A quasi-optimal stacking method for up-the-ramp readout images postprint

Authors: Guanghuan Wang, Hu Zhan, Zun Luo, Chengqi Liu, Youhua Xu, Chun Lin, Yanfeng Wei, Wenlong Fan, Hu Zhan

Date: 2025-04-24T09:31:31+00:00

Abstract

A detector' s nondestructive readout mode allows its pixels to be read multiple times during integration, enabling generation of a series of "up-the-ramp" images that continuously accumulate photons between successive frames. Because noise is correlated across these images, optimal stacking generally requires the images to be weighted unequally to achieve the best possible target signal-to-noise ratio (SNR). Objects in the sky present wildly varied brightness characteristics, and the counts in individual pixels of the same object can also span wide ranges. Therefore, a single set of weights cannot be optimal in all cases. To ensure that the stacked image is easily calibratable, we apply the same weight to all pixels within the same frame. In practice, results for high-SNR cases degraded only slightly when we used weights derived for low-SNR cases, whereas the low-SNR cases remained more sensitive to the weights. Therefore, we propose a quasi-optimal stacking method that maximizes the stacked SNR for the case where the RSN=1 per pixel in the last frame and use simulated data to demonstrate that this approach enhances the SNR more strongly than the equal-weight stacking and ramp fitting methods. Furthermore, we estimate the improvements in the limiting magnitudes for the China Space Station Telescope using the proposed method. When compared with the conventional readout mode, which is equivalent to selecting the last frame from the nondestructive readout, stacking 30 up-the-ramp images can improve the limiting magnitude by approximately 0.5 mag for the telescope' s near-infrared observations, effectively reducing readout noise by approximately 62%.

Full Text

Preamble

Astronomical Techniques and Instruments, Vol. 2, March 2025, 119–126

Article Open Access

A Quasi-Optimal Stacking Method for Up-the-Ramp Readout Images

Guanghuan Wang[1,2], Hu Zhan[1,3*], Zun Luo[1,2], Chengqi Liu[3], Youhua Xu[1], Chun Lin[4], Yanfeng Wei[4], Wenlong Fan[5]

[1]Key Laboratory of Space Astronomy and Technology, National Astronomical Observatories, Chinese Academy of Sciences, Beijing 100101, China
[2]University of Chinese Academy of Sciences, Beijing 101408, China
[3]Kavli Institute for Astronomy and Astrophysics, Peking University, Beijing 100871, China
[4]National Key Laboratory of Infrared Detection Technologies, Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai 200083, China
[5]Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai 200083, China

*Correspondence: zhanhu@nao.cas.cn

Received: October 16, 2024; Accepted: December 27, 2024; Published Online: February 18, 2025
https://doi.org/10.61977/ati2024058; https://cstr.cn/32083.14.ati2024058

Citation: Wang, G. H., Zhan, H., Luo, Z., et al. 2025. A quasi-optimal stacking method for up-the-ramp readout images. *Astronomical Techniques and Instruments*, 2(2): 119−126. https://doi.org/10.61977/ati2024058.

Abstract

A detector’ s nondestructive readout mode allows its pixels to be read multiple times during integration, enabling generation of a series of “up-the-ramp” images that continuously accumulate photons between successive frames. Because noise is correlated across these images, optimal stacking generally requires the images to be weighted unequally to achieve the best possible target signal-to-noise ratio (SNR). Objects in the sky present wildly varied brightness characteristics, and the counts in individual pixels of the same object can also span wide ranges. Therefore, a single set of weights cannot be optimal in all cases. To ensure that the stacked image is easily calibratable, we apply the same weight to all pixels within the same frame. In practice, results for high-SNR cases degraded only slightly when we used weights derived for low-SNR cases, whereas the low-SNR cases remained more sensitive to the weights.

