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

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Abstract

To improve the pointing and tracking accuracy of the Coude focus of alt-azimuth solar telescopes, this paper first simulates the tracking errors introduced at the Coude focus by misalignments of the principal optical axis, azimuth axis, altitude axis, and derotator axis in the Coude optical path, and analyzes the complexity of these pointing and tracking errors—a problem that cannot be resolved by the pointing model of the Cassegrain focus of night astronomical telescopes. This 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 empirical 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 value is 3.98 arcseconds, and the 30-minute tracking error is 1.10 arcseconds. These results demonstrate that the Support Vector Regression modeling method based on machine learning can effectively improve the pointing and tracking accuracy of the Coude focus of alt-azimuth solar telescopes.

Full Text

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

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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 main optical axis, azimuth axis, altitude axis, and derotation axis are non-concentric in the coude optical path. The analysis reveals that the pointing and tracking errors of the coude focal plane are highly complex and cannot be resolved by conventional pointing models designed for night astronomical telescopes at the coudé focus. Subsequently, the paper proposes a support vector regression method based on machine learning to construct a pointing and tracking model for solar telescope coude focal planes, and conducts experimental validation using the NVST telescope. Experimental results demonstrate that before model correction, the NVST' s pointing error at the coude focal plane 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, the RMS value decreased to 3.98 arcseconds, and the 30-minute tracking error improved 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 the coude focal plane in altazimuth solar telescopes.

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 major development direction for ground-based solar observation instruments today. To achieve high temporal and spatial resolution observations of the Sun, these telescopes demand extremely 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 surface and keep them stable 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 Ken Inouye Solar Telescope (DKIST) in the United States requires 5 arcseconds. All these telescopes demand open-loop tracking accuracy of 1-2 arcseconds within 30 minutes.

Solar telescopes feature unique scientific instrumentation with stringent stability requirements. Unlike night astronomical telescopes that mount instruments at the coudé focus and rotate with the telescope, solar telescopes typically have their instruments fixed at the coude focal plane. Consequently, the primary and secondary mirror systems in solar telescopes require complex relay optics to guide the main optical axis through the altitude axis, azimuth axis, and derotation axis, ultimately reaching the stationary coude focal point. Figure 1(a) shows the RC system of the Lijiang 2.4m telescope, where the terminal instrument operates at the coudé focus with a relatively simple optical path. In contrast, Figure 1(b) illustrates the NVST solar telescope at Fuxian Lake, where the Gregorian optical system employs a complex relay path from the Gregorian focus (coudé focus) to the coude focal plane.

During pointing and tracking operations of altazimuth solar telescopes, the relay optical system must move synchronously 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 with the telescope' s azimuth; M1, M2, and M4 have fixed relative positions but move with the altitude axis; and finally, to eliminate image rotation, the optical path must also rotate with the derotation axis. Due to inevitable manufacturing and alignment errors, the telescope' s main optical axis, altitude axis, azimuth axis, and derotation axis cannot be perfectly aligned. This misalignment causes complex motion of the image at the coude focal plane even when the image at the Gregorian focus remains stationary—a phenomenon known as secondary tracking error at the coude focal plane, which poses a significant challenge for achieving high-precision pointing and tracking. For the AIMS solar telescope with its off-axis Gregorian system, the image motion at the coude focal plane becomes even more complex.

Pointing models serve as a control strategy to improve telescope pointing accuracy and open-loop tracking precision. The process involves collecting pointing errors from stars with known positions across the entire sky to build a model that can predict and correct errors in real time. While pointing models for night astronomical telescopes are well-established, with TPOINT and STARCAL being widely used, these models fail to achieve satisfactory pointing and open-loop tracking accuracy when applied to the coude focal plane of altazimuth solar telescopes. The fundamental reason is that these models are based on physical mechanisms applicable to the coudé focus, such as errors from non-perpendicular azimuth axes, non-horizontal altitude axes, and flexure of the primary-secondary optical axis. However, they lack terms to describe errors in the coude optical path beyond the coudé focus, particularly those related to the non-concentricity of rotation axes. These error terms depend heavily on the alignment accuracy between the main optical axis, altitude axis, azimuth axis, and derotation axis, and are closely associated with each solar telescope' s specific axis alignment errors. Accurate measurement of these axes' rotation centers at the coude focal plane would be required to incorporate such error terms into conventional models.

