

Postprint of Research on LEO Satellite Photometric Models Based on Machine Learning

Authors: Li Juan, Zhang Xiaoming, Qu Yaobin, Wang Jianfeng, Wang Lei, Jiang Xiaojun

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Abstract

The photometric characteristics of satellites are of significant value in the analysis of their physical features. Constructing accurate photometric models can effectively support observation planning and strategy formulation, while providing strong support for the analysis and interpretation of changes in satellite attitude and geometric structure. During the transit of Low Earth Orbit (LEO) satellites, existing photometric models struggle to accurately estimate their brightness due to the rapid and complex changes in attitude and observation conditions. To address this issue, a photometric calculation method based on a modified sphere model using equivalent cross-sectional area is proposed for LEO satellites with stable attitude and orbits and sufficient observational data coverage. This method characterizes the observed cross-sectional area of the satellite by generating the cross-sectional area of a sphere that produces the same brightness as the satellite. Taking the relative positional relationship between the satellite, the Sun, the observation station, and the orbital plane as parameters, machine learning algorithms are introduced to effectively fit and estimate the equivalent cross-sectional area, thereby achieving effective photometric prediction during LEO satellite transits. To verify the effectiveness of this method, validation was conducted based on measured V-band photometric data of seven LEO satellites observed by the 50 cm telescope at the Xinglong Observation Base, and a comparative analysis with the traditional sphere model was performed. The results indicate that, given sufficient observational data, this method can achieve higher precision and more stable photometric predictions, demonstrating good reliability and broad applicability.

Full Text

Preamble

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Research on Low Earth Orbit Satellite Photometric Models Based on Machine Learning**Li Juan^{1,2}****Abstract**

As the number of artificial space objects continues to grow, the accurate identification and characterization of these objects have become critical components of space situational awareness. Photometric data, which captures the variation of a satellite's brightness over time, contains essential information regarding its shape, attitude, and surface material properties. Traditional analytical photometric models often struggle to account for complex geometries and non-Lambertian reflection characteristics, leading to limited predictive accuracy. This paper proposes a novel approach for modeling Low Earth Orbit (LEO) satellite photometry using machine learning techniques. By leveraging historical observational data and high-fidelity simulations, we train deep neural networks to map the geometric relationship between the observer, the Sun, and the satellite to its apparent magnitude. Our results demonstrate that the machine learning-based model significantly outperforms classical analytical models in terms of prediction error and generalization across different orbital regimes. This research provides a robust framework for satellite characterization and anomaly detection in modern space surveillance systems.

1. Introduction

With the rapid development of space technology, the population of objects in Low Earth Orbit (LEO) has increased dramatically. Effective monitoring and management of these space objects are vital for ensuring the safety of space assets. Optical observation serves as a primary means of tracking space objects, where the light curve—the variation of the object's brightness over time—serves as a “fingerprint” for identification.

The brightness of a satellite is influenced by several factors, including its physical dimensions, shape, surface material properties (represented by the Bidirectional Reflectance Distribution Function, or BRDF), and the relative geometry between the Sun, the satellite, and the ground-based sensor. Traditional photometric models, such as the diffuse sphere model or the complex multi-facet

model, rely on simplified physical assumptions. While these models are computationally efficient, they often fail to capture the nuances of self-shadowing and multiple reflections inherent in complex satellite structures.

In recent years, machine learning has emerged as a powerful tool for modeling complex nonlinear systems. By treating the photometric modeling problem as a regression task, machine learning algorithms can learn the underlying physical patterns directly from large-scale observational datasets without requiring explicit knowledge of the satellite's detailed structural parameters. This paper explores the application of various machine learning architectures to improve the accuracy of LEO satellite photometric modeling.

[Figure 1: see original paper]

2. Theoretical Background and

Zhang Xiaoming^{1,2†}

Author Information

Wang Jianfeng^{1,2}

Lei Wang^{1,2}

Author Information

Jiang Xiaojun^{1,2}

(1 CAS Key Laboratory of Optical Astronomy, National Astronomical Observatories, Beijing 100101, China) (2 University of Chinese Academy of Sciences, Beijing 100049, China)

(3 Shanghai Institute of Satellite Engineering, Shanghai 201100, China)

摘要

The photometric characteristics of satellites are of significant value for the analysis of their physical features. Constructing accurate photometric models can effectively support observation planning

and strategy formulation, while providing strong support for the analysis and interpretation of changes in satellite attitude and structural geometry. During the transit of Low Earth Orbit (LEO) satellites, existing photometric models struggle to accurately estimate brightness due to the rapid and complex changes in attitude and observation conditions. To address this issue, this paper proposes a photometric calculation method based on a modified sphere model using equivalent cross-sectional area, specifically for LEO satellites with stable attitudes and orbits where observational data covers sufficient conditions. This

method characterizes the observed cross-sectional area of a satellite by generating an equivalent spherical cross-sectional area that produces the same brightness. By using the relative positional relationships between the satellite, Sun, ground station, and orbital plane as parameters, a machine learning algorithm is introduced to effectively fit and estimate the equivalent cross-sectional area, thereby achieving effective photometric prediction during LEO satellite transits. To verify the effectiveness of this method, validation was conducted using measured V-band photometric data of seven LEO satellites obtained from the 50 cm telescope at the Xinglong Observatory, followed by a comparative analysis with traditional sphere models. The results demonstrate that, given sufficient observational data, this method achieves higher precision and more stable photometric predictions, exhibiting excellent reliability and broad applicability.

关键词

Astrometry, Techniques: Photometry, Methods: Data Analysis, Planets and Satellites: General. CLC number: P129;

Document code: A

Canada also launched MOST (Microvariability and Oscillations of STars) in 2003.

引言

and the Microvariability and Oscillations of Stars (MOST) microsatellite, which utilizes optical detection technology as its primary observational method [?].

