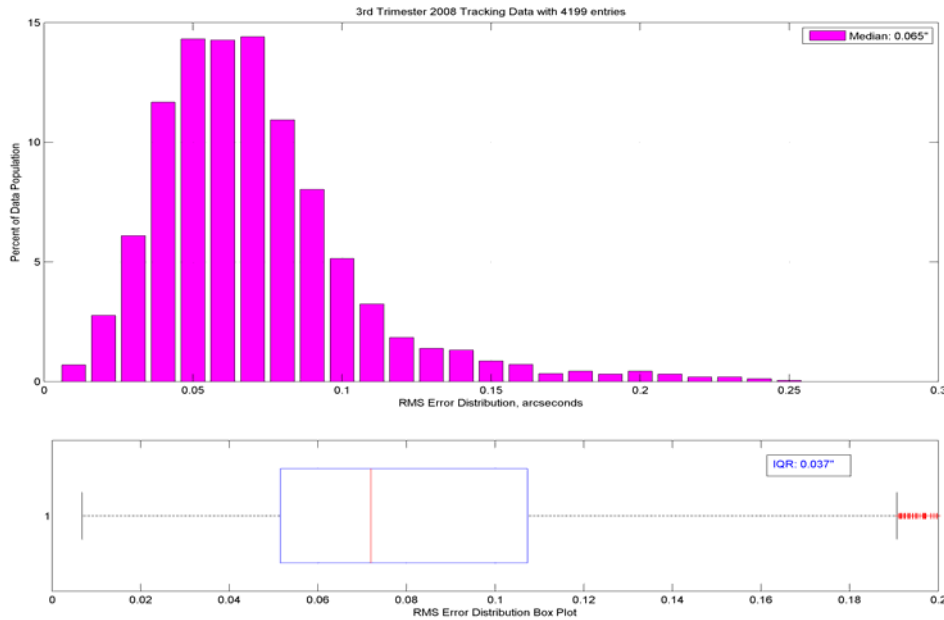
The pie chart below shows the distribution of the RMS error population. The legend at right for the pie chart shows the edge value for each bin.



For the peak-to-peak error data, we have the distribution plot below (zoomed a bit):



If we remove those data entries with a peak-to-peak value of more than 1.7'' (the guard value for outliers from the `boxplot` routine), the RMS error distribution becomes as shown below; 865 entries were removed from the data population by this exclusion -- the median error is 0.065'', with an IQR of 0.037'', similar to the above table.

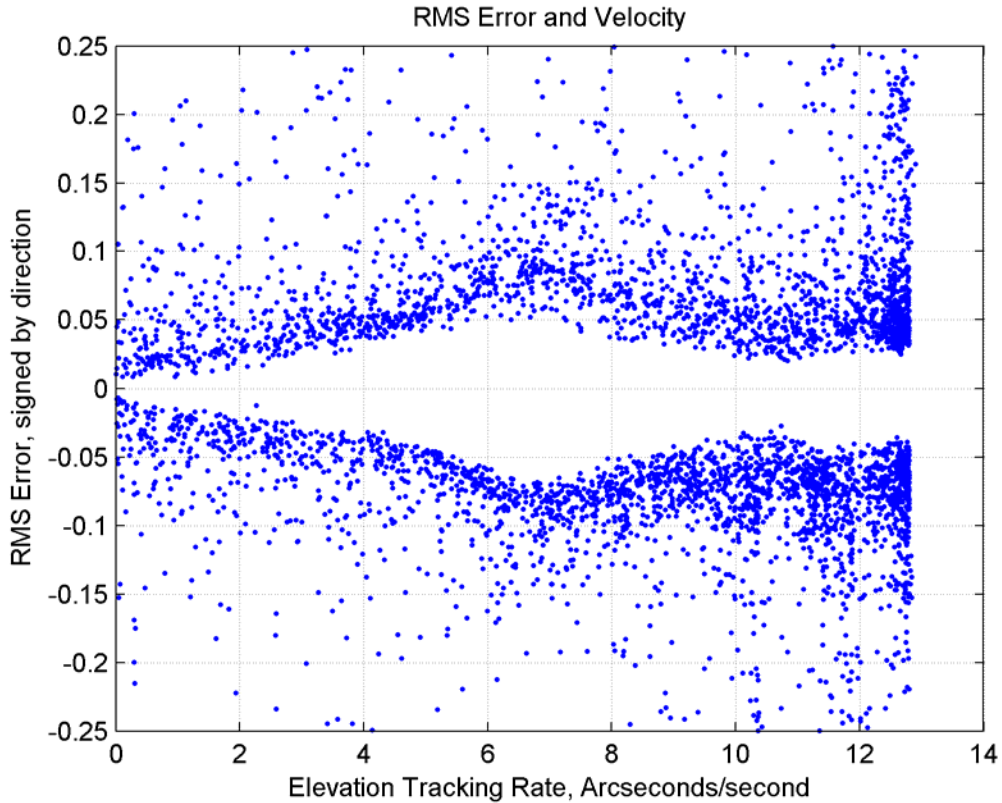


Error Distributions

Detailed visualizations of the error data help illuminate the dependencies of the tracking performance on position, velocity, and the environment. Evidence that the elevation controller experiences limit cycling based on encoder quantization and other non-linear physical processes (i.e. friction) is difficult to determine when using one, or few, tracking files. The large data set makes the existence of limit cycling much easier to detect.

