Neural Network-Based Photometric Orbit Determination Method for Semi-Detached Binaries Postprint

Authors: Xiong Jianping, Liu Chao, Li Jiao, Li Chunqian, Zhao Yongheng

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Abstract

Semi-detached binary stars are of significant importance for studying the formation and evolution of interacting binary systems. With the arrival of the era of large-scale time-domain surveys, a substantial number of such objects are expected to be discovered. To address the massive time-domain observational datasets, a rapid modeling tool is required for automated light curve analysis of semi-detached binary stars. We construct a rapid photometric orbital solution model for semi-detached binary stars based on neural networks. This model models the orbit of semi-detached binary stars based on the light curve and known primary star temperature, obtaining four fundamental parameters: orbital inclination, relative radius, mass ratio, and temperature ratio. The results demonstrate that the neural network orbital solution model for semi-detached binary stars can rapidly model a light curve. When the photometric error is less than 1% of the light curve amplitude, the measurement errors for orbital inclination, relative radius, mass ratio, and temperature ratio are 1.251, 0.004, 0.008, and 0.003, respectively, for semi-detached binary stars with orbital inclination close to 90°, temperature ratio of approximately 0.6, and light variation amplitude of 1.84 mag. Furthermore, application results on Kepler observed light curves indicate that the model can relatively accurately model light curves of pulsating eclipsing binaries (goodness of fit can achieve above 0.9). Moreover, as a general tool, this model can be migrated to different photometric survey projects.

Full Text

Light Curve Modeling of Semidetached Binaries Based on Neural Networks

Xiong Jianping[12], Liu Chao[12*], Li Jiao[12], Li Chunqian[12], Zhao Yongheng[12]

[1]National Astronomical Observatories, Chinese Academy of Sciences, Beijing 100101, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: Semi-detached binaries are important targets for studying the formation and evolution of interacting binary systems. With the advent of large-scale time-domain surveys, a rapid modeling tool is urgently needed for automated light curve analysis of semi-detached binaries. This work proposes a neural network-based model for fast photometric orbital solution of semi-detached binaries. The model derives four fundamental parameters–orbital inclination, relative radius, mass ratio, and temperature ratio–from the light curve and known primary star temperature. Results demonstrate that the neural network model can rapidly model a light curve. For semi-detached binaries with orbital inclinations near 90°, temperature ratios around 0.6, and light curve amplitudes of 1.84 mag, the measurement errors for orbital inclination, relative radius, mass ratio, and temperature ratio are 1.251°, 0.004, 0.008, and 0.003, respectively, when photometric errors are less than 1% of the light curve amplitude. Application to Kepler light curves shows the model can accurately model pulsating eclipsing binaries (fitting degree >0.9). Furthermore, as a general tool, the model can be transferred to different photometric surveys.

Keywords: stellar physics; eclipsing binaries; close binaries; machine learning; data analysis

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1 Neural Network Modeling for Light Curve Solution

The shape of eclipses in binary light curves reflects the orbital inclination, while the duration and relative positions of eclipses reveal orbital eccentricity, longitude of periastron, and the sum of the radii of both components. The depth ratio of the two eclipses indicates the relationship between surface temperatures and eclipsed areas of the two stars. Additionally, gravity darkening, limb darkening, reflection coefficients, starspots, and circumstellar material also manifest in light curves. Through light curve modeling, we can extract binary system characteristics such as period, orbital inclination, luminosity ratio, and relative radius ($r = R/a$, where R is the equivalent radius of the component and a is the semi-major axis of the binary orbit). Statistical analysis of near-contact binary light curves shows that near-contact binaries are typically observed only when orbital inclinations exceed 70°, and most consist of A- or F-type primary stars with secondary stars one to two spectral types later.

1.1 Model Sample Data

Semi-detached binaries can be classified into two types based on which component fills its Roche lobe: (1) the primary star (more massive component) fills its Roche lobe while the secondary is underfilled or nearly filled; (2) the secondary star (less massive component) fills its Roche lobe while the primary is underfilled or nearly filled.