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 inevitable non-concentricity of the main optical axis, altitude axis, azimuth axis, and derotation axis. During telescope tracking, the image at the coude focal plane rotates, and to compensate, the derotation system must rotate in the opposite direction. For altazimuth solar telescopes, this image rotation comprises three components: rotation about the primary-secondary optical axis (resulting from the transformation between equatorial and horizontal coordinate systems), rotation about the altitude axis, and rotation about the azimuth axis (both caused by the telescope' s tracking motion). According to reference [5], these three rotation angles can be expressed by equation (1):

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

$$\theta_H = \theta_A + \theta_E \tag{2}$$

$$\theta_A = \arcsin\left(\frac{\sin\phi\sin H}{\cos\theta}\right) \tag{3}$$

where θ_E represents the object field rotation angle generated by the horizontal coordinate system, θ is the altitude angle, A is the azimuth angle, θ_H and θ_A are image field rotation angle components, ϕ is the geographic latitude, δ is the target declination, and H is the hour angle.

The positions and relationships of these three rotation centers at the coude focal plane are determined by each telescope' s specific optical and mechanical manufacturing and alignment errors. While the derotation axis center can be conveniently measured, the optical axis cannot be directly measured, and the altitude and azimuth axes are similarly difficult to quantify. To analyze these complex tracking errors, we referenced the alignment tolerances for mirrors in the coude optical path [6] and assumed positions for these three rotation centers on the CCD, as shown in Figure 2(a), where one pixel corresponds to 0.3 arcseconds. Using NVST as an example, we analyzed the secondary tracking errors introduced at the coude focal plane during the half-hour period around solar transit on the summer solstice.

As demonstrated 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 fails to 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) presents the pointing and tracking error analysis for a 30-minute period around solar noon on the summer solstice, showing 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, leading to even greater tracking errors.

The simulation analysis demonstrates that secondary tracking errors at the coude focal plane of altazimuth solar telescopes are extremely complex. Physically modeling these errors would require precise measurement of the optical axis, azimuth axis, altitude axis, and derotation axis positions at the coude focal plane—a formidable task. To address this challenge, we have developed a measurement-based modeling approach using machine learning.

2 Machine Learning-Based Modeling for Coude Focal Plane Pointing and Tracking Errors

2.1 Overview

Machine learning can generate pointing and tracking error models through algorithms that generalize from measured error data, even when the underlying physical model is unknown. These models predict the required telescope azimuth and altitude coordinates in real time to achieve high-precision pointing and tracking. During measurement of coude focal plane pointing errors, the control system records both the theoretical horizontal coordinates (A_S, E_S) of the target star and the actual telescope coordinates (A_T, E_T) when the star is centered on the focal plane detector (CCD). In an ideal system, A_S would equal A_T and E_S would equal E_T, but pointing errors prevent this equality. In practice, 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 that constitute a classic regression task.

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, which would necessitate extensive measurements and make practical implementation difficult. Therefore, this paper employs SVR, which handles small sample sizes effectively and exhibits strong generalization capability [8].

2.2 Principles of Support Vector Regression

Following the methodology described in references [8-9], SVR can be summarized as follows: First, given a sample set $S = \{(x_i, y_i)\}_{i=1}^{n}$ where x_i is the input vector and y_i is the corresponding output vector, the algorithm employs a nonlinear mapping to transform the sample set from low-dimensional space to high-dimensional space for final fitting. This mapping can be defined as $f(x) = \omega \cdot \phi(x) + b$, where x is the input data, ϕ is the nonlinear mapping function, ω is the weight vector, and b is the bias term.

According to the structural risk minimization principle, $f(x)$ can be equivalently obtained by 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]:

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

$$\text{subject to } y_i - \omega \cdot \phi(x_i) - b \leq \varepsilon + \xi_i \tag{5}$$

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

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

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

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

$$\text{subject to } \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \tag{9}$$

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

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

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

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

$$K(x_i, x) = (x_i \cdot x + 1)^d$$

where d represents the polynomial degree. Higher values of d increase complexity and computational load. In the actual pointing error modeling process, the input vector can be expressed as $x = (A, E)$, representing azimuth and altitude coordinates.

