Postprint: Modeling of Pointing and Tracking Errors at the Coude Focal Plane of Alt-azimuth Solar Telescopes

Authors: Liu Ronghui, Liu Hui, Mu Hengyu, Liu Guangqian

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Abstract

To improve the pointing and tracking accuracy at the Coude focus of alt-azimuth solar telescopes, this paper first simulates the tracking errors introduced at the Coude focus due to misalignment among the principal optical axis, azimuth axis, altitude axis, and derotator axis in the Coude optical path, and analyzes the complexity of pointing and tracking errors at the Coude focus—a problem that cannot be solved by the pointing model for the Cassegrain focus of night astronomical telescopes. The paper then proposes a Support Vector Regression method based on machine learning to construct a pointing and tracking model for the Coude focus of solar telescopes, and conducts actual measurement modeling and experimental verification on the NVST telescope. Experimental results show that before model correction, the maximum pointing error of NVST at the Coude focus is 650.55 arcseconds, the RMS is 115.88 arcseconds, and the 30-minute tracking error is 6.46 arcseconds; after model correction, the maximum pointing error is 25.02 arcseconds, the RMS is 3.98 arcseconds, and the 30-minute tracking error is 1.10 arcseconds. This demonstrates that the Support Vector Regression modeling method based on machine learning can effectively improve the pointing and tracking accuracy at the Coude focus of alt-azimuth solar telescopes.

Full Text

Preamble

Study on Pointing and Tracking Error Modeling for the Coude Focal Plane of Altazimuth Solar Telescopes

Liu Ronghui[1,2], Liu Hui[1], Mu Hengyu[1], Liu Guangqian[1]
[1]Yunnan Astronomical Observatory, Chinese Academy of Sciences, Kunming,

Yunnan 650011, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: To improve the pointing and tracking accuracy of the coude focal plane in altazimuth solar telescopes, this paper first simulates the tracking errors introduced at the coude focal plane when the principal optical axis, azimuth axis, altitude axis, and derotation axis are non-concentric. The analysis reveals the complexity of coude focal plane pointing and tracking errors, which cannot be resolved by conventional night telescope Cassegrain focus pointing models. Subsequently, the paper proposes a machine learning-based support vector regression method to construct a pointing and tracking model for solar telescope coude focal planes, and conducts experimental validation on the NVST telescope. Experimental results demonstrate that before model correction, the NVST's coude focal plane pointing error reached a maximum of 650.55 arcseconds with an RMS of 115.88 arcseconds, and the 30-minute tracking error was 6.46 arcseconds. After model correction, the maximum pointing error reduced to 25.02 arcseconds with an RMS of 3.98 arcseconds, and the 30-minute tracking error decreased to 1.10 arcseconds. These results confirm that the support vector regression modeling approach based on machine learning can effectively enhance the pointing and tracking accuracy of altazimuth solar telescope coude focal planes.

Keywords: Pointing and tracking accuracy; Pointing model; Altazimuth solar telescope; Coude focal plane; Support vector regression

0 Introduction

Large-aperture altazimuth solar telescopes represent a key development direction for ground-based solar observation instruments today. To achieve high temporal and spatial resolution observations of the Sun, these telescopes demand exceptionally high pointing and tracking accuracy. Pointing accuracy refers to the precision with which the telescope's optical axis aligns with the observation target, while tracking accuracy refers to the precision of maintaining that alignment during prolonged observations. High-precision pointing and tracking enable solar telescopes to accurately target specific small-scale features on the solar disk and maintain their stability in the field of view for extended periods, facilitating high-precision long-duration imaging or spectroscopic observations. For instance, the 1-meter New Vacuum Solar Telescope (NVST) at Yunnan Astronomical Observatory requires a pointing accuracy of 5 arcseconds, the Accurate Infrared Magnetic field measurements of the Sun (AIMS) system at the National Astronomical Observatories requires 10 arcseconds, and the Daniel K. Inouye Solar Telescope (DKIST) in the United States requires 5 arcseconds. All these telescopes demand closed-loop tracking accuracy of 1–2 arcseconds over 30 minutes.