Since we cannot directly determine from the light curve whether a semi-detached binary has a primary-filled or secondary-filled configuration, and because degeneracies exist between these states in certain parameter spaces, training on both types simultaneously would reduce model accuracy due to parameter degeneracy, leading to inaccurate predictions and inability to determine the system' s state. Therefore, this work constructs separate light curve modeling models for primary-filled and secondary-filled states. For an observed light curve, the model provides optimal parameter solutions under both configurations. PHOEBE then reproduces light curves using both parameter sets, and the fitting degree is calculated by comparing these with the observed light curve. The configuration with higher fitting degree is adopted as the final state and parameters.

We set the primary star temperature T_1 range to 5000–10000 K, defining the "primary" as the more massive component (also designated as "Star 1"). Orbital inclination (incl) ranges from 60° to 90°, mass ratio (q) from 0.1 to 1, and secondary temperature (T_2) from 3800–10000 K. The critical Roche lobe radii for the components are given by:

$$r_{\rm cr} = \frac{0.49q^{2/3}}{0.6q^{2/3} + \ln(1 + q^{1/3})} \quad (1)$$

$$r'_{\rm cr} = \frac{0.49q^{-2/3}}{0.6q^{-2/3} + \ln(1 + q^{-1/3})} \quad (2)$$

Relative radii (R/a) are randomly generated within these ranges. For the primary-filled model, we use orbital inclination, mass ratio, temperature ratio, and secondary relative radius as free parameters. Each parameter is uniformly and randomly sampled within its specified range to generate light curves with 100 phase points using PHOEBE in the 0–1 phase interval. Flux values are converted to Kepler magnitudes. Since PHOEBE uses "flux" to represent light curve amplitude, we standardize the generated curves using:

$$m = -2.5\log_{10}\left(\frac{f}{\langle f\rangle}\right) \quad (3)$$

where f represents the 100 flux sample points from PHOEBE and $\langle f\rangle$ is the mean flux. The same method constructs the dataset for the secondary-filled model.

Approximately 300,000 light curves were generated for each model. Figure 1: see original paper and (b) show the frequency distribution histograms of the dataset across parameters. The non-uniform distribution in relative radius and temperature ratio arises from parameter interdependencies. To address this, we randomly sample 50,000 data points from the training set for each iteration until convergence. Additionally, primary temperature, orbital inclination, mass ratio, temperature ratio, and secondary relative radius are standardized using sklearn' s StandardScaler. The dataset is split into training, validation, and test sets in a 7:2:1 ratio.

1.2 Neural Network Architecture for Light Curve Solution

[Figure 2: see original paper] illustrates the network architecture. Based on a Multi-Layer Perceptron (MLP) structure, the network comprises one input layer, eight hidden layers, and one output layer. The input layer contains 101 neurons: 100 data points from the light curve and the primary star temperature (T_1). Each hidden layer is fully connected (FC), with neuron counts shown in [Figure 2: see original paper]. To reduce feature loss during propagation, residual blocks are introduced. Hidden layers use the tanh activation function to enhance nonlinear expression capability. The model is trained using backpropagation with the Adam optimizer and L2 loss function:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (4)$$

where y_i is the true value and $\hat{y}_i$ is the predicted value. The model outputs four parameters: orbital inclination (incl), relative radius (R/a), mass ratio (q), and temperature ratio (T_2/T_1).

1.2.1 Primary-Filled Light Curve Model For the primary-filled model, we train the mapping between light curves and parameters using 100-point light curves and primary temperature (T_1) as inputs, and orbital inclination, secondary relative radius (R_2/a), mass ratio (q), and temperature ratio (T_2/T_1) as outputs. [Figure 3: see original paper] shows the test results. Deviations between predicted and true values are 0.039°, 0.000, -0.003, and -0.002 for orbital inclination, secondary relative radius, mass ratio, and temperature ratio, respectively. Standard deviations of residuals are 0.238°, 0.003, 0.010, and 0.024.

