Deep-Dark-Net: A Guide Star Camera Dark Current Prediction Model Based on Generative Adversarial Networks (Postprint)

Authors: Qu Bohuan, Yang Hejun, He Yuxuan, Guo Yuanhao, Liu Yu, Cao Zihuang, Qi Chaoxiang, Yu Yong, Wang Peipei, Zhao Yongheng, Yong Zhang, Wang Shuqing, Jian Li, Guanru Lü, Cao Xinghua, Xiang Ming, Qiu Hongyun

Date: 2024-12-31T00:00:00+00:00

Abstract

Dark current degrades image quality, reduces the signal-to-noise ratio of stellar images, and consequently compromises the precision of star position and flux measurements; therefore, accurate estimation and removal of dark current is essential in astronomical data processing. The requirements for LAMOST guide star image processing include: high-precision processing of historical guide star image data in the absence of dark frames, simplification of the dark frame acquisition procedure for the guide star camera, and leveraging the characteristics of guide star images to invert and generate high-precision, reliable dark frames. By exploiting the properties of LAMOST guide star raw data, we propose a novel method—Deep-Dark-Net—for accurately estimating dark current based on a Generative Adversarial Network model. This method utilizes a conditional Generative Adversarial Network to construct a correlation model linking the Overscan region and Optical Black region of guide star images with the noise in the corresponding effective imaging area, thereby enabling the inversion and reconstruction of high-precision dark frames from these regions. Experimental results demonstrate that Deep-Dark-Net's predicted dark current exhibits higher consistency with the true dark current than traditional methods, meeting the dark frame requirements for LAMOST telescope guide star image processing. This work not only provides a new perspective and methodology for dark current processing in astronomical images, but also offers important insights and exemplars regarding the potential value and application directions of deep learning technology in astronomical image processing.

Full Text

Preamble

Vol. 42, No. 4

December 2024

PROGRESS IN ASTRONOMY Vol. 42, No. 4 Dec., 2024
doi: 10.3969/j.issn.1000-8349.2024.04.10

Deep-Dark-Net: A Dark Current Prediction Model for Guide Star Cameras Based on Generative Adversarial Networks

QU Bohuan[1], YANG Hejun[2;3], HE Yuxuan[1], GUO Yuanhao[1], LIU Yu[1], CAO Zihuang[3;5], QI Zhaoxiang[4;5], YU Yong[4;5], WANG Peipei[3;5], ZHAO Yongheng[3;5], ZHANG Yong[3], WANG Shuqing[3], LI Jian[3], LÜ Guanru[3], CAO Xinghua[3], XIANG Ming[3], QIU Hongyun[6]

(1. International School of Information Science and Engineering, Dalian University of Technology, Dalian 116620, China; 2. Beijing University of Technology, Beijing 100124, China; 3. National Astronomical Observatories, Chinese Academy of Sciences, Beijing 100191, China; 4. Shanghai Astronomical Observatory, Chinese Academy of Sciences, Shanghai 200030, China; 5. University of Chinese Academy of Sciences, Beijing 100049, China; 6. Light Speed Vision (Beijing) Co., Ltd., Beijing 102206, China)

Abstract: Dark current affects image quality, reduces the signal-to-noise ratio of star images, and consequently impacts the precision of star position and flux measurements. Therefore, accurate estimation and removal of dark current is essential in astronomical data processing. The requirements for LAMOST guide star image processing are: high-precision processing of historical guide star image data without dark field images, simplifying the procedure for capturing dark field images with guide star cameras, and leveraging the characteristics of guide star images to invert and generate high-precision, reliable dark field images. Utilizing the properties of LAMOST guide star raw data, this paper proposes a novel method based on generative adversarial network models to precisely estimate dark current—Deep-Dark-Net. This approach employs a conditional generative adversarial network to construct a correlation model between the Overscan region, Optical Black region, and the corresponding effective imaging region noise in guide star images, thereby enabling inversion and reconstruction of high-precision dark field images through these regions. Experiments demonstrate that the dark current predicted by Deep-Dark-Net shows higher agreement with real dark current than traditional methods, satisfying the dark field image requirements for LAMOST telescope guide star image processing. This work not only provides a new approach and methodology for handling dark current in astronomical images, but also offers important perspectives and examples regarding the potential value and application directions of deep learning technology in astronomical image processing.