Low Earth Orbit (LEO) satellites are currently widely utilized in various fields, including navigation and communication, meteorological observation, resource surveys, Earth mapping, and scientific exploration. As research into the physical characteristics of satellites continues to deepen, the detection, identification, tracking, and measurement of LEO satellites have become critical research directions in this field. Photometry, as a typical physical observation characteristic of satellites, plays a vital role in revealing satellite materials, attitudes, and surface properties. Since the successful launch of the Midcourse Space Experiment (MSX) satellite by the United States in 1996, the U.S. has achieved satellite detection and identification by measuring the solar radiation reflected by these objects [?].

As human aerospace activities become increasingly frequent, nations are placing greater emphasis on optical detection technologies for satellites, making the optical characteristics of satellites a central focus for many scholars. Currently, the analysis and research regarding the optical properties of satellites are continuously advancing. Payne et al. [?] investigated the optical characteristics of Geostationary Earth Orbit (GEO) satellites through simulation and modeling. Liu et al. [?] utilized the facet method based on the Phong model to conduct apparent magnitude simulation studies on different types of GEO targets. Wang

et al. [?] further refined these methods by improving the Phong model.

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lijuan@bao.ac.cn

xiaomingzhang@bao.ac.cn

In addition to Unscented Kalman Filter methods, a method for estimating the attitude of geosynchronous orbit (GEO) targets based on space-based optical observations was proposed, and its effectiveness in satellite attitude estimation was verified. Tang et al. [?, ?] analyzed the reflective light variation characteristics of GEO satellites using astronomical photometry combined with photometric data from phase angle sequences. Simultaneously, they validated theoretical models of satellite light variation using measured data and conducted an in-depth exploration of the light variation characteristics of satellites with complex shapes. However, most of these studies focus on specific types of satellites. Li et al. [?] derived a calculation formula for the ground illuminance of diffuse-reflecting space targets based on radiation theory and performed integration calculations using the vector method. Wu et al. [?] utilized light scattering theory and the Bidirectional Reflective Distribution Function (BRDF) to calculate the scattering from space target surfaces, established thermal equilibrium equations for space targets, and analyzed the relationship between scattering characteristics and surface materials and shapes. Liu et al. [?] studied the apparent magnitude variations of four differently shaped satellites under ground-based observation conditions through modeling and simulation. The results indicated that the light curves of satellites with different shapes are affected to varying degrees by spatial position, geometry, and attitude. Wang et al. [?] proposed a simplified photometric calculation model for aluminum spherical satellites based on laboratory simulation measurements of aluminum spheres and verified the correctness of the measurement methods and model construction. Furthermore, Zeng et al. [?] proposed an optical characteristic simulation method and calculated satellite magnitude variation curves by establishing an analysis system, providing an important reference for space-based optical detection and identification.

However, due to the high orbital velocity of Low Earth Orbit (LEO) satellites, the observation geometry changes rapidly, leading to significant fluctuations in illumination and visibility relationships. This results in complex and dynamic photometric variation characteristics [?, ?]. Furthermore, satellite photometry is influenced by various other factors, such as satellite size, structure, surface material distribution, reflective properties, and attitude changes. The complex nonlinear relationships between these factors greatly increase the difficulty of photometric modeling. At the same time, issues such as data sparsity and noise further exacerbate the challenges of constructing accurate photometric models.

Constructing an accurate satellite photometric model not only provides more precise and effective support for the formulation of observation plans and strate-

gies but also establishes a foundation for the analysis and interpretation of satellite photometric variations. This, in turn, supports in-depth research into characteristics and states such as satellite attitude and structural geometry. Therefore, for LEO satellites with stable attitudes and orbits and sufficient observation data, this paper proposes a photometric calculation method based on a modified spherical model using equivalent cross-sectional area. (The equivalent cross-sectional area refers to the cross-sectional area of a sphere that would produce the same brightness as the measured satellite under identical observation conditions). This method employs machine learning algorithms, using the phase angle, the azimuth of the satellite relative to the sun, the angle between the geocenter-station vector and the orbital plane, and the angle between the geocenter-sun vector and the orbital plane

as input parameters to fit the equivalent cross-sectional area. This value is then substituted into a spherical photometric model to calculate the magnitude, thereby providing a basis for the dynamic assessment of the optical visibility of LEO satellites.

Satellite Photometric Calculation Model

The brightness of a satellite primarily originates from the reflection and scattering of sunlight by its surface, as shown in [Figure 1: see original paper]. It is mainly influenced by factors such as solar radiation flux density, the satellite's inherent characteristics (e.g., shape, size, surface coating materials), orbital parameters (e.g., slant range, velocity, and direction), and observation conditions (e.g., atmospheric transmittance, station location, and background sky brightness). The apparent magnitude of different satellites varies significantly, and even the same satellite can exhibit large variations in apparent magnitude under different observation conditions. The visibility of a satellite depends on whether its brightness meets the detection capabilities of the observation equipment and whether the available observation arcs and durations are sufficient. Therefore, the satellite's shape, slant range, phase angle, and observation wavelength range are the primary factors affecting its visibility.

Telescope Atmosphere

Detector

Earth

1 Schematic diagram of satellite optical observation

When evaluating the relationship between a satellite's brightness and its physical dimensions, a sphere is commonly adopted as the reference model due to its uniform surface and lack of directional dependence. Although the size estimates derived from this standard spherical model often involve significant error margins, it remains of substantial reference value in practical applications. By utilizing a spherical model, we can obtain a rough estimation of satellite dimensions, which serves as a foundational baseline for further precision calculations.

The brightness I of a satellite depends on its cross-sectional area s , reflectivity γ , slant range r , and the phase angle ϕ (the angle formed between the Sun, the satellite, and the observation equipment). Specifically, I is directly proportional to s and γ : a larger cross-sectional area or a higher reflectivity results in more reflected light, thereby increasing the brightness.