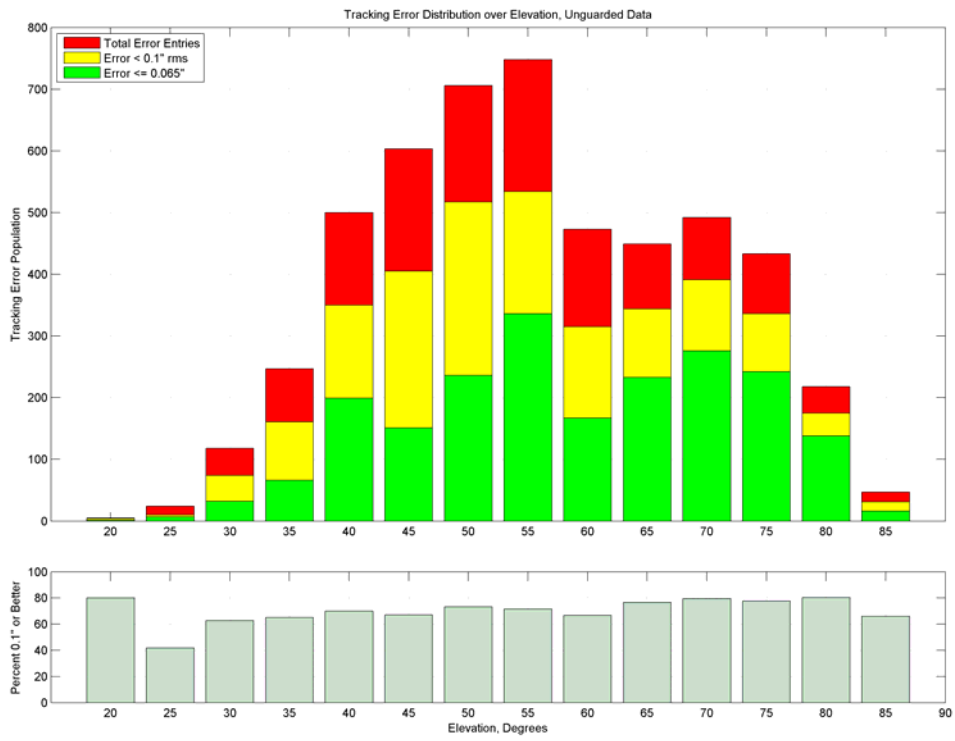
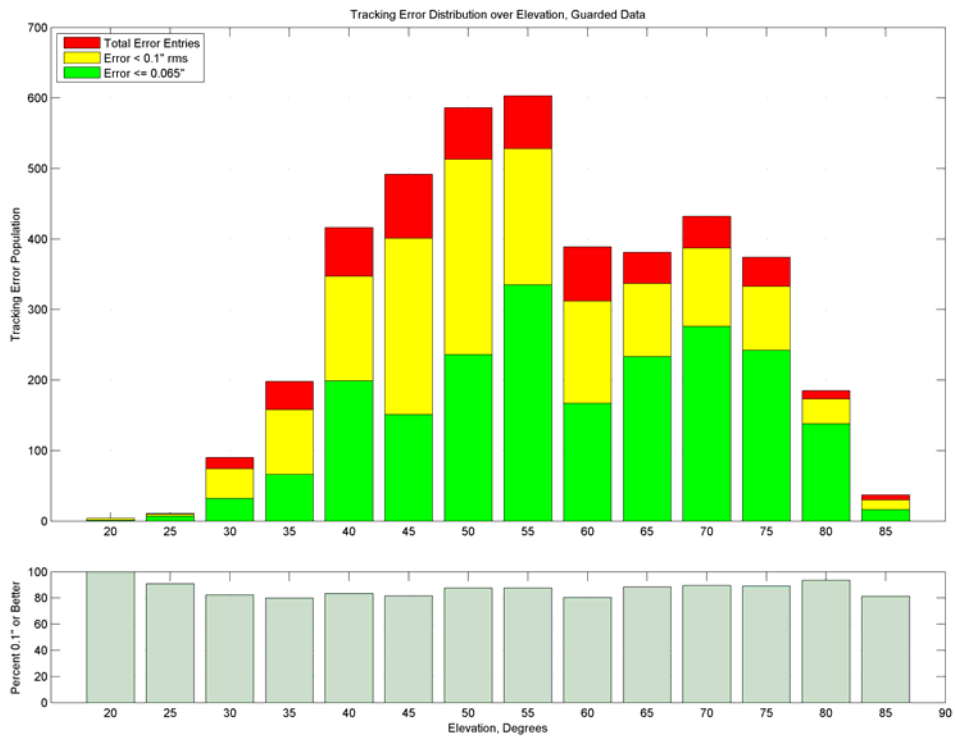
To explore the relationship of tracking speed and tracking error, we have the figure below. In this, the absolute value of the tracking rate for each entry in the data population is used for the x-axis. For the y-axis, the RMS error associated with each tracking rate entry is multiplied by the original sign of the velocity. This gives a “negative error” when tracking down to the horizon, and positive when tracking towards zenith. In this way, the empty center of the graph shows a lower limit to tracking smoothness (e.g. perfectly smooth tracking is zero error) that is related to friction, encoder quantization, and other non-linear effects. While the figure is zoomed for clarity, the careful reader will note that a cut-off at about 13 arcseconds/second appears. This is due to the fact that for any altitude-azimuth telescope, the tracking rate for sidereal objects in elevation is naturally