Solar telescope instrumentation is distinctive, requiring extremely high system stability, with scientific instruments typically fixed at the coude focal plane rather than rotating with the telescope as in night astronomical telescopes at Cassegrain focus. Consequently, solar telescope primary and secondary mirror systems require complex folded optical paths that direct the principal optical axis through the altitude axis, azimuth axis, and derotation axis, ultimately extending to a stationary coude focus. Figure 1(a) illustrates the RC system of the Lijiang 2.4m telescope, where the terminal instrument operates at the Cassegrain focus with a relatively simple optical path. In contrast, Figure 1(b) shows the NVST solar telescope at Fuxian Lake, where the Gregorian optical system's Gregorian focus (Cassegrain focus) requires a complex folded optical path to reach the coude focal plane.

During pointing and tracking operations of altazimuth solar telescopes, the folded optical system must rotate with the telescope's altitude axis, azimuth axis, and derotation axis. Using NVST as an example, mirrors M1, M2, M3, M4, M5, M6, and M7 move synchronously with the telescope's azimuth; M1, M2, and M4 remain relatively fixed but move with the altitude axis; finally, to counteract image rotation, the optical path must also rotate with the derotation axis. Due to inevitable manufacturing and alignment errors, the telescope's principal optical axis, altitude axis, azimuth axis, and derotation axis cannot be perfectly concentric. This misalignment causes complex motion at the coude focal plane even when the image at the Gregorian focus remains stationary, resulting in secondary tracking errors that pose a significant challenge for high-precision pointing and tracking at the coude focal plane of altazimuth solar telescopes. For the off-axis Gregorian AIMS solar telescope, the image motion at the coude focal plane becomes even more complex.

Pointing models are control strategies used to improve telescope pointing and closed-loop tracking accuracy. The process involves pre-establishing a model by uniformly and densely collecting pointing errors across the entire sky for stars with known positions, then using the model to predict and correct errors in real-time during observations. Pointing models for night astronomical telescopes are well-developed, with TPOINT and STARCAL being the most widely used. However, applying these models to altazimuth solar telescope coude focal planes fails to achieve satisfactory pointing and tracking accuracy. The reason is that these models are built upon physical mechanisms specific to Cassegrain focus, such as errors describing azimuth axis non-verticality, altitude axis non-horizontalism, and primary-secondary mirror axis misalignment. They lack terms to describe errors in the coude optical path beyond Cassegrain focus, particularly those related to the non-concentricity of rotating axes, which depend heavily on the coaxiality of the principal optical axis, altitude axis, azimuth axis, and derotation axis, and are closely associated with the axis alignment errors unique to each solar telescope. Accurate measurement of these axes' rotation centers at the coude focal plane is required to establish corresponding error terms in the model.

1 Coude Focal Plane Tracking Error Simulation Analysis

The complex secondary tracking errors at the coude focal plane of altazimuth solar telescopes arise from the non-concentricity of the principal optical axis, altitude axis, azimuth axis, and derotation axis. During telescope tracking, the image at the coude focal plane rotates, and to eliminate this rotation, the derotation system must rotate in the opposite direction. The image rotation at the coude focal plane of altazimuth solar telescopes consists of three components: rotation about the principal optical axis of the primary-secondary mirror system (caused by coordinate transformation between equatorial and horizontal systems), rotation about the altitude axis, and rotation about the azimuth axis (resulting from the telescope's tracking motion, which requires the coude optical path to rotate about the altitude and azimuth axes). According to reference [5], these three rotation angles can be described by equation (1):

$$\theta_E = \arcsin\left(\frac{\sin\phi\sin\delta}{\cos\delta}\right) \tag{1}$$

$$\theta_H = \arcsin\left(\frac{\sin\phi\sin A}{\cos a}\right) + \arcsin\left(\frac{\sin\phi\sin a}{\cos a}\right) \tag{2}$$

$$\theta_A = \arcsin\left(\frac{\sin\phi\sin\delta}{\cos\delta}\right) - \arcsin\left(\frac{\sin\phi\sin a}{\cos a}\right) \tag{3}$$

where θ_E is the object field rotation angle generated by horizontal coordinates, H is the altitude angle, A is the azimuth angle (both H and A are image field rotation angle components here), ϕ is the geographic latitude, δ is the target declination, and a is the hour angle.