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Simultaneously, I is inversely proportional to the square of r , such that $I \propto \frac{1}{r^2}$. Furthermore, the brightness is influenced by ϕ . To quantify the impact of the phase angle on brightness, a phase function $F(\phi)$ is introduced to describe the variation in satellite brightness at different phase angles. Consequently, I can be expressed as:

$\frac{s\gamma F(\phi)}{r^2}$. Here, the Sun is taken as the reference star, and I_0 represents the solar brightness. According to the definition of apparent magnitude, the relationship between the satellite's apparent magnitude m and I is given by [?]: $m = m_0 - 2.5 \lg \frac{I}{I_0}$.

In this expression, m_0 represents the apparent magnitude of the Sun. By substituting the expression for I into this equation, we obtain: $m = m_0 - 2.5 \lg \frac{s\gamma F(\phi)}{r^2 I_0}$. For an isotropic, uniform sphere, both the portion illuminated by the light source and the portion visible to the observation equipment are hemispheres; their overlap constitutes the actual visible illuminated area. Therefore, the phase function can be expressed in terms of the illuminated percentage [?]:

$$180 - \phi$$

Modified Sphere Model

Satellites possess complex three-dimensional structures and surface characteristics, causing their brightness to fluctuate under different observation conditions due to changes in attitude and viewing geometry. In particular, even at the same phase angle, factors such as the satellite's orientation and the observer's viewing angle can lead to significant variations in brightness. This presents a substantial challenge for photometric prediction of satellites with unknown attitudes or non-cooperative targets. However, parameters such as slant range and phase angle are typically known or relatively fixed, leaving only the optical cross-sectional area and reflectivity in the observation direction as the primary unknowns.

To address this issue, this paper proposes a modified sphere model method to estimate satellite brightness. By fixing the reflectivity, this method simplifies the variation in satellite brightness into changes in its equivalent cross-sectional area, thereby bypassing the need for precise modeling of complex satellite shapes. Especially when the satellite's attitude and orbit are stable, the equivalent cross-sectional area can be fitted based on observation conditions to predict brightness variations. Here, the equivalent cross-sectional area is defined as the

cross-sectional area of a sphere that would produce the same brightness as the measured satellite under identical observation conditions (where the satellite brightness accounts for actual observed effects including shadowing, attitude, and specular reflection). This method primarily utilizes photometric observation data from multiple orbital passes and employs machine learning algorithms to fit the patterns of change in the satellite's equivalent cross-sectional area, thereby establishing a photometric prediction model.

The equivalent cross-sectional area is not only related to the geometric characteristics of the satellite but is also influenced by the illumination-visibility relationship, making it closely tied to observation conditions. Specifically, the equivalent cross-sectional area is correlated with the following angular parameters: the satellite's azimuth and elevation relative to the Sun (ω, ϕ), the angle between the geocenter-station vector and the orbital plane (β), and the angle between the geocenter-Sun vector and the orbital plane (λ). This study aims to comprehensively represent these angular relationships through a function $S = f(\omega, \phi, \beta, \lambda)$, where S denotes the equivalent cross-sectional area. To construct this functional relationship, it is necessary to accurately calculate the relevant angular parameters for each satellite at every observation moment, ensuring that the modified sphere model can effectively capture the patterns of photometric variation as a function of observation conditions.

2.2.1 数据处理与光度参数获取

The experimental data for this study were obtained from the 50 cm optical telescope at the Xinglong Observatory of the National Astronomical Observatories of China (NAOC), utilizing the V-band for observations. We performed rigorous data filtering to exclude targets with unstable attitudes that exhibited significant light variations. Ultimately, seven low-Earth orbit (LEO) satellites with relatively stable attitudes and orbits were selected as the primary research subjects. Table 1 provides the fundamental information for these satellites, including their satellite identification numbers, names, orbital parameters, and corresponding schematic diagrams.

$I = I_0$

$F(\phi) =$

According to the Lambertian diffuse reflection model, the intensity of light reflected from an ideal diffuse surface is proportional to the cosine of the angle between the incident light and the surface normal vector [?, ?]. For a satellite conforming to the Lambertian diffuse sphere model, the apparent magnitude is calculated as:

$$m = m_0 - 2.5 \lg \left[\frac{s\gamma}{\pi} \left(\frac{180 - \phi}{180} \right) \right]$$

However, with the widespread application of 3-axis stabilized platforms, the

number of box-shaped and other complex-geometry satellites has gradually increased. In practical observations, the brightness variations of such satellites with respect to the phase angle differ significantly from the standard spherical model. This discrepancy primarily arises from the complex structural geometry of the satellites and the rapid changes in illumination and observation directions during the overpass of Low Earth Orbit (LEO) satellites, which lead to more intricate brightness fluctuations. These variations are not only influenced by reflectivity but are also closely related to factors such as satellite attitude, illumination visibility geometry, and surface roughness. Consequently, using traditional spherical models to estimate the apparent magnitude of box-shaped and other complex satellites tends to introduce substantial errors.

During the data acquisition and processing phase, we obtained the standard extra-atmospheric photometry of the satellites through image collection and data processing, followed by flux calibration using V-band standard stars. Simultaneously, orbital calculations were performed using satellite orbital elements to determine the observational parameters at specific timestamps.

These parameters include the satellite's phase angle, azimuth, elevation, and slant range. Ultimately, the output information comprises the satellite identification number, observation time, flux, magnitude, azimuth, elevation, slant range, and phase angle. This comprehensive dataset provides a reliable foundation for subsequent photometric modeling and analysis.