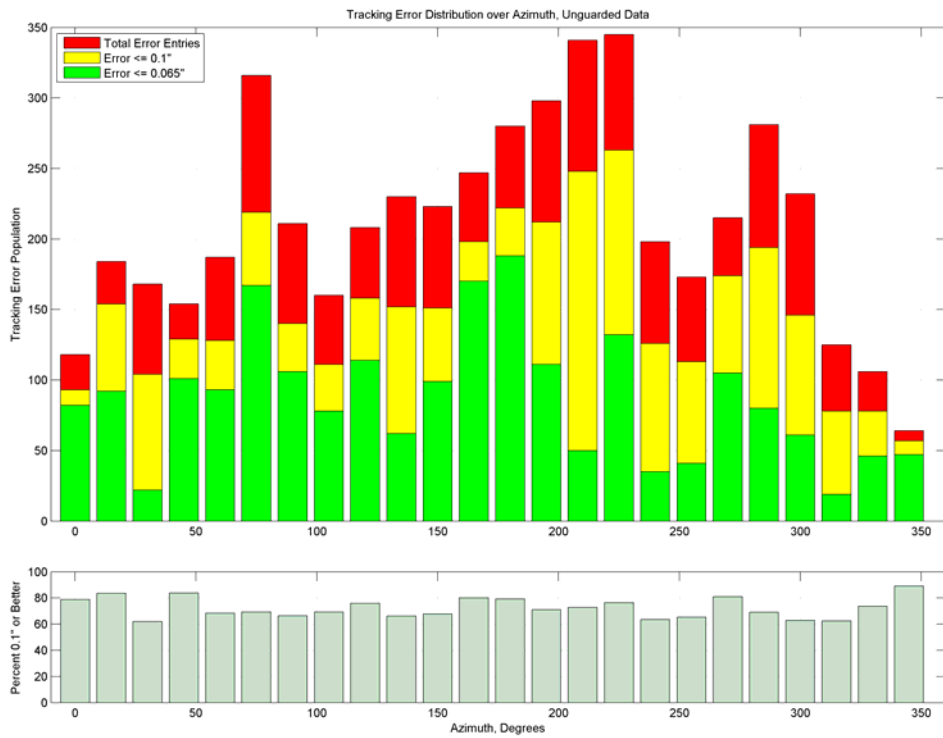
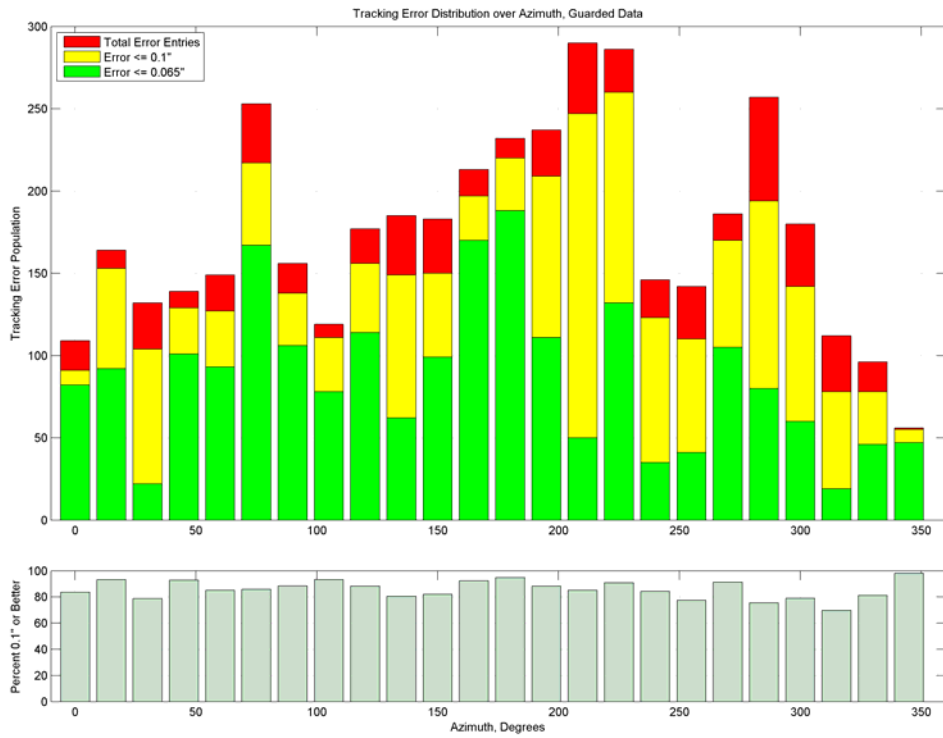
limited to ~ 12.8 arcseconds/second. See A. Poyner's discussion of this in an MMTO Technical Memorandum at <http://tinyurl.com/cdqqtqx> for details.