Keywords: dark current; deep learning; conditional generative adversarial networks; Deep-Dark-Net; LAMOST

1 Introduction

The guide star system of the Guo Shoujing Telescope (Large Sky Area Multi-Object Fiber Spectroscopy Telescope, LAMOST) is crucial for ensuring observation efficiency and quality, involving precise measurement of the telescope's azimuth, altitude, focal plane rotation angle, and focal length, as well as accurate calculation of errors and transmission of correction commands to relevant control systems. Its core task is to capture images using guide star cameras, obtain necessary data through image processing, star identification and matching, star centroid measurement, and error equation solving. With technological advancements, LAMOST's guide star cameras have been upgraded to the second generation, featuring a photosensitive area four times larger than before, significantly improved field of view (FOV), and an increase in camera count from four to eight units. This new hardware system has prompted LAMOST to develop a more advanced second-generation astrometric support system to improve astrometric precision, support point spread function measurement and photometry, and enable measurement of atmospheric transmission, image quality, and focal plane attitude. The dark current of guide star cameras includes thermal noise from the photosensitive device, its own readout noise, and readout noise from peripheral amplifier circuits, all of which significantly reduce the signal-to-noise ratio of astronomical images and the accuracy of data analysis. Regarding dark current, the traditional solution is to capture and calculate a "median" image reflecting dark current distribution—that is, a dark field image—and then subtract this dark field image from each target image during data processing. Although this method has been widely validated as effective in long-term astronomical observations, due to hardware differences among LAMOST guide star cameras, some cameras do not support dark field capture functionality, making the dark field image capture process cumbersome. Moreover, since historical LAMOST guide star camera data does not include dark field images, a method must be found to accurately invert dark field images to support high-precision data processing.

In recent years, deep learning technology has been widely applied in astronomy. George and Huerta[1] pioneered the use of deep convolutional neural networks for gravitational wave signal detection; Akeret et al.[2] employed U-Net networks to identify and mitigate radio frequency interference signals in time-frequency diagrams; Ruhe[3] summarized applications of machine learning in imaging Cherenkov and neutrino astronomy; Tao et al.[4] provided an overview of deep learning applications in astronomy. In deep learning, the competition between generator and discriminator in Generative Adversarial Networks (GAN) can effectively learn data distributions, demonstrating unique advantages in simulating and understanding complex data distributions and generating approximately realistic images[5]. In astronomy, GAN has shown great potential in processing complex astronomical data; for example, Geyer et al.[6] utilized GAN to generate large amounts of training data for radio galaxy images. With the rise of conditional GAN (cGAN)[7], image generation content became controllable—cGAN can generate specific outputs by introducing additional conditional variables into model inputs, such as generating an image related to a specific input image's content. This mechanism not only enhances the flexibility of generative models but also improves the accuracy and diversity of generated results[8–11]. These studies not only demonstrate the broad applicability of deep learning in astronomy but also provide valuable references and insights for dark current prediction and dark field image inversion work for LAMOST guide star cameras.

This paper is organized as follows. Section 2 details relevant principles and methods, covering dark current characteristics of guide star camera sensors, raw data structure of guide star cameras, dark field image capture, and image preprocessing procedures. Additionally, this section thoroughly explores the network structure and loss function design of the Deep-Dark-Net model, laying a solid foundation for understanding the model's working principles and optimization strategies. Section 3 describes experimental design and results in detail, including datasets for training and testing the model, parameter configurations for model training and testing, experimental result comparisons, and ablation experiments. These experimental results validate the effectiveness and reliability of the Deep-Dark-Net model in predicting and inverting dark field images. Section 4 summarizes the research findings and provides an outlook on future research directions.

2.1 Dark Current Characteristics of Guide Star Camera Sensors

Dark current is an important parameter of CCDs. Its generation mechanism can be summarized as follows: electron-hole pairs generated by the photoelectric effect in semiconductor materials will recombine if not separated in time, requiring a bias voltage on the gate electrode. Under the bias voltage, holes in the semiconductor material are driven away to form a depletion layer—a region of particularly low potential for negatively charged electrons, where electrons accumulate, forming a "potential well." During normal CCD exposure, dark current and photoelectrons accumulate simultaneously in the potential well. Dark current increases noise and occupies space for storing valid signals, both of which negatively impact image signal-to-noise ratio. As shown in Equation (1), in the absence of photons, the noise intensity of dark current inside the semiconductor is related to temperature and integration time:

$$\sigma_{dark} = \sqrt{I_d \cdot t}$$

where σ_{dark} is the dark current noise intensity, I_d is the dark current, and t is the integration time.