Object

Orbit

Lincoln Calibration Sphere (LCS)-1

2704 km × 2869 km, 32.1

05398[11]

LCS-4

795 km × 913 km, 87.6 °

Cosmos-2414

908 km × 965 km, 82.95 °

Formosat-3B

700 km × 700 km, 72 °

Hinode-(Solar-B)

279 km × 672 km, 98.33 °

Lapan-Tubsat

635 km × 635 km, 98 °

Globalstar-M071

1410 km \times 1410 km, 52°

<https://sat.huijiwiki.com/wiki/>

<https://space.skyrocket.de/>

<https://www.esa.int>

Image

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Furthermore, we performed data cleaning on the observational data, employing an iterative method based on Gaussian smoothing to eliminate outliers. The specific process is as follows: first, the standard deviation of the Gaussian filter was set to 3 to control the smoothing intensity, and a dynamic threshold mechanism was defined. This mechanism compares 5% of the absolute magnitude of the smoothed values with the standard deviation of the original magnitude sequence, selecting the larger of the two as the threshold for outlier detection. If the deviation of an observed magnitude from the smoothed trend exceeds this threshold, the observation point is identified as an outlier. During the cleaning process, we extracted magnitude and corresponding phase angle data from the time series of each observation pass and processed these data iteratively (with the number of iterations set to 3). In each iteration, the data were smoothed using a one-dimensional Gaussian filter, and anomalous data were identified and removed according to the predefined threshold conditions. Figure 2 [Figure 2: see original paper] illustrates the results of the data cleaning for two observation passes of satellite 01361. In the figure, circular scatter points represent normal observational data, upper-triangle scatter points denote the removed outliers, and the curves represent the photometric variation trends after Gaussian smoothing. It is clearly observable from the figure that there are distinct differences between the anomalous and normal data. The data cleaning step effectively removes outliers and noise, preserving the authentic trend of the satellite's photometric variations. This facilitates the model's ability to accurately capture the underlying patterns of the data, thereby enabling a more precise evaluation and prediction of satellite photometric trends.

2.2.2 修正球模型输入参数计算

Based on the acquired photometric parameters, the three angular parameters ω , β , and λ are further calculated. [Figure 3: see original paper] provides a visual representation of the geometric parameters and their corresponding relationships involved in the modified sphere model within the Earth-Centered Inertial (ECI) coordinate system.

These parameters include the unit normal vector of the satellite's orbital plane n_s , the angle between the geocentric-station vector and the orbital plane normal η_c , and the angle between the geocentric-Sun vector and the orbital plane normal

η_{\odot} . The specific calculation process is as follows: (1) Azimuth of the satellite relative to the Sun: Based on the observation time, the satellite azimuth μ_s in the horizontal coordinate system is calculated. This is combined with the station position to determine the solar azimuth μ_{\odot} .

The azimuth of the satellite relative to the Sun can then be calculated using the following formula:

$$\begin{cases} 2\pi - (\mu_{\odot} - \mu_s), & \text{if } \mu_{\odot} > \mu_s \\ \mu_s - \mu_{\odot}, & \text{if } \mu_{\odot} \leq \mu_s \end{cases} \quad (6)$$

The transformation from the horizontal coordinate system to the Cartesian coordinate system is given by:

$$\begin{cases} x_{u,s} = r \cos(h_s) \cos(\mu_s) \\ y_{u,s} = -r \cos(h_s) \sin(\mu_s) \\ z_{u,s} = r \sin(h_s) \end{cases}$$

In this expression, $t_{u,s} = (x_{u,s}, y_{u,s}, z_{u,s})$ represents the position vector of the satellite within this Cartesian coordinate system.

Magnitude

Normal values Outliers Smoothed curve

Phase angle/°

Magnitude

Normal values Outliers Smoothed curve

Phase angle/°

- (b) December 4, 2015. [Figure 2: see original paper] Data cleaning results for satellite 01361 over two orbital observation arcs: (a) December 7, 2014; (b) December 4, 2015.

Since the position of the observation station is known, the station's coordinates in the Earth-Centered, Earth-Fixed (ECEF) coordinate system can be obtained as $p_{e,c} = (x_c, y_c, z_c)$. Subsequently, the Cartesian coordinates of the satellite are transformed into the Earth-Centered Inertial (ECI) coordinate system using the following formula to obtain the satellite's position coordinates $t_{i,s}$ in that frame:

$$t_{i,s} = R_{e,i} \cdot R_{u,e} \cdot t_{u,s}^T + p_{e,c}^T$$

- (2) Satellite orbital plane normal vector To calculate β and λ , it is first necessary to determine the normal vector of the orbital plane. Based on orbital calculations, the azimuth μ_s , elevation angle h_s , and range r at the time

of observation can be obtained in the topocentric coordinate system. The satellite observation data is then transformed from the...

$$- \cos(lg) \sin(la) \sin(lg) \cos(lg) \cos(la) \quad Ru, e = - \sin(lg) \sin(la) - \cos(lg) \sin(lg) \cos(la) \quad , \cos(la) \sin(la)$$

$$\cos \eta_c =$$

Here, lg represents the longitude of the observation station, la denotes the latitude of the station, and θ is the Greenwich Sidereal Time at the moment of observation. In this study, we neglect the minor errors introduced by precession and nutation, accounting only for the coordinate transformations caused by the Earth's rotation.

Normal vector n_s

Orbital plane

(4) Angle between the Geocenter-Sun Vector and the Orbital Plane

Based on the observation epoch, the position of the Sun in the Geocentric Celestial Reference System (GCRS) can be obtained as $(\alpha_{\odot}, \delta_{\odot}, r_{\odot})$, where α_{\odot} represents the Sun's right ascension, δ_{\odot} denotes the Sun's declination, and r_{\odot} is the distance from the geocenter to the Sun. These coordinates are then converted into the Cartesian coordinate system as follows:

$$\begin{cases} x_{\odot} = r_{\odot} \cos(\delta_{\odot}) \cos(\alpha_{\odot}) \\ y_{\odot} = r_{\odot} \cos(\delta_{\odot}) \sin(\alpha_{\odot}) \\ z_{\odot} = r_{\odot} \sin(\delta_{\odot}) \end{cases}$$

Satellite

Observatory

$$\beta = 2 - \eta_c \quad \lambda = 2 - \eta$$

3 Schematic diagram of geometric parameters and

Since the Geocentric Celestial Reference System (GCRS) and the Earth-Centered Inertial (ECI) coordinate system are very similar, the coordinates of the Sun in the GCRS are used as an approximation for its coordinates in the ECI frame, denoted as $p_{i,\odot} = (x_{\odot}, y_{\odot}, z_{\odot})$. Similarly, the formula for calculating λ based on η_{\odot} is given by:

$$\frac{p_{i,\odot} \cdot n_s}{|p_{i,\odot}| |n_s|} = \cos \eta_{\odot}$$

angular relationships in the modified sphere model

In the Earth-Centered Inertial (ECI) coordinate system, three distinct observation timestamps are randomly selected from each satellite's observation dataset.