[Figure 4: see original paper] validates the model using a simulated semi-detached binary light curve with parameters $T_1 = 6000$ K, incl $= 85°$, $R_2/a = 0.3$, $q = 0.5$, and $T_2/T_1 = 0.866$. The model predicts incl $= 84.95°$, $R_2/a = 0.299$, $q = 0.499$, and $T_2/T_1 = 0.867$. The reproduced light curve (red line) matches the original well. Residuals are larger at eclipse phases due to fewer sampling points in those regions from uniform phase sampling. The residual between reproduced and original curves is less than 0.005 mag, with a fitting degree (R^2) of 0.994, defined as:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (6)$$

1.2.2 Secondary-Filled Light Curve Model Similarly, for the secondary-filled model, we use light curves and primary temperature (T_1) as inputs and orbital inclination, primary relative radius, mass ratio, and temperature ratio as outputs. [Figure 5: see original paper] shows test results with deviations of 0.013°, 0.000, 0.002, and -0.001, and residual standard deviations of 0.291°, 0.004, 0.013, and 0.016 for the four parameters, respectively.

[Figure 6: see original paper] validates this model using a light curve with $T_1 = 7600$ K, incl = 85°, $R_1/a = 0.4$, $q = 0.2$, and $T_2/T_1 = 0.684$. The model predicts incl = 84.88°, $R_1/a = 0.399$, $q = 0.200$, and $T_2/T_1 = 0.681$. The reproduced light curve (red line) matches the original (blue points) well, with residuals below 0.005 mag and $R^2 = 0.9957$.

3 Application to Kepler Data

3.1 Light Curve Modeling of Kepler Semi-Detached Binaries

NASA' s Kepler satellite, launched in March 2009, has a 1.4 m primary mirror (0.95 m effective aperture) and a 105 deg^2 field of view, providing long-cadence (LC; 29.4 min) and short-cadence (SC; 58.8 s) data. Slawson et al. (2011) classified 2,165 eclipsing binaries from Kepler data, including 1,261 detached, 152 semi-detached, and 469 overcontact systems. We selected five semi-detached binaries with known orbital solutions to test our model on real observations.

The modeling procedure involves: (1) Light curve preprocessing: fold the data using Kepler periods, standardize using equations (2) and (3), remove points with errors $>3\sigma$, bin the data into 100 phase bins, and use bin means as input. Figure 7: see original paper-(e) shows preprocessed light curves for KIC10581918, KIC10619109, KIC06669809, KIC06206751, and KIC06048106, with gray points representing original data and blue points showing the preprocessed input. (2) Input the preprocessed light curve and primary temperature (from Kepler or spectroscopy) into both models, reproduce light curves using predicted parameters, calculate R^2 values, and select the configuration with higher R^2.

Figure 8: see original paper-(e) shows modeling results for the five targets. Gray points are observed light curves, orange dashed lines show primary-filled model results, and blue lines show secondary-filled model results. All five systems achieve better fits with the secondary-filled model, consistent with literature classifications.

compares parameters derived from our neural network model with literature values obtained using PHOEBE or WD code. Most parameters agree within literature error bounds. For KIC06669809 and KIC06206751, R^2 values are below 0.9, likely due to: (1) asymmetric light curves outside eclipse (phases 0.25 and 0.75) from starspots or hot spots; (2) for KIC06669809, orbital inclination $<70°$ reduces accuracy; (3) for KIC06206751, possible orbital eccentricity (primary-secondary eclipse separation = 0.5008). The model achieves $R^2 > 0.9$

for symmetric pulsating eclipsing binaries without spot-induced asymmetries, providing an important tool for analyzing stellar pulsation mechanisms and identifying systems with special characteristics.