From a microscopic perspective, CCD dark current levels are primarily influenced by semiconductor materials and manufacturing processes, with main sources including: thermal charges generated after powering the substrate material, thermal charges from the region between silicon and its oxide, and thermal charges from the potential well. From a macroscopic perspective, CCD dark current levels are mainly affected by CCD operating temperature. Figure 1 shows the correlation between dark current and temperature for the Kodak KAF-4320 CCD used in LAMOST guide star cameras. The figure demonstrates that CCD dark current levels typically decrease with lower cooling temperatures, showing an approximately linear relationship within a certain range, with a temperature interval of 6.4°C for dark current halving. Taking typical working conditions for guide star CCDs as an example: cooling temperature of -15°C and exposure time of 30 s, the theoretical dark current per pixel is approximately 240 electrons.

We observed that due to manufacturing process variations, the distribution of sensor dark current exhibits non-uniformity. To more intuitively demonstrate this effect, we captured a 10-minute dark field image using a guide star camera under ambient temperature of 17.6°C without cooling. After ZScale contrast stretching in DS9 software, the image shows obvious concentric ring patterns, as illustrated in Figure 2 [Figure 2: see original paper]. This dark current distribution pattern originates from the chemical mechanical polishing (CMP) process during CCD manufacturing and is closely related to the position of polishing fluid droplet centers and grinding paths. Therefore, considering this characteristic of guide star camera CCDs, this paper specifically emphasizes the need for high-precision reconstruction of dark current spatial distribution.

Note: Bright spots in the figure represent thermal noise, while larger-scale concentric ring patterns are caused by the chemical mechanical polishing process during CCD manufacturing.

2.2 Raw Data Structure of Guide Star Cameras

From the design stage, LAMOST guide star cameras emphasized preserving detector and peripheral circuit electronic working conditions and characteristics through raw image data. Figure 3 [Figure 3: see original paper] shows the restoration of camera output raw data into a two-dimensional image matrix. Due to different output principles, several distinct functional regions exist within the image, which play important roles in camera performance analysis, testing, and various effect corrections during later image processing. The following analysis and description explain each region:

(1) **A1, A2 (dark gray regions)**: When the analog-to-digital converter (AD) initiates data processing for a row of the corresponding CCD channel, 3-pixel-wide data is output—this is the "PreScan" region, containing the AD's own noise level and "contaminated" signals caused by voltage pull-up to enter the working range.

(2) **B1, B2 (red regions)**: When reading out a row of a CCD channel, the CCD outputs 1-pixel-wide invalid data.

(3) **C1, C2 (blue regions)**: Before CCD row readout, the internal amplifier outputs a 4-pixel signal containing CCD internal amplifier noise, residual signals from previous row readouts, external follower circuit noise, and AD noise.

(4) **D1, D2 (green regions)**: The 4-pixel-wide regions around the CCD perimeter have their pixel surfaces masked (blackened) by the manufacturer and are called "Optical Black" regions. Except for being unable to receive external photons, their physical and electrical properties are identical to photosensitive region pixels. These regions contain CCD dark current, CCD internal amplifier noise, external follower circuit noise, and AD noise.

(5) **E1, E2 (gray regions)**: After the AD finishes reading each row of CCD pixels, it reads 46-pixel-wide empty data, referred to as the "Overscan" region, which contains the AD's own noise level.

(6) **F1, F2, F3, F4 (light gray regions)**: Due to odd row counts, each channel of the LAMOST guide star camera CCD reads out the middle row, producing row data. After restoration and verification, this portion cannot reliably reproduce the photosensitive conditions of the physical pixels in the middle row and is completely removed in this work.

(7) **I, II, III, IV (white regions)**: The effective photosensitive regions of the CCD, containing all valid photoelectron signals along with CCD dark current, CCD internal amplifier noise, external follower circuit noise, AD noise, etc.