Using Equation (8), the satellite's coordinates in the ECI frame are calculated for these three moments, denoted as $t_{i,s1}$, $t_{i,s2}$, and $t_{i,s3}$. These three time points are arranged in chronological order such that $t_{i,s1}$ is the earliest and $t_{i,s3}$ is the latest. Subsequently, the vector differences between satellite positions at adjacent timestamps (representing differential velocity vectors) are calculated as $v_{2,1} = t_{i,s2} - t_{i,s1}$ and $v_{3,2} = t_{i,s3} - t_{i,s2}$. Finally, the unit normal vector of the satellite's orbital plane is obtained using the following formula:

$$v_{2,1} \times v_{3,2} / |v_{2,1} \times v_{3,2}|$$

Since the geocentric position of the station varies with the observation time, the parameter β also changes accordingly. When $\cos \eta_c > 0$, it indicates that the station is currently located above the orbital plane; conversely, when $\cos \eta_c < 0$, the station is located below the orbital plane. Here, "above the orbital plane" refers to the direction of the orbital normal vector n_s , which follows the right-hand rule—pointing toward the side perpendicular to the satellite's orbital velocity vector. Based on the position of the station relative to the orbital plane, the parameter β is calculated as follows:

$$\beta = \begin{cases} \arcsin(\cos \eta_c), & \text{if } \cos \eta_c \geq 0 \\ -\arcsin(|\cos \eta_c|), & \text{else} \end{cases} \quad (13)$$

$$\cos \theta \sin \theta \ 0 \ \text{Re},i = -\sin \theta \ \cos \theta \ 0 \ .$$

$$p_{i,c} \cdot n_s / |p_{i,c}| |n_s|$$

$$\arcsin(\cos \eta_c), \text{ if } \cos \eta_c \geq 0 - \arcsin(|\cos \eta_c|), \text{ else}$$

Similarly, when $\cos \eta_{\odot} > 0$, the Sun is located above the orbital plane at the current moment; conversely, when $\cos \eta_{\odot} < 0$, the Sun is located below the orbital plane.

- (3) The angle between the geocentric-station vector and the orbital plane. The position coordinates of the observation station in the Earth-Centered Fixed (ECF) coordinate system are denoted as $p_{e,c}$ and are already known. It is necessary to use the formula $p_{i,c} = R_{e,i} \cdot p_{e,c}^T$ to transform the

Machine Learning-Based Photometric Modeling and Experiments

For each Low Earth Orbit (LEO) satellite with relatively stable attitude and orbit, we first sort the observation passes by date. The data is then partitioned into a training set and a testing set using a 9:1 ratio (ensuring

station position into the Earth-Centered Inertial (ECI) coordinate system. To calculate the value of β , it is necessary to first determine η_c . The calculation formula is:

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the number of observation passes in the test set is no less than 3). The training set is utilized to train the machine learning model for parameter fitting, while the test set is used to evaluate the

predictive performance of the model. shows the number of observation passes and the corresponding time spans for the training and testing sets of each satellite.

each satellite Object

Training orbital arcs

Testing orbital arcs

Training time span

Testing time span

The optimal hyperparameter settings for the Support Vector Regression (SVR) and Random Forest (RF) models corresponding to each satellite are detailed.

Construction and Fitting of the Photometric Model

During the training phase, we fixed $\gamma = 0.2$ for the observation data of each Low Earth Orbit (LEO) satellite and inverted the equivalent cross-sectional area S for each observation epoch using the magnitude calculation formula (5). Using this as a basis, we performed regression fitting on S using machine learning models, with the parameters ω , ϕ , β , and λ as input variables. Finally, the predicted magnitude is obtained by substituting the model-output S back into formula (5). In this study' s fitting of the modified sphere model, we employed two machine learning algorithms: Random Forest (RF) [?, ?] and Support Vector Regression (SVR) [?, ?]. These algorithms effectively learn the complex nonlinear relationships within the training data, thereby revealing the mapping between the illumination-visibility geometry and the equivalent cross-sectional area. This approach provides a more accurate estimation of the equivalent cross-sectional area for the modified sphere model. Models were fitted independently for each satellite' s data.

During the hyperparameter tuning process of the machine learning models, the settings for the Random Forest model were as follows: the number of trees was set to 50, 100, 150, and 200, while the maximum depth of each tree was set to 5, 10, 15, and 20. For the Support Vector Regression model, we selected the polynomial kernel and the Radial Basis Function (RBF) kernel, with error tolerance (ϵ) set to 0.001, 0.01, and 0.1, and the regularization parameter (C) set to 1, 10, and 100. To identify the optimal hyperparameter combinations, we utilized the Grid Search (GridSearchCV) method to systematically search and optimize the hyperparameter space for each model. Through this process, we determined the best hyperparameter combinations for each satellite' s machine learning model, as detailed in .

Analysis of Equivalent Cross-Sectional Area and Photometric Prediction Results

In the test set, we loaded the trained model weights for each satellite and predicted the equivalent cross-sectional area based on the parameters ω , ϕ , β , and λ at each observation epoch. These predicted values were then substituted into formula (5) to calculate the predicted magnitudes. Based on these model predictions, we further evaluated and compared the photometric prediction performance of the different models for each satellite.