3.2 Analysis of Model Performance

For Kepler, photometric precision is ~100 ppm (~0.0001 mag) for stars with $K_p < 13$ mag at 30-min exposure. However, for binaries, observational error (σ) affects parameter measurement in relation to light curve amplitude (Δm). We define relative measurement error as $\sigma/\Delta m$ to characterize this impact. Using KIC10581918 (amplitude ~1.84 mag) as a template, we performed Monte Carlo simulations to estimate parameter measurement errors under different observational errors. After adding noise corresponding to various relative errors, we binned the data and used the secondary-filled model to estimate parameters.

[Figure 9: see original paper] shows parameter measurement errors versus relative error. Errors increase with relative error. At $\sigma/\Delta m = 0.01$, measurement errors for orbital inclination, relative radius, mass ratio, and temperature ratio are 1.251°, 0.004, 0.008, and 0.003, respectively. Compared with , deviations from literature values fall within error bounds for relative radius, mass ratio, and temperature ratio. The orbital inclination deviation is ~-1.2°. As relative error increases, predicted orbital inclination, primary relative radius, and temperature ratio show increasing trends because noise affects the shallow secondary eclipse more than the primary eclipse, leading to larger measured inclination, smaller secondary radius (manifesting as larger primary relative radius), smaller mass ratio, and larger temperature ratio.

In summary, the model accurately derives binary parameters from Kepler data, achieving $R^2 > 0.9$ for symmetric semi-detached binaries. At $\sigma/\Delta m = 0.01$, measurement errors are 1.251°, 0.004, 0.008, and 0.003 for orbital inclination, relative radius, mass ratio, and temperature ratio, respectively, providing a solid foundation for statistical studies of mass and angular momentum transfer in close binary systems.

The neural network model dramatically reduces computation time: modeling a 100-point light curve takes ~5 ms on a 2.10 GHz Intel Xeon Gold 5218R CPU with 128 GB memory, compared to ~4 s using PHOEBE. MCMC+PHOEBE fitting with 80 walkers and 2000 steps requires >10 hours for the same data.

4 Summary and Outlook

This work presents a neural network-based rapid photometric orbital solution model for semi-detached binaries, including separate primary-filled and secondary-filled models. Using light curves and primary temperatures, the model derives orbital inclination, relative radius, mass ratio, and temperature ratio. For synthetic data, the primary-filled model achieves residual standard deviations of 0.238°, 0.003, 0.010, and 0.024 for the four parameters, with $R^2 \approx 0.99$. The secondary-filled model achieves 0.291°, 0.004, 0.013, and

0.016, also with $R^2 \approx 0.99$. Application to Kepler semi-detached binaries shows accurate parameter estimation for symmetric light curves ($R^2 > 0.9$). At $\sigma/\Delta m = 0.01$, measurement errors are 1.251°, 0.004, 0.008, and 0.003. The model accurately models pulsating eclipsing binaries, which is crucial for analyzing stellar pulsation mechanisms and identifying binaries with special characteristics.

This modeling tool significantly reduces computational time, enabling rapid derivation of orbital parameters from massive light curve datasets. These parameters provide essential data for studying mass and angular momentum transfer, loss, and redistribution in close binary systems. Light curve modeling is fundamental for investigating pulsation mechanisms in eclipsing binaries; removing eclipse effects reveals non-radial oscillations for asteroseismic analysis, constraining overshooting parameters and providing insights into stellar interiors. The model can be transferred to different surveys through transfer learning—e.g., using TESS bandpass data for TESS analysis. This rapid modeling tool is essential for statistical studies of semi-detached binaries and efficient identification of systems with special physical mechanisms.

References

[1] MINK S, LANGER N, IZZARD R G, et al. The rotation rates of massive stars: the role of binary interaction through tides, mass transfer, and mergers [J]. The Astrophysical Journal, 2013, 764(2): 638.

[2] ELDRIDGE J J, STANWAY E R, XIAO L, et al. Binary population and spectral synthesis version 2.1: construction, observational verification, and new results[J]. Publications of the Astronomical Society of Australia, 2017, 34: e058.