Tracking smoothness appears unaffected by the tracking direction, but cannot go below about ± 2 encoder counts. In addition, the tracking error shows a non-linear dependence on the tracking rate. Work on encoder feedback improvements (i.e. improved alignment, period counting) would help make this lower limit on tracking error smaller.

To investigate error dependence on position, the azimuth and elevation angles were binned, and the population of error entries for each bin were totaled into a) the total number of data entries, b) the number of entries where the RMS error was $\leq 0.1''$, and c) the number of entries where the RMS error was at the guarded median of $0.065''$ or better. The bar charts below show these totals in red, yellow, and green. An associated bar plot shows the percentage of the tracking population for each bin where the RMS error was $0.1''$ or better.

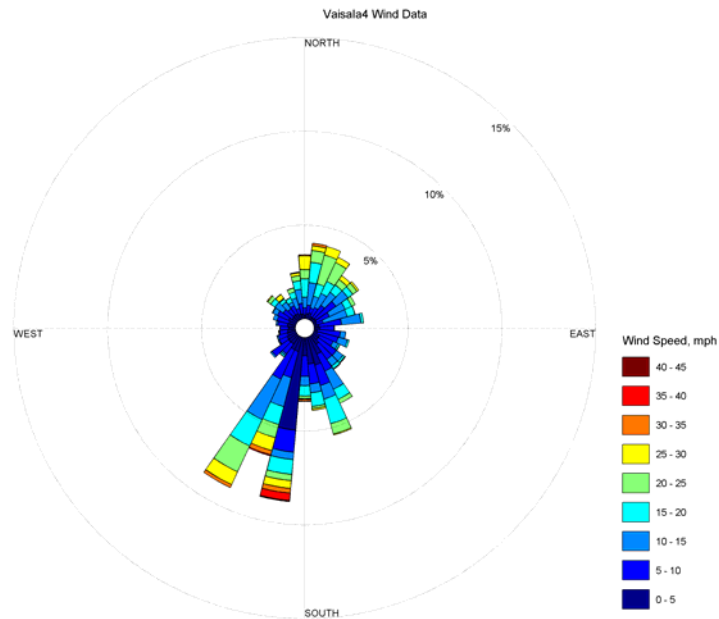




Wind Data

A small Python application was written to acquire wind data from the *Vaisala 3* and *Vaisala 4* sensors, located on the east and west sides of the MMT building, respectively. The Python application filters the wind data to output only samples at or near the timestamps of the tracking file data for correlation of the wind and tracking performance.

