Postprint of Transient Source Detection Methods Based on CSST

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Abstract

The China Space Survey Telescope (CSST) is a 2,m aperture space optical telescope planned and constructed under China' s manned space engineering program, with large-scale astronomical sky survey as its primary mission, featuring both high spatial resolution and large field-of-view capabilities with excellent performance. Transient sources represent one of the important scientific objectives of CSST. As a space telescope, CSST exhibits significantly different image noise composition compared to ground-based telescopes. Therefore, transient source detection schemes from previous ground-based survey projects cannot be directly applied, necessitating the development of dedicated detection methods specifically tailored for CSST. The CSST transient source detection method is developed and validated based on CSST simulation data, aiming to identify transient sources in CSST main survey data as accurately as possible. The method is founded on image subtraction, first obtaining the residual image corresponding to the observation image and utilizing filtering methods to determine the Poisson noise distribution of the residual image; then employing gradual thresholds to indirectly unify the background noise level, performing target source photometry on the residual image to obtain a candidate source list; finally, screening real transient sources by assessing the deviation of candidate sources from local Poisson noise, and after incorporating original image information and observation image photometric classification information, further eliminating false sources from the candidate list to ultimately output a transient source catalog. In multiple rounds of simulation tests totaling 20000 transient sources, the method can screen transient sources in observation images with an average accuracy of 95.9%. Compared to previous work, it also provides more comprehensive and quantitative detection rates for transient sources of different brightness levels obtained from the tests. The test conclusions validate the feasibility, generalization capability, and stability of the CSST transient source detection method. This method also provides theoretical and programming foundations for transient source detection missions of space telescopes.

Full Text

Transient Detection Method Based on CSST

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ABSTRACT

The China Space Survey Telescope (CSST) is a 2-meter aperture optical space telescope planned by the China Manned Space Program, with the primary focus on large-scale surveys, which combines high spatial resolution and a large field of view. Transients are one of the important scientific objectives of CSST. As a space telescope, the image noise composition of CSST is significantly different from that of ground-based telescopes. Therefore, it is unsuitable to directly apply the transient detection scheme of previous ground-based survey projects, and it is necessary to develop an independent detection method for CSST. The CSST transient detection method is developed and validated based on CSST simulation data, aiming to identify transients in CSST main survey data as accurately as possible. The method is based on Difference Image Analysis (DIA), which first obtains the residual images corresponding to the observed image, and then uses a filtering method to obtain the local Poisson noise distribution of the residual image. The method then uses a changing threshold to indirectly unify the image noise level, and performs photometry and source extraction on the residual image to obtain a list of candidate sources. Next, the real sources are filtered by judging the deviation of the candidate sources from local Poisson noise. After combining the photometric classification information of the observed image and the information of the original image, the fake sources in the candidate source list are further eliminated. The final output is a transient list. The method is able to filter transients in the observed images with an average accuracy of 95.9% in a multi-round simulation test with a total of 20000 transients. Compared with previous work, the test also quantifies the detection rates of transients with different brightness more comprehensively. The conclusions of the test validate the feasibility, generalization, and stability of the CSST transient detection method. The method also provides a theoretical and programming basis for transient detection missions of space telescopes.

Key words: methods: data analysis, techniques: image processing, telescopes, surveys

2. Data Processing Method

The CSST transient detection method is based on Difference Image Analysis (DIA) and consists of four main steps: (1) obtaining the residual image, (2) performing photometry and source extraction on the residual image, (3) filtering real sources based on local Poisson noise characteristics, and (4) eliminating fake sources by combining photometric classification information from the observed image and original image information. The final output is a transient catalog.

2.1 Noise Model

The noise model is fundamental to transient detection. For CSST images, the primary noise sources include photon-counting Poisson noise from celestial bodies and the sky background, as well as Gaussian readout noise from the detector. The observed image intensity distribution can be described as follows: the Poisson distribution for photon counting can be approximated by a Gaussian distribution with equal mean and variance. For an input image I_{input}, the output image I after exposure time t and gain g follows:

$$E(I_{\text{input}}) = \alpha\Phi tg, \quad \sigma^2(I_{\text{input}}) = (\alpha\Phi + n)tg^2 + \sigma_{\text{add}}^2 = E(I_{\text{input}})g + ntg^2 + \sigma_{\text{add}}^2$$

where α is the CCD response coefficient, Φ is the flux, n is the background photon count, and σ_{add} is the additive noise standard deviation.

In CSST observations, the gain $g = 1.1$ and exposure time $t = 150$ s. The CCD parameter α relates to the instrumental magnitude. The noise model must account for both Poisson noise from photon statistics and additive Gaussian readout noise. The residual image noise characteristics differ from the original image, requiring careful modeling for accurate source detection.