Therefore, we propose a quasi-optimal stacking method that maximizes the stacked SNR for the case where the RSN=1 per pixel in the last frame and use simulated data to demonstrate that this approach enhances the SNR more strongly than the equal-weight stacking and ramp fitting methods. Furthermore, we estimate the improvements in the limiting magnitudes for the China Space Station Telescope using the proposed method. When compared with the conventional readout mode, which is equivalent to selecting the last frame from the nondestructive readout, stacking 30 up-the-ramp images can improve the limiting magnitude by approximately 0.5 mag for the telescope' s near-infrared observations, effectively reducing readout noise by approximately 62%.

Keywords: Astronomical detectors; Infrared observatories; Astronomy data reduction; Astronomy image processing

1. Introduction

Infrared detectors are often designed to have a nondestructive readout mode that can sample the signal in a pixel multiple times during integration without altering that signal. The nondestructive readout mode is used extensively in astronomical infrared cameras, including: the Near-Infrared Camera and the Multi-Object Spectrometer and Wide Field Camera 3 (WFC3) on the Hubble Space Telescope; the infrared array camera of the Spitzer Space Telescope; all infrared cameras of the James Webb Space Telescope; the near-infrared spectrograph and photometer of the Euclid mission; and the wide field instrument on board the forthcoming Nancy Grace Roman Space Telescope. The China Space Station Telescope (CSST) will also observe in the near infrared (NIR) using detectors made by the Shanghai Institute of Technical Physics.

The nondestructive readout mode offers several advantages. First, multiple frames that have been sampled during integration can be reduced to a single frame to mitigate the effects of readout noise and improve the data quality. Additionally, the data losses caused by cosmic rays can at least be recovered partially from the nondestructive readout data. Pixels that have been struck by cosmic rays exhibit jumps in their integration ramps and appropriate algorithms can be used to identify and remove these jumps. Finally, the pixel values that are read out before saturation is reached can be used to perform nonlinearity correction to increase the detector' s effective dynamic range and thus enable richer details to be captured.

The sequence of output frames acquired with increasing exposure time in nondestructive readout mode forms a three-dimensional data cube. Hereafter, we refer to this series of images as up-the-ramp images, or as ramp images for short. A reduction strategy is required to combine the series into a single image and enhance the signal-to-noise ratio (SNR). An equal-weight stacking method is used in WFC3 to reduce the effective readout noise. Because the SNR increases with increasing exposure time, weighting all the frames equally biases against the high-SNR frames, thus causing the stacked SNR to even be below the SNR of the final frame in the signal-dominant regime. It is also possible to fit the integration ramp for each pixel before saturation and then obtain the value at the exposure time for the last frame to construct a "combined" image, although this ramp fitting method becomes unstable when the number of up-the-ramp exposures is insufficient. In this paper, we develop a weighted stacking method that maximizes the SNR of the stacked image for the low-SNR target case while also maintaining good performance over the entire SNR range.

Simulations demonstrate that the proposed quasi-optimal stacking method achieves a higher SNR than both the equal-weight stacking method and the ramp fitting method, and the proposed method can be particularly helpful for faint object detection applications with observations acquired in the readout noise-dominant regime.

The remainder of this paper is organized as follows. In Section 2, we derive the optimal weights and examine their performances when the target case is mismatched with the actual observations. We then compare the performance of our method with the current commonly used reduction methods under various conditions in Section 3. Section 4 provides an estimate of the improvement produced by the quasi-optimal stacking method for CSST NIR observations. The conclusions from the study are drawn in Section 5.

---

2. Quasi-Optimal Stacking

In a series of ramp images, the pixel values in each frame are accumulated on top of the previous frame. Although the optimal stacking weights are dependent on the signal and the noise, which will vary from pixel to pixel, we have chosen to apply the same weight to all pixels in a single frame. When this approach is used, the stacking is not optimal for all pixels, but the flux calibration of the stacked image can be conducted in the usual manner. If the weights are optimized for each pixel individually based on their specific signal and noise characteristics, which are not generally known a priori, the stacking results in low-SNR regions can be affected significantly by random fluctuations in the noise and thus potentially bias the flux calibration.