2.3 Dark Field Image Capture and Image Preprocessing

Guide star camera dark field image capture was conducted in a constant-temperature 24°C dust-free room at the LAMOST optical laboratory. The camera core and semiconductor cooling device were powered by two separate 12V linear power supplies to improve power quality. The guide star camera was placed in a light-tight dark box, with cables routed outside to the control computer. The camera was connected to a water chiller with cooling temperature set to -1°C—5°C above the theoretical environmental dew point temperature to prevent condensation. The camera target surface cooling temperature was set to -15°C, matching the target cooling temperature when the camera operates on the LAMOST focal plane. The internal temperature control precision was $±$1°C.

To meet model input size requirements, we first segmented the original images (2,200 pixel × 2,094 pixel) by different readout channels to obtain sub-images for each of the 4 CCD readout channels and their corresponding ADs. Next, according to the LAMOST guide star camera raw data schematic (Figure 3), we segmented the effective imaging region images, Overscan region images, and Optical Black region images from the 4 sub-images. Each sub-image's effective imaging region was 1,042 pixel × 1,042 pixel, Overscan region was 46 pixel × 1,042 pixel, and Optical Black region was 4 pixel × 1,042 pixel (column direction) + 1,038 pixel × 4 pixel (row direction). We cropped the Overscan region images to 46 pixel × 1,024 pixel as conditional image A1; cropped the Optical Black region's column direction to 4 pixel × 1,024 pixel as conditional image A2; cropped the Optical Black region's row direction to 1,024 pixel × 4 pixel as conditional image A3; and cropped the effective imaging region images to 1,024 pixel × 1,024 pixel as target image B. Images A1, A2, and A3 were then upsampled to 1,024 pixel × 1,024 pixel using bilinear interpolation. This process ensures image sizes are powers of 2 for convenient model processing. Finally, we normalized all cropped images, converting 16-bit pixel values to floating-point numbers in the range [0,1] for model training and prediction.

2.4.1 Deep-Dark-Net Model Fundamentals

The guide star camera contains 4 readout channels, with each channel's readout image matrix including: the CCD effective imaging region (white regions in Figure 3, marked I, II, III, IV), Overscan region (gray regions in Figure 3), and Optical Black region (green regions in Figure 3). The Overscan region reflects the characteristics of peripheral circuit readout noise, while the Optical Black region characterizes the sum of thermal noise from the photosensitive device, the device's own readout noise, and peripheral amplifier circuit readout noise. On a camera's output channel, the dark current patterns contained in the AD's Overscan and Optical Black images correlate with the dark current patterns in the corresponding sensor's effective imaging region.

Under LAMOST guide star camera standard working conditions—fixed target surface cooling temperature and exposure time—we utilize Overscan and Optical Black images to predict the dark current in the corresponding effective imaging region. The core of this algorithm lies in constructing a correlation model of dark current distribution between Overscan regions, Optical Black regions, and imaging regions through learning from large amounts of data. This approach not only avoids the need for LAMOST to separately capture dark field images before and after observations, reducing operational complexity, but also helps reconstruct dark current in historical images to improve data processing precision. Furthermore, since Overscan and Optical Black region images contain the camera's working conditions during capture, this facilitates inversion of dark current variations in the effective imaging region over time. To solve the problem of predicting effective imaging region dark current based on Overscan and Optical Black region images, we designed and implemented an image-to-image mapping technical solution that effectively reflects dark current distribution characteristics across the image.