Since the positions and relationships of these three rotation centers at the coude focal plane are determined by the specific manufacturing and alignment errors of each telescope, and except for the derotation axis center which can be conveniently measured, the optical axis cannot be practically measured, while the altitude and azimuth axes are also difficult to measure. To analyze the complex tracking errors at the coude focal plane of altazimuth solar telescopes, we reference the alignment tolerances for mirrors in coude optical paths [6] and assume positions for these three rotation centers on the CCD, as shown in Figure 2(a). Each pixel corresponds to 0.3 arcseconds. Using NVST as an example, we analyze the secondary tracking errors introduced at the coude focal plane during the half-hour period around solar transit on the summer solstice.

As shown by the trajectory comparison before and after derotation in Figure 2(a), although the derotation system eliminates image rotation at the coude focal plane, the image cannot return to its original position due to the different centers of the rotation axes, resulting in additional image motion—this is the secondary tracking error. Figure 2(b) selects a 30-minute period around solar transit on the summer solstice to analyze pointing and tracking errors, revealing a maximum error of 8.90 arcseconds. With larger optical and mechanical alignment errors, the rotation centers of each axis would be more dispersed at the coude focal plane, and the tracking errors would be even greater.

The simulation analysis demonstrates that secondary tracking errors at the coude focal plane of altazimuth solar telescopes are extremely complex. To model them physically, accurate measurement of the specific positions of the optical axis, azimuth axis, altitude axis, and derotation axis at the coude focal plane is necessary—an extremely difficult task. To address this challenge, this paper develops a machine learning-based empirical modeling approach.

2 Machine Learning Based Coude Focal Plane Pointing and Tracking Error Modeling

2.1 Overview

Machine learning can generate pointing and tracking error models through algorithmic induction and abstraction of measured pointing error data without requiring a priori physical models. During coude focal plane error measurement, the control system records the horizontal coordinates of the target star (A_S, E_S) and the telescope's horizontal coordinates (A_T, E_T) when the star is centered on the focal plane detector (CCD). Ideally, A_S would equal A_T and E_S would equal E_T, but pointing errors cause discrepancies. A_T is a function $f_A(A_S, E_S)$ and E_T is a function $f_E(A_S, E_S)$, representing two error surface fitting problems—this constitutes a typical regression problem.

Common regression algorithms in machine learning include Support Vector Regression (SVR), logistic regression, generalized local linear models, and polynomial regression [7]. Most regression algorithms require large training datasets, necessitating extensive measured pointing errors that are impractical to obtain observationally. Therefore, this paper employs SVR, which handles small sample sizes effectively and offers strong generalization capability [8].

2.2 Principles of Support Vector Regression

Following the methodology in references [8-9], SVR can be summarized as: First, the sample set is defined as $S = \{(x_i, y_i)\}_{i=1}^{n}$, where $x_i \in \mathbb{R}^n$ is the input vector and $y_i \in \mathbb{R}^n$ is the corresponding output vector. This algorithm uses nonlinear mapping to transform samples from low-dimensional space to high-dimensional space for fitting. The mapping can be defined as [9]:

$$f(x) = \omega^T \phi(x) + b$$

where x is the input data, $\phi(x)$ is the nonlinear mapping function, ω is the weight vector, and b is the bias term. According to structural risk minimization principles, $f(x)$ can be equivalently expressed as solving the optimization problem [9]:

$$\min_{\omega,b,\xi,\xi^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n} L(f(x_i), y_i)$$

where L is the loss function and C is the penalty factor. Introducing slack variables $\{\xi_i\}_{i=1}^n$ and $\{\xi_i^*\}_{i=1}^n$ to account for irregularities yields [9]:

$$\min_{\omega,b,\xi,\xi^*} \quad \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{4}$$

$$\text{s.t.} \quad y_i - \omega^T\phi(x_i) - b \le \varepsilon + \xi_i \tag{5}$$

$$\omega^T\phi(x_i) + b - y_i \le \varepsilon + \xi_i^* \tag{6}$$

$$\xi_i, \xi_i^* \ge 0 \tag{7}$$

where ε is the insensitive loss factor (maximum allowed error), with $\varepsilon > 0$. Converting this regression problem to minimize the objective function and applying duality theory with Lagrange multipliers transforms it to [9]:

$$\max_{\alpha,\alpha^*} \quad -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) - \varepsilon\sum_{i=1}^{n}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{n} y_i(\alpha_i - \alpha_i^*) \tag{8}$$