We begin with the case of a single pixel for simplicity. This case can also be regarded as a ramp series of flat-field images with identical pixels. By assuming that both the bias correction and the nonlinear correction have been conducted already, we obtain the following pixel value in the i-th frame:

$$f_i = s_i + \Delta s_i + b_i + \Delta b_i + \Delta r_i \quad (1)$$

where s_i and Δs_i are the mean signal of the source and the associated Poisson fluctuation, respectively, b_i and Δb_i are the mean background (including contributions from dark current and the sky background) and the associated Poisson fluctuation, respectively, and Δr_i is the Gaussian fluctuation due to the readout noise. The circuit gain is irrelevant during the stacking process and is thus omitted from Equation (1) without loss of generality. Both s_i and b_i increase linearly with time. The fluctuation terms Δs_i, Δb_i, and Δr_i are all independent of each other, which means that the covariance of the pixel values between the different frames becomes:

$$\mathrm{Cov}(f_i, f_j) = \mathrm{Cov}(\Delta s_i, \Delta s_j) + \mathrm{Cov}(\Delta b_i, \Delta b_j) + \mathrm{Cov}(\Delta r_i, \Delta r_j) = s_{\min(i,j)} + b_{\min(i,j)} + r^2 \delta_{ij} \quad (2)$$

where δ_{ij} is the Kronecker delta function, and the readout noise r is assumed to be the same in all frames. In matrix form, we obtain:

$$C = \begin{pmatrix} s_1 + b_1 + r^2 & s_1 + b_1 & \cdots & s_1 + b_1 \\ s_1 + b_1 & s_2 + b_2 + r^2 & \cdots & s_2 + b_2 \\ \vdots & \vdots & \ddots & \vdots \\ s_1 + b_1 & s_2 + b_2 & \cdots & s_N + b_N + r^2 \end{pmatrix} \quad (3)$$

The readout noise is not correlated between the frames and only appears on the diagonal of the covariance matrix. The off-diagonal element values correspond to the Poisson noise in the previous frame, which is not correlated with either the signal or the background that is accumulated in the later frames.

We apply a series of weights $\omega = [\omega_1, \omega_2, \dots, \omega_N]^T$ to the ramp images and then obtain the stacked pixel value $\omega^T f$. The SNR of the stacked pixel can be expressed as $R_{SN} = \omega^T s / \sqrt{\omega^T C \omega}$, where $s = [s_1, s_2, \dots, s_N]^T$. To determine the weights that maximize the SNR, we set the derivative of the SNR with respect to the weights to zero, i.e., $\partial R_{SN} / \partial \omega = 0$. Because both $\omega^T s$ and $\omega^T C \omega$ are scalars, the optimal weight vector must satisfy $\omega_{\text{opt}} \propto C^{-1} s$. The solution is therefore given by:

$$\omega_{\text{opt}} = \frac{C^{-1} s}{\mathbf{1}^T C^{-1} s} \quad (6)$$

with the maximum SNR of:

$$R_{SN,\text{opt}} = \sqrt{s^T C^{-1} s} \quad (8)$$

The weights in Equation (7) are determined up to a scaling factor. A proper normalization of ω_{opt} is to match the "stacked exposure time" with the exposure time of the last frame, i.e., $\omega_{\text{opt}}^T t = t_N$, where $t = [t_1, t_2, \dots, t_N]^T$ contains the exposure time for each frame. The signal count rate is then $S = s_i / t_i$, and that of the background is $B = b_i / t_i$. We assume hereafter for convenience that the frames are equally spaced in time, i.e., $t_i = i \Delta t$.

Fig. 1 [Figure 1: see original paper] shows the optimal weights for a series of ramp images with the same settings ($N = 30$, $b_i = 0$, $r = 50e^{-}$) with the exception of the signal level. The frames are stacked in the same way in which the stacking of a single pixel is performed. Each line in the figure represents a different case of SNR per pixel in the last frame, $R_{SN,\text{last}}$, which is defined by:

$$R_{SN,\text{last}} = \frac{s_N}{\sqrt{s_N + b_N + r^2}} \quad (10)$$

The green dashed line represents equal-weighted stacking. Each set of weights is normalized according to Equation (9).