We adopt cGAN to construct the mapping relationship between guide star camera Overscan and Optical Black regions and dark current distribution in effective imaging regions. Using dark field images' Overscan and Optical Black region images as input, cGAN predicts the corresponding imaging region images. This study employs the classic cGAN model—Pix2Pix[12]—as the base model. By constructing numerous paired images combining dark current Overscan and Optical Black regions with effective imaging region images to drive model training, we optimize the base model's training process and improve the training mode, enabling the model to learn dark current distribution under specific imaging conditions (temperature, exposure duration), ultimately achieving precise prediction of guide star camera dark current. We designate this method for predicting and inverting dark field images as Deep-Dark-Net. Specifically, as shown in Figure 4 [Figure 4: see original paper], the method consists of three steps: image acquisition and preprocessing, model training, and model application. Step 1: First, the guide star camera captures numerous dark field images under guide star working conditions, containing dark current under specific conditions; second, Overscan and Optical Black region images are cropped and normalized according to preset positions; these input images are concatenated as a whole to serve as model input, with effective imaging region images as output. Step 2: During training, we design a generator based on the U-Net model[13] to synthesize predicted imaging region images $\hat{B}$ corresponding to blank input images A; both $\hat{B}$ and real imaging region images B are input to the discriminator, which is essentially a binary classification model that always considers $\hat{B}$ as fake and B as real. Through adversarial training between generator and discriminator, the generator can synthesize images $\hat{B}$ very close to real images B that can "fool" the discriminator. Essentially, the model constructs the mapping relationship between input images A and real images B by learning the distribution of real images B. Step 3: During testing, we input any guide star camera dark field image, including Overscan and Optical Black region images from 4 readout channels, to predict near-real dark field images for the effective imaging regions corresponding to the 4 readout channels through the trained model, and compare them with actual dark field images of the effective imaging regions.

2.4.2 Deep-Dark-Net Network Architecture

The Deep-Dark-Net model architecture is shown in Figure 5 [Figure 5: see original paper], consisting primarily of a generator and a discriminator. The generator adopts a modified U-Net structure[13], comprising three parts: a downsampling convolution stage, cascaded convolution stages, and an upsampling convolution stage. Each convolution layer is implemented through residual modules[14], using skip connections to link features from the downsampling stage with same-scale features from the upsampling stage to improve fusion efficiency of low-level and high-level features.

Specifically, the input module first maps input images to feature space using a reflection padding layer and a 7$\times 7 convolutionlayerforpreliminaryfeatureextraction, followedbybatchnormali$ $Net-likefeatureextractionnetwork, wherethedownsamplingconvolutionstageusesconsecutiveconvolution-$

downsamplingoperationstoextractmulti−scalefeatures, andtheupsamplingconvolutionstageusesupsampling
convolutionoperationstograduallyreconstructimagefeatures.DifferencesfromU−
Netinclude : (1)*onlytwodownsamplingoperationsareused*; (2)*thethird* −
*levelfeatureextractionstageconsistsof*9*cascadedconvolutionlayers*; (3)*eachconvolutionlayercomprisesresidu*
reflectionpaddinglayer, 64×2^l − *dimensional*3×$3 convolution layer (where l represents the l-th feature extraction stage), and corresponding feature normalization layer and ReLU activation layer. Features output from each downsampling convolution stage are concatenated with same-scale features from the upsampling convolution stage through skip connections (dashed arrows in Figure 5) and serve as input to the residual modules of the corresponding convolution stage. This classic feature skip connection structure aims to simultaneously preserve same-scale local features and high-level semantic features obtained from upsampling. Finally, the output layer is implemented through reflection padding and 3$×$3 convolution layers, using a Tanh activation function to map outputs to the range [0,1].

The discriminator network employs a small PatchGAN classifier, whose basic principle is to divide images into patches and generate corresponding feature maps for each image sub-block. Each position in the feature map reflects the probability that the corresponding image sub-block in the input image belongs to real data. Averaging these probability values forms a comprehensive score for judging the authenticity of the entire image. The discriminator network structure consists of three convolutional layers, batch normalization layers, and Leaky-ReLU activation layers. Except for the final convolutional layer, each layer uses 4$×$4 convolution kernels with stride 2; the final convolutional layer uses stride 1 to maintain output feature map dimensions. The first convolutional layer's output channel number is set to 64, doubling with each additional layer until reaching 512. To adapt to different-scale feature representations in the network, we use batch normalization and Leaky-ReLU nonlinear activation functions to process inter-layer outputs, with Leaky-ReLU slope set to 0.2 to enhance model sensitivity to subtle changes in input data.

2.5 Loss Function

The generator in a generative adversarial network model synthesizes near-realistic images to "fool" the discriminator, while the discriminator tries to identify synthesized images as "fake." Based on this analysis, we designed corresponding loss functions to drive model training.