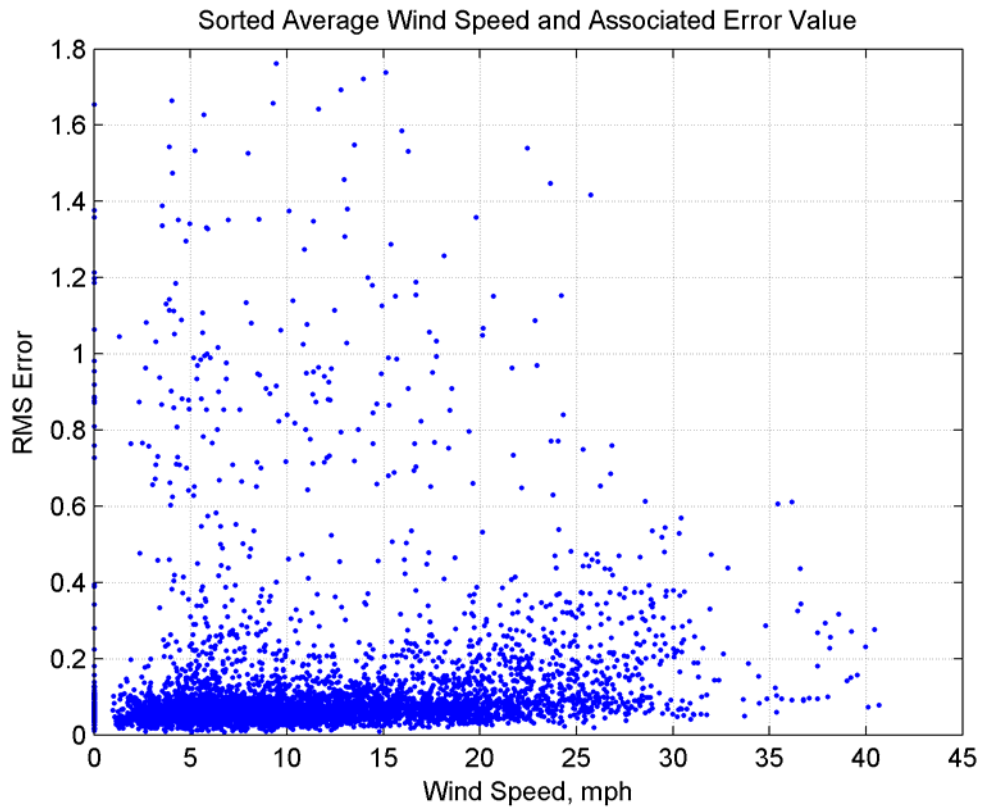
Examination of the data from the *Vaisala 3* sensor showed poor data distributions when compared to that from the *Vaisala 4*, as well as bad data entries (“NaNs”). Many operational issues were encountered with the *Vaisala 3* unit during the 3rd trimester of 2008 (bird and water damage, calibration, lightning, software problems), so its data was discarded in favor of *Vaisala 4*'s output.



The wind speed intensity and wind azimuth values from the Python filter operation is shown above. The *Vaisala 3* sensor has since been repaired, and we await more data from it as a check on the *Vaisala 4* output.

Wind Influence on Tracking

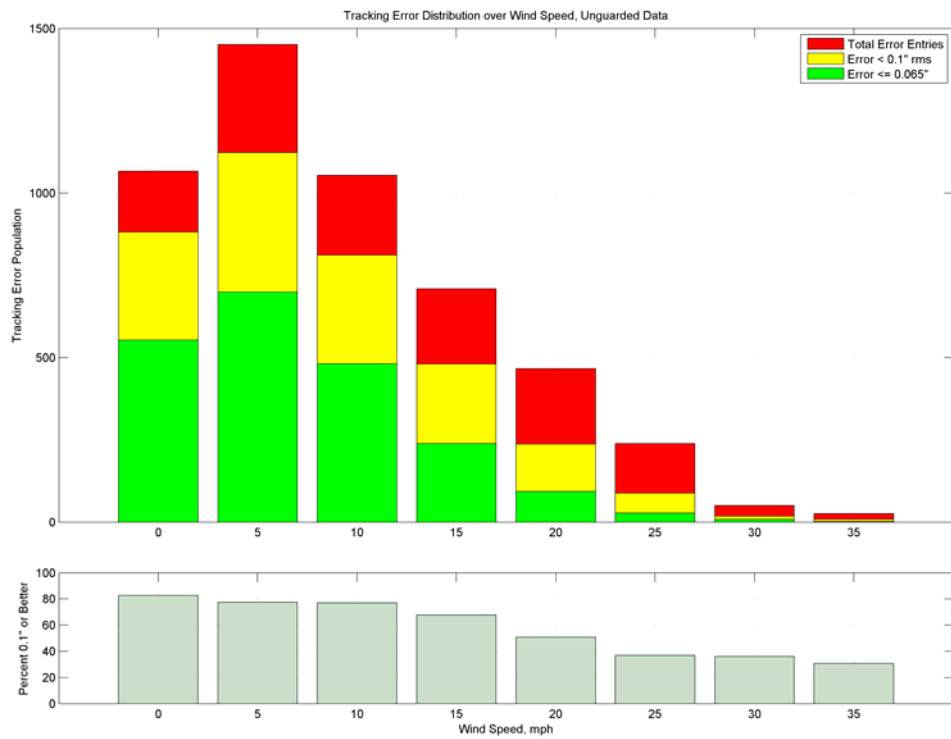
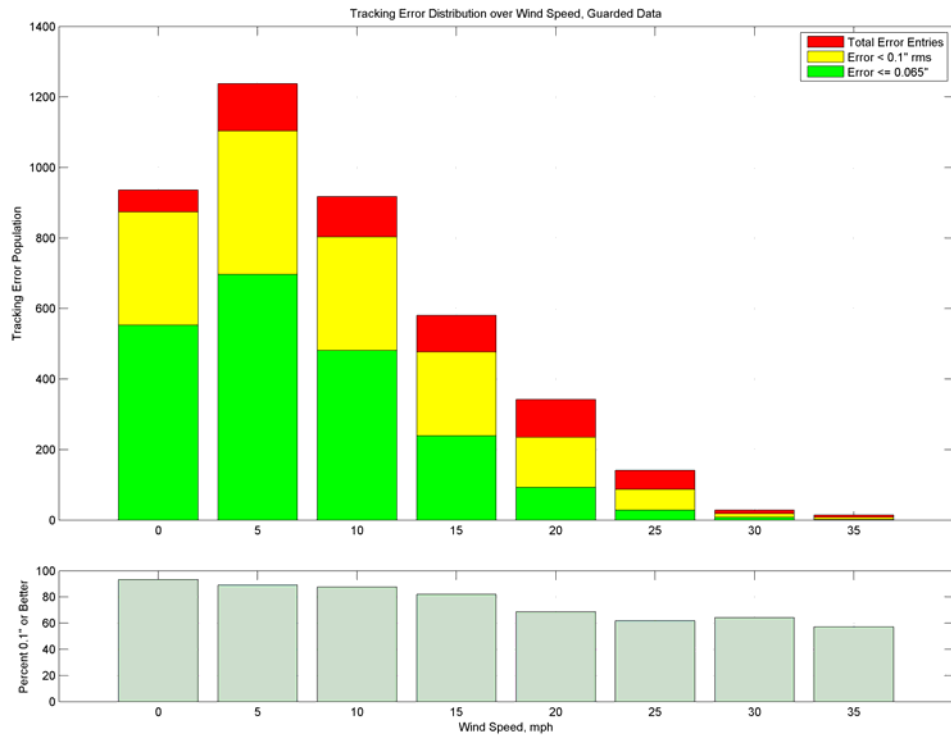
For all the data entries, the average wind speed was sorted in ascending order, and the corresponding RMS error entry for each wind speed value is shown in the plots below:



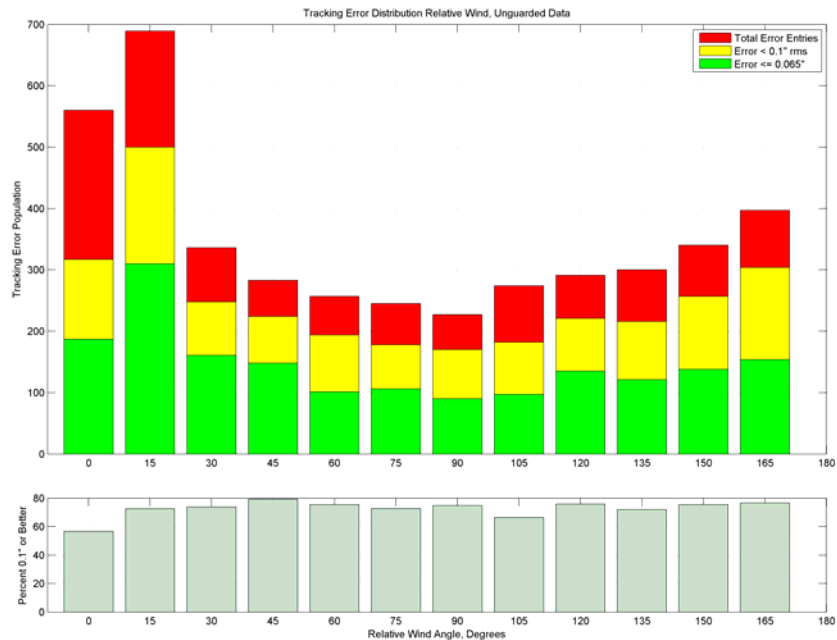
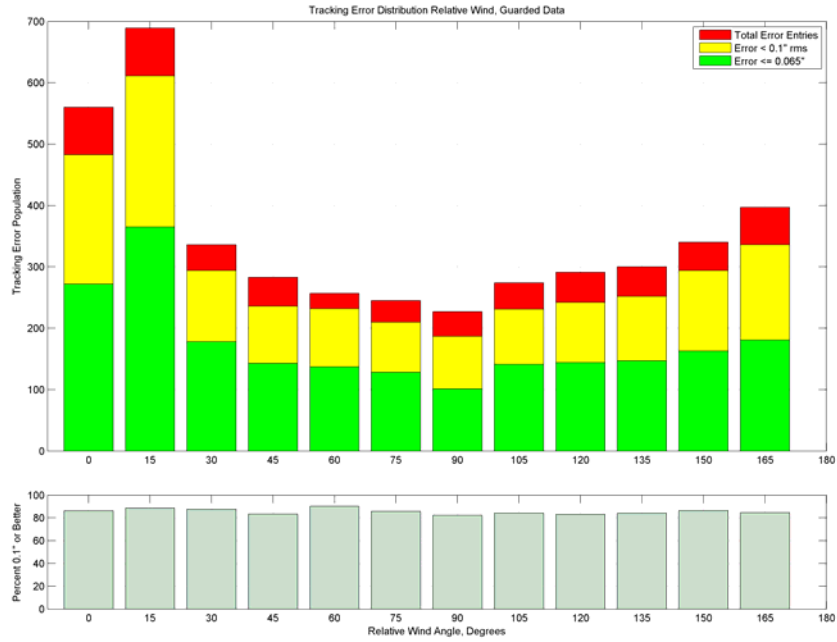
Clearly, a few poor tracking entries exist for all wind speeds in the data, and most of the good tracking is clustered at wind speeds below ~15mph.