In equation (4), the penalty factor C represents a trade-off between model complexity and error precision: larger C values reduce generalization capability, while smaller C values increase training error. The parameter ε indicates the separation degree between samples. Both parameters directly determine SVR accuracy. Since the pointing errors are relatively simple functions of altitude and azimuth values, and based on actual model training results, we set $C = 500$ and $\varepsilon = 0.01$.

3 Experimental Results

3.1 Pointing Error Measurement

During the pointing error measurement process, data were recorded in the format shown in Table 1 . The measurement procedure for A_T and E_T involves: inputting the theoretical horizontal coordinates (A_S, E_S) of a bright star into the telescope control system, commanding the telescope to point to and track the star, acquiring star images in real-time via the coude focal plane CCD, and determining the star' s centroid. Ideally, the centroid should appear at the CCD center (defined as the field center), but system errors cause deviations. The telescope is then 微调 (fine-adjusted) until the centroid aligns with the CCD center, at which point the actual telescope 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 shows the measured error data format. A_S ranges from 0-360 degrees, with 0 degrees at true north and increasing clockwise; E_S ranges from 0-90 degrees, reaching 90 degrees when the telescope points to 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 could only be performed across a limited sky region. Observations were carried out on the night of January 14, 2021, yielding pointing errors for 138 stars. Figure 3 [Figure 3: see original paper] illustrates the distribution of measured pointing errors, showing a maximum error of 650.55 arcseconds and an RMS of 115.88 arcseconds.

The model evaluation metric employs the Root Mean Square (RMS) value, where smaller RMS indicates better prediction performance. In the horizontal coordinate system, the RMS is calculated as:

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

where $\Delta A_i = A_{T_i} - A_{S_i}$ and $\Delta E_i = E_{T_i} - E_{S_i}$.

3.2 Model Establishment

To generate multiple distinct training and test sets and evaluate the sensitivity of the modeling method to data variations, the 138-star error dataset was divided into six samples using stratified sampling to ensure uniform sky distribution.

Each sample contained 23 stars, designated as 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 data points). The second iteration used train001-train005 as the training set with train000 as the test set, and this rotation continued for six total experiments. The statistical results from all six test sets were then compared to assess consistency.

The prediction error distribution for the test sets is shown in Figure 4 [Figure 4: see original paper]. Figure 4(a) demonstrates the close fit between predicted and actual values, while Figure 4(b) reveals that the maximum prediction error in the test set is 12.89 arcseconds with an RMS of 2.89 arcseconds, indicating strong predictive performance.

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

Six experiments using different training and test set combinations produced the results summarized in Table 2 . The test set RMS values consistently range between 3-4 arcseconds, demonstrating the effectiveness of the SVR-based pointing model.

3.3 Field Verification Results

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

Pointing error verification: Using 138 stars distributed across the sky as shown in Figure 6(a) [Figure 6: see original paper], the post-correction measurements shown in Figure 6(b) demonstrate a maximum error of 25.02 arcseconds and an RMS of 3.98 arcseconds.

Tracking error verification: On the night of January 22, 2022, a long-duration tracking observation of a single star was performed on NVST, with 30-minute tracking sessions conducted both with and without the model. The results are presented in Figure 7 [Figure 7: see original paper]. Figure 7(a) shows the star image trajectories on the detector, where dots represent the trajectory with model correction and squares represent the uncorrected trajectory. Figure 7(b) displays the 30-minute tracking error statistics, revealing that the tracking error decreased from 6.46 arcseconds pre-correction to 1.10 arcseconds post-correction.

The concentricity of the main 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 these axes' precise positions at the coude focal plane is extremely difficult, conventional software like TPOINT cannot model such errors. To address this limitation, this paper proposes a novel method using support vector regression to construct a coude focal plane pointing and tracking model, with successful implementation and testing on NVST. The results demonstrate that the new model effectively corrects coude focal plane pointing and tracking errors. Prior to correction, NVST exhibited a pointing error RMS of 115.88 arcseconds and a 30-minute tracking error of 6.46 arcseconds at the coude focal plane. After correction, these values improved to an RMS of 3.98 arcseconds and a tracking error of 1.10 arcseconds. These findings confirm that the machine learning-based support vector regression modeling approach can significantly enhance the pointing and tracking accuracy of the coude focal plane in altazimuth solar telescopes.

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