3.2.1 不同模型的光度预测性能对比

To evaluate the predictive performance of the models, we employ the following regression evaluation metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Based on these metrics, we compare the differences between the predicted magnitudes and the measured magnitudes for Support Vector Regression (SVR) and Random Forest (RF) models under their optimal hyperparameter configurations for each satellite, thereby quantifying the prediction accuracy of the models. Furthermore, to verify the effectiveness of the modified sphere model, we conduct a comparative analysis against the prediction results of the traditional sphere model. presents the comparison of predictive performance across different models on the test set. In this context, SVR and RF represent two distinct methods used by the modified sphere model to calculate the equivalent cross-sectional area; both sets of results represent the performance of the modified sphere model in low-Earth orbit (LEO) satellite photometric estimation. Additionally, the minimum values for each error metric for a given satellite are highlighted in bold for clarity.

As can be observed from , for the majority of LEO satellites with relatively stable attitudes and orbits, the predictive performance of both the Support Vector Regression and Random Forest models outperforms that of the traditional sphere model.

This indicates that the modified sphere model can accurately predict the equivalent cross-sectional area through illumination-visibility relationships, thereby significantly improving the accuracy of photometric estimation for LEO satellites. The specific analysis is as follows:

Object

Support vector regression

Random forest

Kernel function

Epsilon

Regularization parameter

Number of trees

Maximum depth

Polynomial
Polynomial
Polynomial
Model Object
Support vector regression
Random forest
Spherical model
2.99%
4.14%
5.99%
2.77%
3.43%
6.75%
3.61%
3.64%
4.19%
7.52%
7.92%
10.34%
7.91%
7.88%
9.34%
6.53%
6.58%
7.46%
5.02%
8.07%
4.95%

First, the Support Vector Regression (SVR) model demonstrates outstanding performance in the photometric prediction of most satellites, achieving the minimum error across multiple evaluation metrics. For instance, regarding satellite ID 05398, the SVR model yielded an RMSE of only 0.26, an MSE of 0.07, an

MAE of 0.21, and a MAPE of 2.99%. These results indicate that the SVR model effectively captures the patterns of brightness variation for this satellite under diverse observation conditions. Similar performance was observed in the predictions for satellite IDs 29479,

31576, and 29048. The SVR model consistently achieved the lowest errors in the photometric estimation of these satellites, further validating its reliability in photometric prediction.

Secondly, the Random Forest (RF) model also performs exceptionally well in the photometric prediction of certain satellites, even outperforming the SVR model in specific cases. For example, in the photometric predictions for satellite IDs 01361 and 28521, the RMSE values for the Random Forest model were

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0.46 and 0.68, respectively, which are very close to the prediction errors of the SVR model. Overall, both the SVR and Random Forest models effectively capture the photometric variation patterns of low-Earth orbit (LEO) satellites. This suggests that the modified spherical model can effectively reduce errors caused by complex satellite shapes and attitude changes, thereby improving the prediction accuracy for LEO satellites.

But for satellite ID 29709, the prediction accuracy of the modified spherical model was actually lower than that of the traditional spherical model. This discrepancy arises because the number of observed orbital passes was small and the coverage of observation conditions was limited. Consequently, the modified spherical model could not leverage sufficient observational data for training, leading to a predictive performance inferior to that of the traditional spherical model. Due to its simpler form and lower data requirements, the traditional spherical model is capable of providing relatively stable prediction results even when data is limited. This indicates that the effectiveness of the modified spherical model is highly dependent on a sufficient volume of data and extensive coverage of observation conditions. Its advantages in enhancing the accuracy of LEO satellite photometric prediction can only be fully realized when adequate training data and comprehensive observational coverage are available.

3.2.2 单星的模型光度预测性能分析

3. Detailed Analysis of LEO Satellites

In this section, we conduct a more in-depth analysis of two specific Low Earth Orbit (LEO) satellites. By examining their orbital characteristics and signal propagation environments, we aim to provide a comprehensive understanding of the challenges and opportunities inherent in satellite-to-ground communication. Our investigation focuses on the dynamic nature of these satellite links, particularly the rapid changes in Doppler shift and path loss that occur during

a typical pass. Through this detailed evaluation, we establish a baseline for the performance metrics discussed in subsequent chapters.

2018-12-04 Observed value 2018-12-04 Predicted value 2018-12-06 Observed value 2018-12-06 Predicted value 2018-12-07 Observed value 2018-12-07 Predicted value 2018-12-14 Observed value 2018-12-14 Predicted value 2018-12-16 Observed value

2018-12-16 Predicted value 2019-02-23 Observed value 2019-02-23 Predicted value 2019-02-25 Observed value 2019-02-25 Predicted value 2019-03-12 Observed value 2019-03-12 Predicted value 2019-03-14 Observed value 2019-03-14 Predicted value

2018-12-04 Predicted error 2018-12-06 Predicted error 2018-12-07 Predicted error 2018-12-14 Predicted error 2018-12-16 Predicted error

2019-02-23 Predicted error 2019-02-25 Predicted error 2019-03-12 Predicted error 2019-03-14 Predicted error

Phase angle/°

2018-12-04 Observed value 2018-12-04 Predicted value 2018-12-06 Observed value 2018-12-06 Predicted value 2018-12-07 Observed value 2018-12-07 Predicted value 2018-12-14 Observed value 2018-12-14 Predicted value 2018-12-16 Observed value

2018-12-16 Predicted value 2019-02-23 Observed value 2019-02-23 Predicted value 2019-02-25 Observed value 2019-02-25 Predicted value 2019-03-12 Observed value 2019-03-12 Predicted value 2019-03-14 Observed value 2019-03-14 Predicted value

2018-11-12 Predicted error 2018-11-16 Predicted error 2018-11-17 Predicted error 2018-11-18 Predicted error 2018-11-21 Predicted error

2018-12-04 Predicted error 2018-12-06 Predicted error 2018-12-07 Predicted error 2018-12-14 Predicted error 2018-12-16 Predicted error

2019-02-23 Predicted error 2019-02-25 Predicted error 2019-03-12 Predicted error 2019-03-14 Predicted error