$$\text{s.t.} \quad \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \tag{9}$$

$$0 \le \alpha_i, \alpha_i^* \le C \tag{10}$$

where α_i and α_i^* are Lagrange multipliers. Applying Mercer's theorem, the expression can be transformed to [9]:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x) + b$$

where $K(x_i, x) = \phi(x_i)^T\phi(x_j)$ is the kernel function, with $0 \le \alpha_i, \alpha_i^* \le C$. Considering the error distribution in measured data and practical model application, this paper selects a polynomial kernel function defined as:

$$K_{\text{poly}}(x_i, x) = (x_i \cdot x + 1)^d$$

where d represents the polynomial order. Larger d yields more complex polynomials but increases computational load. In the actual pointing error modeling process, the independent variables can be expressed as $x = (A, E)$. The penalty factor C in equation (4) represents a trade-off between model complexity and error precision—larger C reduces generalization capability while smaller C increases training error. The parameter ε determines the discrimination degree between samples. Both parameters directly govern SVR accuracy. Since pointing errors are relatively simple functions of altitude and azimuth values, and based on actual model training results, C is set to 500 and ε to 0.01.

3.1 Pointing Error Measurement

During pointing error measurement, data was recorded using the format shown in Table 1. The measurement process for A_T and E_T involves: inputting a bright star's theoretical horizontal coordinates (A_S, E_S) into the telescope control system, commanding the telescope to point at and track the star, acquiring the star image in real-time via the coude focal plane CCD, and determining its centroid. Ideally, the centroid should be at the CCD center (defined as the field center), but system errors cause offsets. The telescope is then 微调 (fine-adjusted) until the centroid aligns with the CCD center, at which point the telescope's coordinates (A_T, E_T) are recorded. The differences between (A_T, E_T) and (A_S, E_S) constitute the star's pointing errors.

Table 1: Measured Error Data Format

The azimuth A_S ranges from 0–360 degrees, with 0 degrees defined as true north and increasing clockwise. The elevation E_S ranges from 0–90 degrees, with $E_S = 90$ degrees when the telescope points at the zenith.

Measurements were conducted on the NVST telescope using the TiO channel with a CCD pixel scale of 0.04 arcseconds per pixel. Due to NVST's operational constraints, measurements were limited to a portion of the sky. Observations were performed on the night of January 14, 2021, yielding pointing errors for 138 stars. Figure 3 shows the distribution of measured pointing errors, with a maximum error of 650.55 arcseconds and an RMS of 115.88 arcseconds. The model evaluation metric employs RMS (Root Mean Square), where smaller RMS values indicate better prediction performance. In the horizontal coordinate system, the RMS is calculated as:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(\Delta A_i \cos E_i)^2 + (\Delta E_i)^2]}$$

where $\Delta A_i = A_{S,i} - A_{T,i}$ and $\Delta E_i = E_{S,i} - E_{T,i}$.

Figure 3: Distribution of measured data errors

3.2 Model Establishment

To generate multiple distinct training and test sets and assess the sensitivity of the modeling method to data partitioning, the 138-star error dataset was divided into six subsets using stratified sampling to ensure uniform sky distribution. After division, each subset contained 23 stars' pointing error data, labeled train000 through train005. In the first modeling iteration, train000–train004 were combined as the training set (115 data points) with train005 as the test set (23 points). In the second iteration, train001–train005 formed the training set with train000 as the test set. This rotation continued until all six subsets served as test sets, enabling comparison of statistical results across iterations.

The prediction error distribution for the test set is shown in Figure 4. Figure 4(a) compares predicted versus actual values, while Figure 4(b) shows the error distribution. The maximum prediction error in the test set is 12.89 arcseconds with an RMS of 2.89 arcseconds, demonstrating good predictive performance.

Figure 4: Test set prediction error distribution (a) Fitting of predicted and actual values; (b) Error distribution between predicted and actual values

Applying the SVR model to predict the training set yields the results shown in Figure 5. The training set prediction RMS is 2.84 arcseconds with a maximum error of 8.92 arcseconds. Comparing training and test set prediction errors reveals minimal difference between them.

Figure 5: Training set prediction error distribution

Subsequent experiments using different training/test set combinations were performed six times, with results summarized in Table 2. The test set RMS values all fall between 3–4 arcseconds, confirming the effectiveness of the SVR-based pointing model.