Using histograms of the distributions in the data provides a clearer picture. With both the guarded data (again, only entries with a peak-to-peak error of $\leq 1.7''$) and the whole data population, below are the tracking error distributions over wind speed, irrespective of the telescope position.

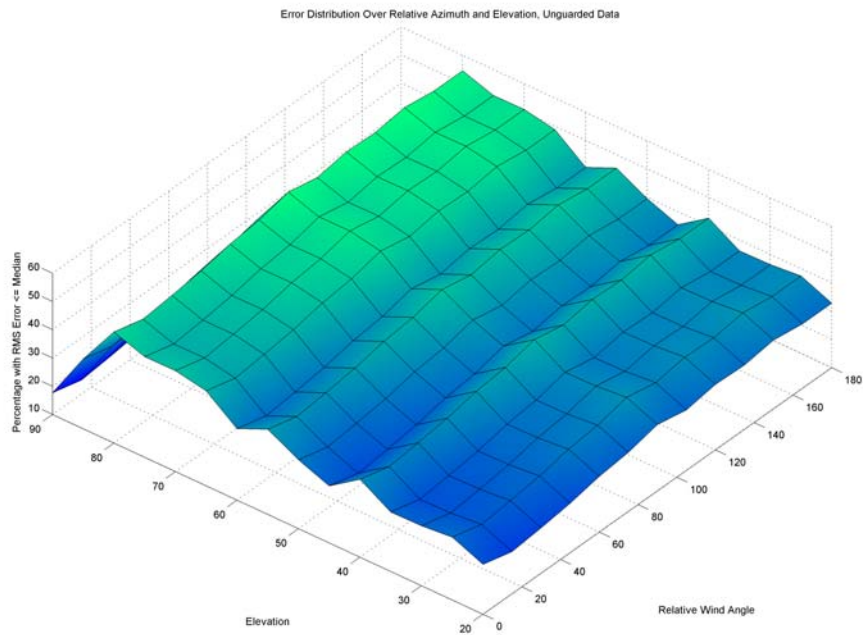
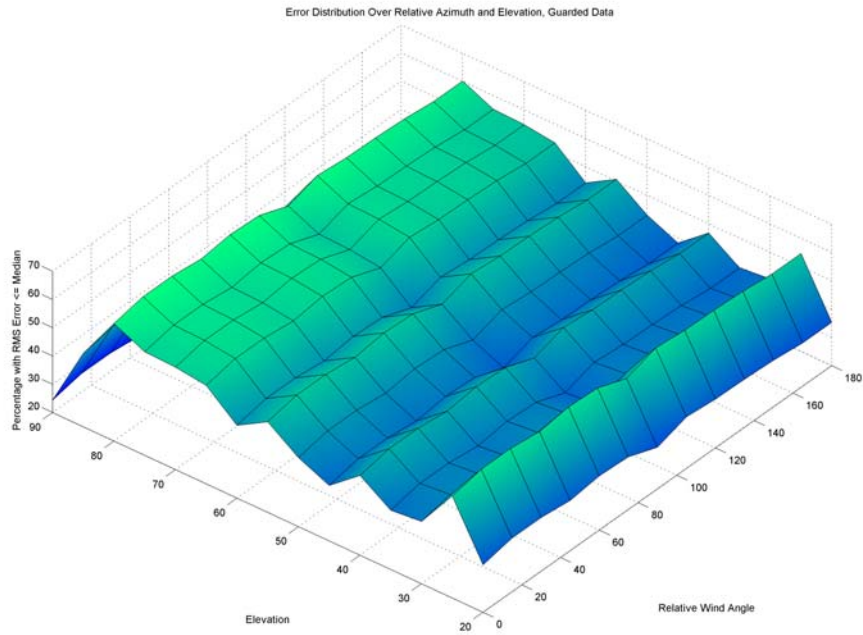
The distribution shape is influenced by the shape of the wind distribution and tracking error populations, but tracking degradation and wind speed as expected are related.