2.2 Source Detection and Classification

After obtaining the residual image, source detection is performed using DAOPHOT (Dominion Astrophysical Observatory PHOTometry) and DAOStarFinder algorithms, which identify point sources by fitting point spread functions. The detected sources are then classified using machine learning methods.

The classification system includes four categories: stars, galaxies, active galactic nuclei (AGN), and fake sources. The input catalog contains both real and fake sources, with the photometry catalog used for training the classifiers. Table 1 shows the proportion of celestial bodies in the input and photometry catalogs.

We evaluated multiple machine learning classifiers for this task, including Kernel Support Vector Machine (Kernel SVM), Multilayer Perceptron (MLP), Random Forest (RF), Adaptive Boosting (AdaBoost), Gradient Boosting Decision Tree (GBDT), XGBoost, and Gaussian Process Classifier (GPC). The performance metrics include average accuracy, false positive rate, and false negative rate for both two-category (real/fake) and four-category classification.

Based on the results in Table 2, XGBoost demonstrates the best performance with an average accuracy of 0.94 ± 0.03 for four-category classification. The classifier effectively distinguishes between different source types while minimizing false positives. The classification process involves training on photometric features extracted from the residual images, with the model subsequently applied to identify and filter fake sources from the candidate list.

3. Residual Image Detection

3.2 Residual Image Processing

The residual image detection module processes the difference image to identify transient candidates. The key challenge is distinguishing real transient signals from noise fluctuations. We employ two approaches for noise modeling: (1) a filtering method that estimates local noise statistics, and (2) a model fitting method that parameterizes the noise distribution.

The filtering method uses median and mean filters to estimate the local background and noise level. For a residual image I, the noise template T is obtained through:

$$\langle I_{\text{input}} \rangle = 2.5 \times \text{Median}_{m\times m} \circ I_{\text{input}}, \quad \text{or} \quad \langle I_{\text{input}} \rangle = 1.5 \times \text{Mean}_{m\times m} \circ I_{\text{input}} - \text{Median}_{m\times m} \circ I_{\text{input}}$$

where $\circ$ denotes convolution. The noise model N is then derived from the residual between the original and filtered images.

[Figure 3: see original paper]

Figure 3 illustrates the two noise modeling approaches. The filtering method (a) directly estimates noise from the residual image, while the model fitting method (b) fits a parametric model to the noise characteristics. The model fitting approach yields a more accurate noise model, especially for bright sources where the Poisson noise variance scales with flux.

For elliptical galaxies, the model fitting method provides better noise characterization than simple filtering. Figure 4 compares the two methods, showing that the model-fitted noise profile (N-model) more closely matches the actual residual profile (RP) than the filtering approach.

[Figure 4: see original paper]

The detection threshold is dynamically adjusted based on local noise statistics. We define a contrast graph S as the ratio of the residual image I to the noise model N. Source detection is performed on both the residual image and the contrast graph using multiple threshold levels: conservative, joint, and lower thresholds. This multi-threshold approach ensures robust detection across varying source brightness and background levels.

[Figure 5: see original paper]

The threshold coefficients for photometry and contrast graph methods correlate with the standard deviation of local noise. Figure 10 shows this relationship, demonstrating that optimal threshold selection depends on the noise characteristics of the specific image region.

[Figure 10: see original paper]

4. Results and Discussion

4.1 Detection Efficiency Quantification

We quantified the detection efficiency using signal-to-noise ratio (S/N) as the primary metric. The detection probability as a function of S/N follows a sigmoid relationship:

$$\text{Detectivity}(S/N) = \frac{1}{1 + e^{-k(S/N - S/N_0)}}$$

In our simulations with 20,000 transients, the method achieved an average detection accuracy of 96% for sources with S/N > 5. The detection rate reaches 100% for bright sources (S/N > 10) while maintaining a low false positive rate of approximately 4%.

[Figure 9: see original paper]

The recall curve fitting shows that the method' s detection efficiency is consistent across different transient brightness levels. The joint threshold approach provides optimal performance, balancing detection completeness and purity.

4.2 Method Applicability and Future Work

The CSST transient detection method demonstrates strong generalization capabilities across different image conditions. The modular design allows adaptation to various survey strategies and instrument configurations. Current limitations include computational efficiency for large-scale surveys and optimization of threshold parameters for specific science cases.

Future improvements will focus on: (1) integrating deep learning-based detection algorithms to enhance sensitivity to faint transients, (2) developing real-time processing capabilities for rapid transient identification, and (3) extending the method to multi-band detection for improved classification accuracy. The method provides a robust foundation for CSST' s transient science program and can be adapted for other space-based survey telescopes.

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