The figure shows that when $R_{SN,\text{last}}$ increases, greater weight is assigned to the later frames. In real observations, the counts in pixels can differ wildly, which means that one set of weights cannot maximize the SNR for all cases. However, to ensure that the final image remains easily calibratable, all pixels in the ramp images should be stacked using the same set of weights. Therefore, it is only possible to select a particular case of $R_{SN,\text{last}}$ as the target, which we label as $R_{SN,\text{target}}$. We use the optimal weights $\omega_{\text{opt}}(R_{SN,\text{target}})$ derived for the target to stack the ramp images. To explore the effects of target setting, we expand the range of the examples shown in Fig. 1 to $1 \leq R_{SN,\text{last}} \leq 100$ and then stack the ramp images with $R_{SN,\text{target}} = 1$, $R_{SN,\text{target}} = 6.5$, and use the optimal weights $\omega_{\text{opt}}(R_{SN,\text{target}})$. Equation (4) is then used to calculate the SNR of the stack, $R_{SN,\text{stack}}(R_{SN,\text{target}})$. The result is normalized based on the matched case of $R_{SN,\text{target}} = R_{SN,\text{last}}$ and is shown as a function of both $R_{SN,\text{target}}$ and $R_{SN,\text{last}}$ in Fig. 2 [Figure 2: see original paper] (see Table 1 for a description of the symbols related to the various weights and SNR values).

As indicated by the values shown in the top-left corner of Fig. 2, setting a brighter target case (i.e., a higher $R_{SN,\text{target}}$) causes a significant reduction in the SNR of the stacked frame for fainter objects (lower $R_{SN,\text{last}}$). A strategy that involves setting a fainter target case allows us to avoid falling into such a circumstance and can realize an SNR that is almost the same as that obtained using true optimal weights (as indicated by the green dashed line). With $R_{SN,\text{target}}$ set to 6.5 (red solid line), the reduction in SNR when compared with use of the true optimal weights is less than 4% when $R_{SN,\text{last}} \lesssim 10$, and when $R_{SN,\text{last}} \gtrsim 130$ (horizontal axis), the degradation does not exceed 1%. In both cases, the resulting $R_{SN,\text{stack}}$ value is still higher than $R_{SN,\text{last}}$ (see similar cases in Section 3).

Given that the detection limit is critical for most projects, the SNR of the faintest detectable objects in the final stack can be boosted by setting a low target $R_{SN,\text{target}}$. This approach is not optimal for all SNR cases, and thus we refer to it as the quasi-optimal stacking method. For a telescope with a point spread function (PSF) that is sampled appropriately, the most compact objects such as stars usually cover more than 10 pixels each. If $R_{SN} = 5$ is used as the threshold, then the average SNR per pixel would be less than 2 for a barely detected star. With extended sources such as galaxies, using the same threshold could mean an average SNR per pixel that approaches unity or even less. Because the SNR of the stacked image is insensitive to the target $R_{SN,\mathrm{target}}$ in low-SNR cases, a reasonably good strategy would be to set the target $R_{SN,\mathrm{target}} = 1$ for optimization.

---

3. Methods

As noted in Section 1, conventional methods for ramp-image reduction include the equal-weight stacking method and the ramp fitting method. The latter approach fits the slope of the integration ramp for each pixel, where the slope represents the count rate in the pixel, and the count rates from all pixels form the final image.

The last frame of a ramp series is equivalent to a frame with the same total exposure time that would be taken in the conventional destructive readout mode. This frame serves as a useful benchmark for comparison of the different ramp-image reduction methods, and we also refer to it as a reduction method for convenience. To evaluate the performance of the quasi-optimal stacking method and the other available methods, we undertake two tests using simulated images: the flat-field test and the point-source test. Details of these tests are given below.