Phase angle/°

2018-11-12 Predicted error 2018-11-16 Predicted error 2018-11-17 Predicted error 2018-11-18 Predicted error 2018-11-21 Predicted error

2018-11-12 Observed value 2018-11-12 Predicted value 2018-11-16 Observed value 2018-11-16 Predicted value 2018-11-17 Observed value 2018-11-17 Predicted value 2018-11-18 Observed value 2018-11-18 Predicted value 2018-11-21 Observed value 2018-11-21 Predicted value

Magnitude Error

Magnitude

2018-11-12 Observed value 2018-11-12 Predicted value 2018-11-16 Observed value 2018-11-16 Predicted value 2018-11-17 Observed value 2018-11-17 Predicted value 2018-11-18 Observed value 2018-11-18 Predicted value 2018-11-21 Observed value 2018-11-21 Predicted value

Analysis. Satellite number 01361 is the American LCS (Lincoln Calibration Sphere) satellite, primarily utilized for radar calibration measurements.

The LCS satellite is an aluminum spherical structure with a diameter of 1.12 m and a wall thickness of 3.2 mm. For satellite 01361 (LCS-1), we utilized data from 135 observation passes for model training and 14 observation passes for testing.

The photometric prediction results and magnitude error distributions for the same observation dates are presented. The upper portion illustrates the trends of measured magnitudes and the model's predicted magnitudes as a function of the observation phase angle. Different colors represent distinct observation dates, where scattered points denote measured magnitude values and curves represent the magnitudes predicted by the model. The lower portion utilizes dashed lines to display the variation of magnitude prediction errors with respect to the phase angle, where the error is calculated as the absolute difference between the measured and predicted magnitudes. The fluctuations in the error curves reflect the fitting precision of the Support Vector Regression (SVR) model across different observation dates. [Figure 4: see original paper] (b) displays the photometric prediction results and corresponding magnitude error distributions for a traditional spherical model, serving as a baseline to compare the photometric prediction capabilities and error distribution characteristics of different models.

Magnitude

Magnitude Error

(b) Photometric prediction and error analysis using the traditional spherical model.

[Figure 4: see original paper] Comparison of observed and predicted magnitudes with error analysis for satellite 01361 using different models. (a) Photometric prediction and error analysis with the support vector regression model. (b) Photometric prediction and error analysis with the traditional spherical model.

2016-02-17 Observed value 2016-02-17 Predicted value 2016-02-23 Observed value 2016-02-23 Predicted value 2016-02-25 Observed value 2016-02-25 Predicted value

2016-02-17 Predicted error 2016-02-23 Predicted error 2016-02-25 Predicted error

2016-02-17 Observed value 2016-02-17 Predicted value 2016-02-23 Observed value 2016-02-23 Predicted value 2016-02-25 Observed value 2016-02-25 Predicted value

Phase angle/° 2016-02-17 Predicted error 2016-02-23 Predicted error 2016-02-25
Predicted error

2016-02-17 Observed value 2016-02-17 Predicted value 2016-02-23 Observed
value 2016-02-23 Predicted value 2016-02-25 Observed value 2016-02-25 Pre-
dicted value

Phase angle/° 2016-02-17 Predicted error 2016-02-23 Predicted error 2016-02-25
Predicted error

Magnitude error

Magnitude error

As shown in [Figure 4: see original paper], the prediction results of the traditional spherical model are generally consistent with the measured values in terms of overall trends. This is because the geometric shape of the satellite aligns with the assumptions of the spherical model, allowing it to simulate photometric variations effectively with relatively ideal predictive performance. The Root Mean Square Error (RMSE) for this satellite is 0.50, which outperforms the prediction results for most other satellites. However, the traditional spherical model exhibits poor generalization capabilities; specifically, within the range of large phase angles, the prediction error curve fluctuates significantly, and the errors become more pronounced, failing to fully reflect the satellite's variations under different observation conditions. Regarding the Support Vector Regression (SVR) model, the results indicate that it can accurately predict the brightness variations of the satellite in terms of overall trends, maintaining small overall prediction errors. Across multiple observation dates, the fluctuation amplitude of its error curve remains low. Furthermore, as shown in , the RMSE for the SVR model on this satellite is 0.47, while the Random Forest (RF) model yields an RMSE of 0.46, both of which are slightly superior to the traditional spherical model. This suggests that the modified spherical model based on the equivalent cross-sectional area can better capture the patterns of satellite brightness as they change with observation conditions, further validating the effectiveness of the modified spherical model for photometric estimation of Low Earth Orbit (LEO) satellites.

The Hinode solar observation satellite (NORAD ID: 29479) is a mission led by the Japan Aerospace Exploration Agency (JAXA). The satellite body measures approximately $1.6 \text{ m} \times 1.6 \text{ m}$ and is equipped with two solar panels, each measuring approximately $4.3 \text{ m} \times 1.1 \text{ m}$, with a total mass of about 900 kg [?]. For this satellite, we utilized data from 19 observation passes for training and 3 passes for testing. [Figure 5: see original paper] sequentially displays the photometric prediction results and magnitude error distributions for the SVR, RF, and traditional spherical models on this satellite. Each sub-figure contains two vertical axes: the left axis corresponds to the magnitude, and the right axis corresponds to the magnitude error. Similarly, the scattered points in the figure represent measured magnitude values, the solid curves represent predicted values, and the dashed lines represent the prediction errors. In [Figure 5: see original paper],

the red and blue curves correspond to the photometric predictions for February 17, 2016, and February 25, 2016, respectively. The “folding” phenomenon observed in the prediction curves occurs because the phase angle first increases and then decreases over time during the observation process. Since the phase angle does not change monotonically in the time series, certain phase angles in the figure correspond to multiple observation timestamps. Consequently, some phase angles are associated with two distinct magnitude values, resulting in the folded characteristic of the prediction curves.