Let the generator be G and the discriminator be D; let input images be x, with corresponding real images y. The generator's goal is to establish mapping between input and output images ($G : x \to y$). Let the "fake" image synthesized by the generator based on input image x be $\hat{y} = G(x)$. The general adversarial loss is designed as follows:

$$\mathcal{L}_{\mathrm{GAN}}(G; D) = \mathbb{E}_y[\log D(y)] + \mathbb{E}_x[\log(1 - D(x, G(x)))]$$

where $\mathbb{E}_y[\log(D(y))]$ represents the discriminator's probability of predicting real images as real, and $\mathbb{E}_x[\log(1-D(x,G(x)))]$ represents the generator's probability of fooling the discriminator with synthesized fake images.

This study improves the above loss function. In image generation tasks, root mean square error (RMSE) is commonly used as a standard for evaluating image reconstruction quality: $\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$, which characterizes the average difference in pixel values between predicted and real images. First, we replace the first term in Equation (2) with mean square error (MSE) loss, while adding MSE loss for the generator to enhance its ability to fool the discriminator:

$$\mathcal{L}_{\mathrm{GAN}}(G;D) = \mathbb{E}_y[(D(y)-1)^2] + \mathbb{E}_x[\log(1-D(x,G(x)))] + \mathbb{E}_x[(D(x,G(x))-1)^2]$$

Second, this study uses paired images as input and output, meaning each input image x always has a corresponding real output image y. Therefore, we adopt the L1 loss function to ensure visual consistency (fidelity) between images synthesized by the generator and real images:

$$\mathcal{L}_{L1}(G) = \sum |y_i - G(x)|$$

Finally, we integrate adversarial loss and supervised loss to drive model training:

$$G^* = \arg\min[\mathcal{L}_{\mathrm{MSE}}(D) + \mathcal{L}_{\mathrm{BCE}}(G) + \mathcal{L}_{\mathrm{MSE}}(G) + \mathcal{L}_{L1}(G)]$$

where $\mathcal{L}_{\mathrm{MSE}}(D) = \mathbb{E}_y[(D(y)-1)^2]$, $\mathcal{L}_{\mathrm{BCE}}(G) = \mathbb{E}_x[\log(1-D(x,G(x)))]$, and $\mathcal{L}_{\mathrm{MSE}}(G) = \mathbb{E}_x[(D(x,G(x))-1)^2]$. During training, the generator's goal is to fool the discriminator as much as possible, making it believe generated images are close to real, so the first optimization direction of the loss function is to minimize loss through generator training. The discriminator's goal is to identify generator-synthesized images as fake and real images as real, so the other optimization direction is to maximize loss through discriminator training. Through this adversarial game training mode, a powerful generator is gradually obtained.

3.1 Dataset and Experimental Configuration

First, we collected over 20,000 dark field images at different CCD cooling temperatures (-5°C, -10°C, -15°C, -25°C), where -15°C is the daily operating temperature for LAMOST guide star cameras. After preprocessing with our designed workflow, we constructed a training set containing 20,000 images (5,000 images captured at each temperature) and a test set containing 4,000 images (1,000 images at each temperature). Collecting images at different temperatures primarily ensures the model can learn and adapt across broad data samples. These two datasets are strictly separated with no overlap between training images, ensuring evaluation accuracy and reliability.

All model training and evaluation were performed on a single NVIDIA GeForce RTX 3090 GPU, with batch size set to 1 and total training epochs set to 40. The Adam optimizer was used with a learning rate of 0.00002.

3.2 Experimental Results Comparison

We first used the traditional method to calculate the median at each pixel position across 20,000 imaging region dark field images in the training set, obtaining a "median image" estimated from training data, then calculated the root mean square error between this median image and 4,000 imaging region dark field images in the test set. Second, we used the traditional method to calculate "median images" for images captured at different temperatures in the training set, respectively, to compute RMSE between test set images at each temperature and their corresponding temperature-specific median images. Finally, after training Deep-Dark-Net on the training set, we predicted corresponding effective imaging region dark field images for 4,000 Overscan and Optical Black images in the test set—effectively obtaining a dark field image for each imaging region—then calculated RMSE between all predicted dark field images and real dark field images in the test set, with statistics compiled by capture temperature. As shown in Table 1 , the traditional method achieved an RMSE of 43.9 across all test images, while Deep-Dark-Net reduced RMSE to 25.5. This error improvement demonstrates that the proposed method can estimate guide star camera dark current more accurately than traditional median methods.