3.1. Flat-field Test

For the flat-field test, we generate ramp images with uniform illumination by setting the signal $s_i = t_i S$ to have the same value for all pixels in the same frame. A uniform background $b_i = t_i B$ is applied similarly. The readout noise r is assumed to be the same for all pixels in all frames. The images are 2000×2000 pixels each in size and are large enough to ensure that the statistical errors are negligible. Randomly drawn values from the Poisson distribution of the signal, that of the background, and the Gaussian distribution of the readout noise are then summed to determine the count in each pixel.

Equation (1) shows that there are three noise types in the pixel: the Poisson (or photon) noise of the source, the Poisson noise of the background, and the Gaussian noise of the readout process. Ramp-image reduction methods can behave differently in regimes dominated by different noise types, so we designed the test accordingly in three cases with their parameters as listed in Table 2 . Specifically, by the dominant noise, we mean the noise with a variance that is greater than that of the other two noise types combined.

The first row in Fig. 3 [Figure 3: see original paper] compares the SNR per pixel values realized by the four ramp-image reduction methods. The SNR is given by the ratio of the standard deviation of all pixels in the reduced image to the mean of these pixels. The results show that our quasi-optimal stacking method consistently outperforms the other methods in all three cases. Because the quasi-optimal stacking method assigns greater weight to frames with more signals, it should always obtain a better SNR than the equal-weight stacking method. Moreover, the results for $R_{SN,\mathrm{target}} = 1$ (red solid curve) and $R_{SN,\mathrm{target}} = 5$ (green dashed curve) are essentially identical, and thus support the strategy of setting $R_{SN,\mathrm{target}} = 1$. The last-frame method actually surpasses $R_{SN,\mathrm{last}}$, which is beyond the range shown in the photon-noise dominant panel. A small degradation in such a high SNR will hardly affect object detection, and thus setting $R_{SN,\mathrm{target}}$ to unity can be regarded as a fail-safe choice for the quasi-optimal stacking method.

Although we usually try not to observe images in the readout-noise-dominant regime, it is sometimes unavoidable. Actually, in this regime, we observe greater enhancement of the SNR over that of the last-frame method by the other three methods than was observed within the background-noise-dominant regime and the photon-noise-dominant regime (collectively, this is the Poisson-noise dominant regime). This indeed manifests as a main advantage of the nondestructive readout mode.

To check the dependence of the SNR of the reduced image on the number of nondestructive readouts during the entire exposure time, we generated another set of ramp images according to Table 2 but with N ranging from 1 to 70 and t_N fixed. The results are shown in the second row of Fig. 3. The stacking methods and the ramp fitting method show convergent behavior as N becomes large enough. The quasi-optimal stacking method realizes the best SNR among the methods above and also robustly outperforms the last-frame method in all three cases shown. The equal-weight stacking method is slightly worse than the last-frame method in the Poisson-noise-dominated regime. The ramp fitting method performs poorly if the number of frames is not large enough. This is consistent with the noise of the ramp fitting method derived in the literature:

$$\sigma^2_{\mathrm{RF}} = \frac{12}{N(N^2-1)}\frac{r^2}{t_N} \quad (11)$$

in the readout-noise-dominated regime and

$$\sigma^2_{\mathrm{RF}} = \frac{6(N^2+1)}{5(N^2-1)}\frac{s_N}{t_N} \quad (12)$$

in the Poisson-noise dominated regime. With a sufficiently large number of frames, the noise of the ramp fitting method approaches a factor of $\sqrt{12/5} \approx 1.55$ greater than that of the equal-weight stacking method in the readout-noise-dominated regime according to Equation (11) and is slightly higher than that of the last frame in the Poisson-noise-dominated regime according to Equation (12).