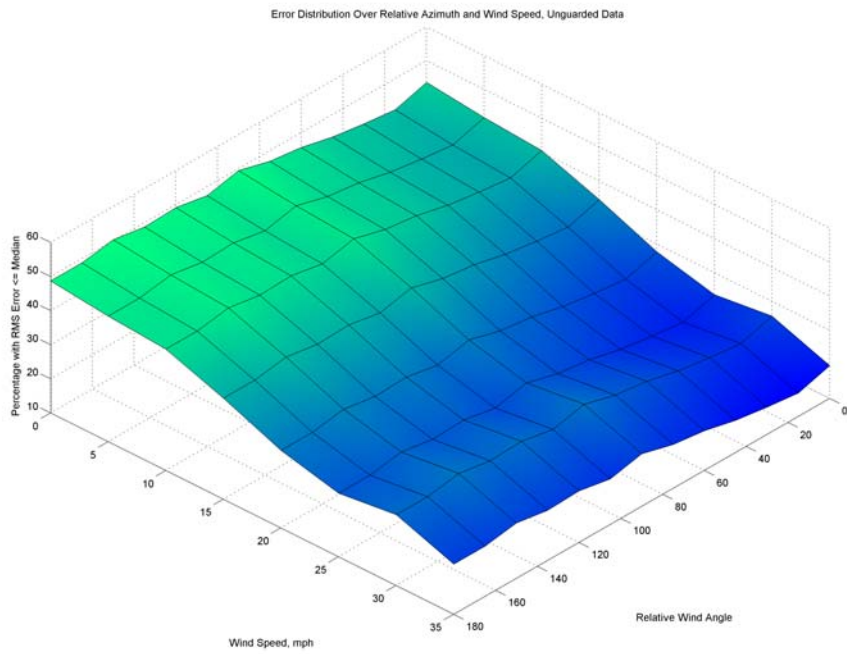
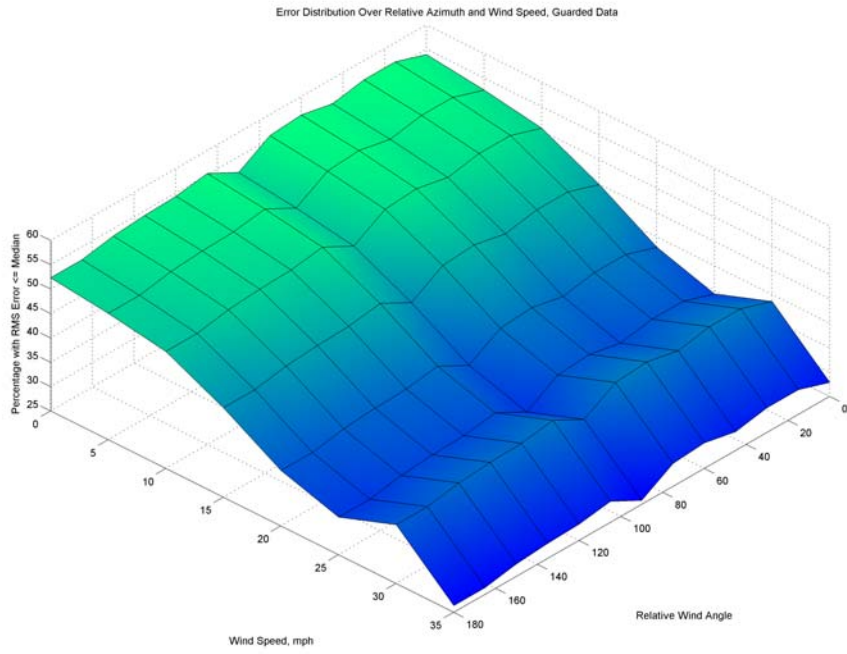
The wind direction and the tracking azimuth were differenced to produce a relative wind angle referred to the telescope azimuth with an absolute domain of 0 to 180°. A relative wind angle of 0° means the telescope is pointing directly into the wind. The resultant distribution of RMS error is shown below, again with both guarded and unguarded data:



For another view, consider the following figures, which join the relative wind azimuth, elevation angle, and RMS error in the range up to the median and below via averaging of the percentages from the wind angle and elevation histograms:



Next, we have these graphs of the relative wind angle and intensity, with the same averaged RMS error in the z-axis, for both guarded and unguarded data:



Conclusion

The MMT elevation tracking for the 3rd trimester of 2008 had a median of 0.065", with a spread of about ± 0.04 ". There is a lower limit to tracking smoothness of about 0.02", or ± 2 encoder counts, with a non-linear dependence on tracking rate. Wind rejection remains an issue, with tracking degradation a (nearly linear) function of the wind speed, regardless of the telescope position. Positions at high elevation angles away from the prevailing wind are more favorable, however. Further study of the reasons for poor tracking in the $\sim 17\%$ of the data population is needed. We plan to regularly repeat this data report.

For the purpose of documenting the data queries and the software used in producing the data and figures in this report, a separate document was produced with this information. Interested readers are directed to the URL:

www.mmt.org/~dclark/Reports/EI_Tracking2008_appendices.pdf.