Table 2: Prediction error statistics for different test sets (unit: arcsec)

Test Set	RMS Error	Maximum Error
train000	3.12	11.45
train001	2.89	12.89
train002	3.45	13.21
train003	3.67	14.02
train004	3.23	12.34
train005	3.01	11.87

3.3 Actual Measurement Results

To validate the model's performance during actual telescope operations, the model was integrated into the control system and tested on NVST for both pointing and tracking errors.

Pointing error measurement: Using 138 stars distributed across the sky as shown in Figure 6(a), the post-model-correction measured errors are displayed in Figure 6(b). The maximum error is 25.02 arcseconds with an RMS of 3.98 arcseconds.

Figure 6: Pointing accuracy measurement results (a) Distribution of 138 stars across the sky; (b) Distribution of measured errors

Tracking error measurement: On the night of January 22, 2022, a long-duration tracking observation of a single star was conducted on NVST, with 30-minute tracking sessions performed both with and without model correction. Results are shown in Figure 7. Figure 7(a) illustrates the star image trajectories on the detector (dots represent model-corrected trajectory, squares represent uncorrected), while Figure 7(b) shows the 30-minute tracking error statistics. The tracking error was 6.46 arcseconds before correction and 1.10 arcseconds after correction.

Figure 7: Measured tracking error results (a) Star image trajectory; (b) Tracking error statistics

Conclusion

The coaxiality of the principal optical axis, altitude axis, azimuth axis, and derotation axis represents a primary factor affecting coude focal plane tracking errors in altazimuth solar telescopes. Since measuring the precise positions of these axes at the coude focal plane is extremely difficult, conventional TPOINT software used for night telescopes cannot model such errors. To improve coude focal plane pointing and tracking accuracy, this paper proposes a novel method using support vector regression to construct a coude focal plane pointing and tracking model, with experimental validation on NVST. The results demonstrate effective correction of coude focal plane pointing and tracking errors. Before model correction, NVST's coude focal plane pointing error RMS was 115.88 arcseconds with a 30-minute tracking error of 6.46 arcseconds. After correction, the pointing error RMS reduced to 3.98 arcseconds with a 30-minute tracking error of 1.10 arcseconds. These findings confirm that the machine learning-based support vector regression modeling approach can significantly improve the pointing and tracking accuracy of altazimuth solar telescope coude focal planes.

References

[1] Liu Z, Deng Y Y, Yang D H, et al. Chinese Giant Solar Telescope (in Chinese). Sci Sin-Phys Mech Astron, 2019, 49: 059604.
[2] Wang X, Pan J H. Optic System Design of a 2.4 m Class Telescope and Several Methods for Testing the Secondary Mirror[J]. Publications of Yunnan Observatory, 2002(02):41-49.
[3] Liu Z, Xu J, Gu B Z, et al. New Vacuum Solar Telescope and Observations with High Resolution[J]. Research in Astronomy and Astrophysics, 2014(6):705-718.

[4] Chen Y C, Liu G Q. The Error Analysis and Correction of NVST's Long-Term Tracking. Astronomical Research and Technology, 2016, 13(2):8.
[5] Liu G Q, Fu Y, Cheng X M. Image-Field Rotation and Control of Counter Rotation for the Spectrograph of the 1m Solar Telescope of the Yunnan Observatory. Astronomical Research and Technology, 2012, 9(1):7.
[6] Zhang L M, Ming M, Yang F, et al. Design for Coude Optic-mechanical Structure of Large Aperture Telescope[J]. Opto-Electronic Engineering, 2011, 38(5):5.
[7] Liu H, Ji K F, Jin Z Y. The application of machine learning in solar physics[J]. SCIENTIA SINICA: Physica, Mechanica & Astronomica, 2019, v.49(10):105-117.
[8] Cortes C, Vapnik V. Support-vector networks[J]. Machine Learning, 1995, 20(3): 273-297.
[9] Xu J N, Ni Y L, Zhu C B. Remaining Useful Life Prediction for Lithium-Ion Batteries Based on Improved Support Vector Regression[J]. Transaction of China Electrotechnical Society, 1995, 20(3): 273.

Note: Figure translations are in progress. See original paper for figures.