Magnitude error

Magnitude

Magnitude

Magnitude

Phase angle/°

- (a) Support vector regression model. (b) Random forest model. (c) Traditional spherical model. [Figure 5: see original paper] Comparison of observed and predicted magnitudes with error analysis for satellite 29479. (a) Support vector regression model. (b) Random forest model. (c) Traditional spherical model.

The model demonstrates strong predictive capability and can accurately forecast the photometric variations of the satellite. The overall prediction error is small, with the majority of errors falling below 0.5 mag.

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Furthermore, the Root Mean Square Error (RMSE) of the model’s predictions is only 0.28, with a mean relative error of 2.77%. The photometric prediction results of the random forest model also perform excellently, exhibiting high fitting precision across most observational data. Its predicted magnitude curve aligns well with the measured magnitudes, and the fluctuation in the prediction error curve remains minimal. This model yields an RMSE of 0.34 and a mean relative error of 3.43%. In contrast, the traditional spherical model performs relatively poorly in photometric prediction; its predicted curve fails to accurately characterize the brightness variation trends of the satellite. Specifically, the prediction error is larger within the range of large phase angles, where the fluctuation amplitude of the error curve increases significantly and peak errors are higher. Prediction errors for this model generally range between 0.5 and 1.3 mag, with an overall RMSE of 0.62 and a mean relative error of 6.75%.

Compared to the random forest model, the RMSE of the traditional spherical model is 0.28 higher, and its mean relative error increases by 3.32%. When compared to the support vector regression model, the traditional spherical model’s RMSE is 0.34 higher, and its mean relative error increases by 3.98%. These

results indicate that while the traditional spherical model can provide photometric predictions for LEO satellites to some extent, its predictive accuracy remains significantly limited for satellites with complex shapes. The modified spherical model based on the equivalent cross-sectional area can more precisely describe the illumination-visibility relationship and improve the calculation accuracy of the equivalent cross-sectional area, thereby enhancing the accuracy of photometric predictions for LEO satellites.

The prediction accuracy was evaluated across seven satellites. Among the models tested, the support vector regression model achieved an average RMSE of 0.55 for predicted magnitude errors, with a maximum value of 0.80.

However, the study also indicates that the volume of data and the coverage of observation conditions are critical to the accuracy of the modified spherical model. Insufficient training data can adversely affect the fitting performance of machine learning models, thereby reducing the precision of photometric predictions. Consequently, future research will focus on expanding the observational datasets, exploring more advanced machine learning models, and conducting in-depth analyses of the impact of attitude changes on photometric variation characteristics. These efforts aim to improve the accuracy and adaptability of the modified spherical model for LEO satellite photometric prediction.

In conclusion, for LEO satellites with stable attitudes and orbits and sufficient observational data coverage, the modified spherical model based on equivalent cross-sectional area can not only accurately predict brightness variations during future transits but also be utilized to invert the satellite's attitude and state changes. This provides an effective technical means for the observation and analysis of non-cooperative targets.

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结论

Devices

To address the issue of photometric modeling for Low Earth Orbit (LEO) satellites, this paper proposes a modified sphere model photometric calculation method based on equivalent cross-sectional area. This method is applicable to LEO satellite transits where the attitude and orbit are stable and the observational data provides sufficient coverage of viewing conditions. The approach comprehensively accounts for various influencing factors, including orbital parameters, solar phase angles, and observation conditions. By calculating four key parameters—the satellite's azimuth relative to the sun, the phase angle, the angle between the geocenter-station vector and the orbital plane, and the angle

between the geocenter-sun vector and the orbital plane—as input variables, the model utilizes Support Vector Regression (SVR) and Random Forest (RF) algorithms to fit and predict the equivalent cross-sectional area. These predicted results are then substituted into the photometric calculation formula to predict the stellar magnitude.

To verify the effectiveness of the proposed method, this study conducts an experimental analysis using photometric data from seven LEO satellites observed by the 50 cm optical telescope at the Xinglong Observatory. The experimental results demonstrate that both the Support Vector Regression and Random Forest models achieve lower prediction errors across multiple LEO satellites compared to the traditional sphere model. Consequently, the modified sphere model exhibits superior photometric prediction capabilities and higher precision.

SPIE:

Multifrequency

Systems

Electronic/Photonic

Dual-Use

Applications.

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ZHANG Xiao-ming^{1,2} WANG Lei^{1,2}

QU Yao-bin³ WANG Jian-feng^{1,2} JIANG Xiao-jun

(1 CAS Key Laboratory of Optical Astronomy, National Astronomical Observatories, Chinese Academy of Sciences, Beijing 100101) (2 University of Chinese Academy of Sciences, Beijing 100049) (3 Shanghai Institute of Satellite Engineering, Shanghai 201100)

Abstract

The photometric characteristics of satellites play an important role in analyzing their physical properties. An accurate photometric model can effectively support observation planning and strategy formulation, while also facilitating the analysis and interpretation of satellite attitude and structural characteristic changes. However, due to the rapid and complex variations in attitude and observation conditions during Low Earth Orbit (LEO) satellite transits, existing photometric models fail to accurately estimate the brightness of these satellites. To address this issue, we propose a modified spherical photometric model based on equivalent cross-sectional area, specifically designed for LEO satellites with stable attitude and orbit, and with observational data that sufficiently covers

various viewing conditions. This method equates the satellite's cross-sectional area to that of a sphere with equal brightness. By incorporating the relative positional relationships among the satellite, the Sun, the observation station, and the orbital plane as key parameters, it employs machine learning algorithms to effectively fit and estimate the equivalent cross-sectional area, thereby enabling accurate photometric predictions during LEO satellite transits. To validate the effectiveness of the proposed method, we conducted performance evaluations using V-band photometric data from 7 LEO satellites observed by the 50 cm telescope at Xinglong Observatory, with comparisons made against the traditional spherical model. The results show that when sufficient observational data is available, the proposed method achieves higher accuracy and greater stability in photometric prediction, demonstrating strong reliability and broad applicability.

Key words general

astrometry, techniques: photometric, methods: data analysis, planets and satellites:

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

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