3.2. Point-source Test

The flat-field test in the previous subsection is reasonably instructive, but it does not encompass the complexity of sky images. Here, we provide a test based on ramp images of a circular Gaussian PSF at various SNRs that is designed to mimic real observations of point sources such as stars. The full width at half maximum (FWHM) value of the PSF is set at 3 pixels, and the background count rate and the total exposure time take the same values from the readout-noise-dominant case given in Table 2. The ramp images consist of $N = 30$ frames and they are processed using the quasi-optimal stacking method ($R_{SN,\mathrm{target}} = 1$), the equal-weight stacking method, the ramp fitting method, and the last-frame method. We then performed aperture photometry measurements on the reduced images using the Python Library for Source Extraction and Photometry (SEP).

The reduced images are shown in Fig. 4 [Figure 4: see original paper]. A star is at the center of each panel. The star' s signal is effectively all contained within 5 pixels from the center, and thus the region outside the star' s footprint is essentially a map of the background and the readout noise. The number on the label in each panel is the star' s SNR within an aperture of 2.3 pixels. The images show that the quasi-optimal stacking method can boost the star' s SNR by 57%-70% over that determined in the last frame. This degree of enhancement can make a difference between detection and nondetection. For example, in the first row in Fig. 4, the star is hardly distinguishable from the background in the last-frame image (in the rightmost panel) but it becomes more discernible in the images processed by the other three methods, with the same rank of performance as seen in the readout-noise dominant case in Fig. 3. The visual impression is consistent with the SNR labeled in each panel, which demonstrates quantitatively that the quasi-optimal stacking method offers the best chance of detection of faint objects close to the detection threshold. It should also be noted that the SNR enhancement is in part caused by the suppression of the readout noise, which can be confirmed visually for the two stacking methods.

---

4. Improvement for the CSST

In this section, we assess the improvement of CSST NIR imaging observations in terms of the limiting magnitude and effective readout noise when using the quasi-optimal stacking method.

The photoelectron count for a star of magnitude m_{AB} in the CSST NIR imager is given by:

$$s_{80} = A_{\mathrm{apr}} T_{\mathrm{sys}} \int f_\nu(m_{AB}) h\nu \, d\nu \quad (13)$$

where s_{80} is the count within the radius encircling 80% of the energy of the PSF (R_{80}), A_{apr} is the area of the telescope aperture, T_{sys} is the system throughput (which is assumed to be constant), $f_\nu(m_{AB})$ is the spectral flux density of the star, and the integration limits are defined by the filter' s cut-on and cut-off frequencies. By definition in the AB magnitude system, the spectral flux density is flat over the range of frequencies and is related to m_{AB} by:

$$m_{AB} = -2.5\log_{10}\left(\frac{f_\nu}{f_0}\right) \quad (14)$$

where $f_0 = 3.631\times10^{-23}\text{W m}^{-2}\text{Hz}^{-1}$. The exposure time is fixed at the nominal value of 150 s. The SNR of the star is determined from the reduced image of the simulated ramp images in the same manner that was used in Section 3.2, except for the fact that the relevant parameters are adjusted to use the values given in Table 3 . We then obtain the limiting magnitude corresponding to the detection threshold where $R_{SN} = 5$.

Table 4 summarizes the improvements observed in the limiting magnitude and the effective readout noise in J' and H' bands as the number of frames in the ramp series (N) increases. The CSST NIR imager was able to output a maximum of approximately 70 frames during each 150 s exposure, and thus Table 4 stops at $N = 70$. In both bands, stacking 30 frames using the quasi-optimal stacking method can increase the limiting magnitude by approximately 0.5 mag when compared with the result from the last frame, which is the same as the $N = 10$ case, and stacking 70 frames can increase this magnitude by approximately 0.6 mag. Given that the limiting magnitude only increases slowly for $N \geq 30$, we recommend that the CSST NIR imager acquires at least 30 frames in the nondestructive readout mode during its nominal 150 s exposures.

When compared with the last frame, the quasi-optimal stacking method requires a lower photoelectron count to achieve the same SNR, and this is equivalent to a reduction in the readout noise. In quantitative terms, we define the effective readout noise as follows:

$$r_{\text{eff}} = \sqrt{\frac{1}{n_{\text{pix}}}\left[\left(\frac{s_{80}}{R_{SN}}\right)^2 - s_{80}\right] - b} \quad (15)$$

where n_{pix} is the pixel number within R_{80}. The results are also shown in Table 4. Stacking 30 frames results in a reduction in the effective readout noise by approximately 62%, while stacking 70 frames reduces the noise further by approximately 71%.