Table 1: Root Mean Square Error (RMSE) from Experiments

Method	Total	-5°C	-10°C	-15°C	-25°C
Traditional Method	43.9				
Current Method	25.5				

Furthermore, we found that both traditional and proposed methods exhibit increased noise estimation at higher CCD temperatures because camera noise patterns become more complex and noise levels increase at elevated temperatures. Considering that -15°C is typically used as the standard imaging environment temperature in practical applications, the proposed model's dark noise prediction performance surpasses traditional methods under these conditions, demonstrating the method's practical advantages.

To deeply analyze our method's performance in image detail reconstruction, we propose two visualization techniques: heatmaps and pixel difference distribution histograms. As shown in Figure 6 [Figure 6: see original paper], we randomly selected an imaging region dark field image from the test set and calculated absolute pixel-wise errors between it and the Deep-Dark-Net predicted dark field image—i.e., the heatmap. We found that differences between Deep-Dark-Net predicted and real dark field images are small, with most pixel value differences within 15 pixels, and these differences are randomly distributed across the image, indicating the model is not overfitting to any particular noise pattern.

Figure 6: Visualization of Pixel Value Differences Between Generated and Real Dark Field Images

As shown in Figures 7 [Figure 7: see original paper] and 8 [Figure 8: see original paper], we respectively compiled pixel value difference distributions between imaging region dark field images and Deep-Dark-Net predicted dark field images for the entire test set and for each temperature. Figure 7 shows that over 90% of pixel value differences fall within [-10, 10] pixels, with mean close to 0.5 pixels. The histogram's symmetry and negative skewness indicate that although some larger differences exist, overall image fidelity is high, so larger pixel value differences in the tail do not affect the method's overall effectiveness. Figure 8 shows that pixel value difference distributions are similar across temperatures, but means increase with temperature, consistent with previous analysis.

Figure 7: Histogram of Pixel Value Differences Between Generated and Real Dark Field Images

Figure 8: Histogram of Pixel Value Differences Between Generated and Real Dark Field Images at Various Temperatures

3.3 Ablation Experiments

In machine learning, "ablation experiments" are methods used to determine the influence or causal relationships of specific factors in a model, primarily employed to objectively verify machine learning model working principles and feature importance. Ablation experiments can effectively demonstrate which features play key roles in improving model prediction performance and how to adjust model structures and parameters under different scenarios to improve performance. Additionally, ablation experiments help explain model decision-making processes and improve model interpretability. Through ablation experiments, we evaluated the "loss function" affecting our method's prediction accuracy, with specific steps as follows: (1) Establish the initial Deep-Dark-Net model; (2) Manipulate variables by selecting different loss functions for ablation experiments and verifying them individually; (3) Observe results by examining how model outputs change when manipulating each variable; (4) Draw conclusions about specific loss functions' impact on model performance or output based on observed results.

We designed different loss function configurations to evaluate each component's impact on model training performance. For the generator, we consistently used L1 loss $\mathcal{L}_{L1}(G)$ as supervised loss across all configurations. The configurations are:

- **Configuration 1**: Pix2Pix model using adversarial loss in the form of binary cross-entropy loss $\mathcal{L}_{\mathrm{BCE}}(D) + \mathcal{L}_{\mathrm{BCE}}(G)$

- **Configuration 2**: Using MSE loss to construct adversarial loss $\mathcal{L}_{\text{MSE}}(D) + \mathcal{L}_{\text{MSE}}(G)$
- **Configuration 3**: Using MSE loss only for the generator part of adversarial loss $\mathcal{L}_{\text{BCE}}(D) + \mathcal{L}_{\text{MSE}}(G)$

To efficiently verify model performance under different configurations, we recollected and created a training and test dataset at the most commonly used CCD cooling temperature (-15°C) for this ablation experiment (training set: 10,000 images; test set: 1,000 images). Using the traditional method, we calculated the "median image" from training set images and computed RMSE between test set images and this median image as 20.6, serving as baseline performance. Experimental results are shown in Table 2 .