[3] CHEN X F, LI Y, HAN Z W. The formation of double compact objects as gravitational wave sources[J]. Scientia Sinica: Physica Mechanica & Astronomica, 2018, 48(7): 26-56.

[4] LIAKOS A. Asteroseismology of Kepler Algol-type oscillating eclipsing binaries[J]. Astronomy & Astrophysics, 2017, 607: A85.

[5] AERTS C, HARMANEC P. Pulsating components in close binaries[C]//Proceedings of the ASP Conference Series. 2004: 325-333.

[6] BORUCKI W J, KOCH D, BASRI G, et al. Kepler planet-detection mission: introduction and first results[J]. Science, 2010, 327(5968): 977-980.

[7] RICKER G R, LATHAM D W, VANDERSPEK R K, et al. Transiting Exoplanet Survey Satellite (TESS)[C]//Proceedings of the American Astronomical Society Meeting. 2010.

[8] BELLM E C, KULKARNI S R, BARLOW T, et al. The Zwicky Transient Facility: system overview, performance, and first results[J]. Publications of the Astronomical Society of the Pacific, 2019, 131(995): 018002.

[9] KOCHANEK C S, SHAPPEE B J, STANEK K Z, et al. The All-Sky Automated Survey for Supernovae (ASAS-SN) light curve server v1.0[J]. Publications of the Astronomical Society of the Pacific, 2017, 129(980): 104502.

[10] KIRK B, CONROY K, PRŠA A, et al. Kepler eclipsing binary stars. VII. The catalog of eclipsing binaries found in the entire Kepler data set [J]. The Astronomical Journal, 2016, 151(3): 68.

[11] CHEN X, WANG S, DENG L, et al. The Zwicky Transient Facility catalog of periodic variable stars[J]. The Astrophysical Journal Supplement Series, 2020, 249(1): 18.

[12] JAYASINGHE T, KOCHANEK C S, STANEK K Z, et al. The ASAS-SN catalogue of variable stars IX: the spectroscopic properties of galactic variable stars[J]. Monthly Notices of the Royal Astronomical Society, 2021, 503(1): 200-235.

[13] DRAKE A J, GRAHAM M J, DJORGOVSKI S G, et al. The catalina surveys periodic variable star catalog[J]. The Astrophysical Journal Supplement Series, 2014, 213(1): 9.

[14] PRŠA A, ZWITTER T. A computational guide to physics of eclipsing binaries. I. Demonstrations and perspectives[J]. The Astrophysical Journal, 2005, 628(1): 426.

[15] WILSON R E, DEVINNEY E J. Realization of accurate close-binary light curves: application to MR Cygni[J]. The Astrophysical Journal, 1971, 166: 605.

[16] ZHU L Y. Photometric and statistical study of near contact binaries[D]. Kunming: Yunnan Observatories, Chinese Academy of Sciences, 2004.

[17] EGGLETON P P. Approximations to the radii of Roche lobes[J]. The Astrophysical Journal, 1983, 268: 368–369.

[18] SLAWSON R W, PRŠA A, WELSH W F, et al. Kepler eclipsing binary stars. II. 2165 eclipsing binaries in the second data release[J]. The Astronomical Journal, 2011, 142(5): 160.

[19] LEE J W, PARK J H. KIC 6206751: the first R CMa-type eclipsing binary with γ Doradus pulsations[J]. Monthly Notices of the Royal Astronomical Society, 2018, 480(4): 4693-4701.

[20] LEE J W. γ Doradus pulsations in the eclipsing binary star KIC 6048106[J]. The Astrophysical Journal, 2016, 833(2): 170.

[21] GILLILAND R L, CHAPLIN W J, DUNHAM E W, et al. Kepler mission stellar and instrument noise properties[J]. The Astrophysical Journal Supplement Series, 2011, 197(1): 6.

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