Note that these performance improvements are achieved via data reduction, with no extra hardware work required.

5. Conclusion

In this work, we have developed a quasi-optimal stacking method for ramp images acquired in nondestructive readout mode. This method is designed to enhance faint object detection by setting a low-SNR target case for optimization. Although the stacking weights obtained are only truly optimal for objects of uniform brightness at a specific $R_{SN,\mathrm{target}}$ per pixel in the last frame, the stacking results for flat-field ramp images and point-source ramp images are not very sensitive to $R_{SN,\mathrm{target}}$ as long as its value remains low. A good choice is $R_{SN,\mathrm{target}} = 1$. The quasi-optimal stacking method outperforms the other methods that were tested in Section 3 except in the case where, in the photon-noise-dominant regime, it was eventually surpassed by the last frame at a sufficiently high SNR. Because of its ability to enhance the SNR in the low-SNR regime, the quasi-optimal stacking method can recoup a sizeable sample of faint objects of interest that are otherwise undetectable and can thus help to improve our knowledge of the faint-end luminosity functions of such objects.

Using the CSST NIR imager as an example, we estimate that the quasi-optimal stacking method can improve its limiting magnitudes in both the J' and H' bands by approximately 0.5 mag (0.6 mag) and can reduce its effective readout noise by approximately 62% (71%) with 30 (70) frames acquired in the nondestructive readout mode within the nominal exposure time of 150 s. These are highly significant improvements, and the reduction method will be worthy of implementation in the CSST NIR data pipeline in the future.

Acknowledgements

This work was supported by the National Key R&D Program of China (2022YFF0503400), the National Natural Science Foundation of China grant (U1931208) and China Manned Space Program through its Space Application System.

Author Contributions

Hu Zhan conceived the ideas and designed the study. Guanghuan Wang implemented the study. Guanghuan Wang and Hu Zhan wrote the paper with equal contribution. Zun Luo, Chengqi Liu and Youhua Xu assisted on simulations and data processing and made suggestions on the writing. Chun Lin, Yanfeng Wei and Wenlong Fan provided detailed characteristics of NIR detectors and provided useful comments on the manuscript. All authors read and approved the final manuscript.

Declaration of Interests

Hu Zhan is an editorial board member for Astronomical Techniques and Instruments and he was not involved in the editorial review or the decision to publish this article. The authors declare no competing interests.

References

1. Skinner, C. J., Bergeron, L. E., Schultz, A. B., et al. 1998. On-orbit properties of the nicmos detectors on hst. In proceedings of SPIE, 3354: 2−13.
2. Baggett, S. M., Hill, R. J., Kimble, R. A., et al. 2008. The wide-field camera 3 detectors. In proceedings of SPIE, 7021: 527−53.
3. Fazio, G. G., Hora, J. L., Willner, S. P., et al. 1998. Infrared array camera (IRAC) for the Space Infrared Telescope Facility (SIRTF). In proceedings of SPIE, 3354: 23−25.
4. Rieke, G. H. 2007. Infrared detector arrays for astronomy. *Annual Review of Astronomy & Astrophysics*, 45: 77−115.
5. Corcione, L., Ligori, S., Bortoletto, F., et al. 2012. The on-board electronics for the near infrared spectrograph and photometer (NISP) of the EUCLID Mission. In proceedings of SPIE, 8442: 1101−1112.
6. Muñoz, A. J., Macías-Pérez, J., Secroun, A., et al. 2021. Euclid: Estimation of the impact of correlated readout noise for flux measurements with the euclid NISP instrument. *Publications of the Astronomical Society of the Pacific*, 133.
7. Casertano, S. 2022. Determining the best-fitting slope and its uncertainty for up-the-ramp sampled images with unevenly distributed resultants. In Technical Report Roman-STScI-000394 (Baltimore: STScI).
8. Rauscher, B. J., Arendt, R. G., Fixsen, D. J., et al. 2019. Principal component analysis of up-the-ramp sampled infrared array data. *Journal of Astronomical Telescopes, Instruments, and Systems*, 5(2): 028001.
9. Zhan, H. 2011. Consideration for a large-scale multi-color imaging and slitless spectroscopy survey on the Chinese space station and its application in dark energy research. *Scientia Sinica Physica, Mechanica & Astronomica*, 41(12): 1441−1447. (in Chinese)
10. Zhan, H. 2021. The wide-field multiband imaging and slitless spectroscopy survey to be carried out by the Survey Space Telescope of China Manned Space Program. *Chinese Science Bulletin*, 66(11): 1290−1298. (in Chinese)
11. Gong, Y., Liu, X. K., Cao, Y., et al. 2019. Cosmology from the Chinese space station optical survey (CSS-OS). *The Astrophysical Journal*, 883(2): 203.
12. Lin, Q. H., Wei, Y. F., Chen, H. L., et al. 2024. Research of IRFPA ROIC for Infrared and Laser astronomy. *Engineering*, 53(1): 1−13. (in Chinese)
13. Sullivan, P. W., Croll, B., Simcoe, R. A. 2014. Near-infrared InGaAs

detectors for background-limited imaging and photometry. In proceedings of SPIE, 9154: 467−475.
14. Anderson, R. E., Gordon, K. D. 2011. Optimal cosmic-ray detection for nondestructive read ramps. *Publications of the Astronomical Society of the Pacific*, 123: 1237.
15. Offenberg, J. D., Fixsen, D. J., Rauscher, B. J., et al. 2001. Validation of up-the-ramp sampling with cosmic-ray rejection on infrared detectors. *Publications of Astronomical Society of the Pacific*, 113: 240.
16. Robberto, M. 2014. A generalized least square algorithm to process infrared data taken in non-destructive readout mode. In proceedings of SPIE, 9143: 1185−1195.
17. Fixsen, D. J., Offenberg, J. D., Hanisch, R. J., et al. 2000. Cosmic-ray rejection and readout efficiency for large-area arrays. *Publications of the Astronomical Society of the Pacific*, 112: 1350.
18. Darson, D., Dubois, J., Bourdernane, M., et al. 2017. Real-time high dynamic range based on multiple non destructive readout during a single exposure: application to ir imaging. In proceedings of the 11th International Conference on distributed smart cameras, 21−28.
19. Peng, J. H. 2010. Research of NDR to enhance the dynamic range of CMOS image sensor. *Microcomputer Information*, 26(10): 7−9. (in Chinese)
20. Dressel, L., Marinelli, M. 2023. WFC3 instrument handbook for cycle 31 v. 15.0, 15: 97−98, 286-290.
21. Gordon, K. D., Rieke, G. H., Engelbracht, C. W., et al. 2005. Reduction algorithms for the multiband imaging photometer for spitzer. *Publications of the Astronomical Society of the Pacific*, 117: 503.
22. Garnett, J. D., Forrest, W. J. 1993. Multiply sampled read-limited and background-limited noise performance. In proceedings of SPIE, 1946: 395−404.
23. Robberto, M. 2007. Analysis of the sampling schemes for WFC3-IR. *Instrument Science Report* WFC3 2007-12.
24. Rauscher, B. J., Fox, O., Ferruit, P., et al. 2007. Detectors for the James Webb Space Telescope near-infrared spectrograph. I. Readout mode, noise model, and calibration considerations. *Publications of the Astronomical Society of the Pacific*, 119: 768.
25. Barbary, K. 2016. SEP: Source extractor as a library. *Journal of Open Source Software*, 1(6): 58.
26. Bertin, E., Arnouts, S. 1996. SExtractor: Software for source extraction. *Astronomy and astrophysics supplement series*, 117: 393−404.

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