Table 2: Ablation Experiment Results

Configuration	Generator G	Discriminator D	RMSE
1	$\mathcal{L}_{\text{BCE}}(G) + \mathcal{L}_{L1}(G)$	$\mathcal{L}_{\text{BCE}}(D)$	21.1
2	$\mathcal{L}_{\text{MSE}}(G) + \mathcal{L}_{L1}(G)$	$\mathcal{L}_{\text{MSE}}(D)$	18.7
3	$\mathcal{L}_{\text{MSE}}(G) + \mathcal{L}_{L1}(G)$	$\mathcal{L}_{\text{BCE}}(D)$	23.2
Deep-Dark-Net	$\mathcal{L}_{\text{BCE}}(G) + \mathcal{L}_{\text{MSE}}(G) + \mathcal{L}_{L1}(G)$	$\mathcal{L}_{\text{MSE}}(D)$	**16.9**

The following conclusions can be drawn from Table 2: (1) Using Configuration 1 with the original Pix2Pix loss function form yields an RMSE of 21.1, with dark field image prediction performance even slightly worse than traditional methods, indicating that simply migrating generic cGAN models for guide star camera dark current prediction performs poorly. (2) In Configuration 2, replacing cross-entropy loss functions in adversarial loss with MSE loss functions reduces RMSE to 18.7, improving dark current prediction accuracy. However, in Configuration 3, using only MSE loss for the generator's adversarial loss causes dramatic performance degradation, indicating that using MSE loss functions for the discriminator's adversarial loss is more beneficial for dark current prediction. (3) Building upon Configuration 2, Deep-Dark-Net adds binary cross-entropy loss to the discriminator's adversarial loss, further improving model performance, indicating that using multiple forms of adversarial loss functions for the generator can enhance synthesized image quality.

In summary, we determined the optimal loss function form. Compared with the comparative experiment results in Section 3.2, this experiment evaluated only on data collected at -15°C, where Deep-Dark-Net's prediction error further decreased from 23.2 to 16.9, still significantly outperforming the traditional method's error of 20.6. This indicates that using images collected in a single environment to train the model can further improve the method's performance.

4 Summary and Outlook

To address LAMOST guide star camera data processing requirements, we propose Deep-Dark-Net, a novel method based on generative adversarial network models for precise dark current estimation. The Deep-Dark-Net model avoids the traditional method's step of separately capturing multiple dark field images to obtain median dark current images. Instead, it can accurately invert dark current images contained in corresponding effective imaging regions through guide star images' Overscan and Optical Black regions. Comparative experiments demonstrate that dark current images predicted by Deep-Dark-Net achieve higher precision than traditional methods, providing a new approach and methodology for image processing in astronomy. Future research will focus on optimizing model training for data from different imaging environments and sensor types, using this algorithm to comprehensively improve the precision and robustness of dark current inversion for various detectors under different imaging conditions, promoting Deep-Dark-Net's applicability and accuracy across multiple application scenarios.

References

[1] George D, Huerta E A. Physics Letters B, 2018, 778: 64
[2] Akeret J, Chang C, Lucchi A, et al. Astronomy and Computing, 2017, 18: 35
[3] Ruhe T. International Journal of Modern Physics A, 2020, 35: 2043004
[4] 陶一寒, 崔辰州, 张彦霞, 等. 天文学进展, 2020, 38(2): 168
[5] Goodfellow I, Pouget-Abadie J, Mirza M, et al. Advances in Neural Information Processing Systems. Montreal: NIPS, 2014: 27
[6] Geyer F, Schmidt K, Kummer J, et al. Astronomy and Astrophysics, 2023, 677: A167
[7] Mirza M, Osindero S. arXiv:1411.1784, 2014
[8] Li L H, Jiang L Q, Peng Y F, et al. 2022 International Conference on Technologies and Applications of Artificial Intelligence (TAAI). Taiwan: IEEE, 2022: 54
[9] Sui F, Guo R, Yue W, et al. 2022 IEEE 35th International Conference on Micro Electro Mechanical Systems Conference (MEMS). Tokyo: IEEE, 2022: 450
[10] Herbsthofer L, Ehall B, Tomberger M, et al. Medical Imaging 2022: Digital and Computational Pathology. San Diego, California: SPIE, 2022: 140
[11] Moazami S, Ray D, Pelletier D, et al. IEEE Transactions on Medical Imaging. Buffalo, New York: IEEE, 2023: 1071
[12] Isola P, Zhu J-Y, Zhou T, et al. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Honolulu, Hawaii: IEEE, 2017: 1125

[13] Ronneberger O, Fischer P, Brox T. Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015, Part III. Munich: Springer, 2015: 234
[14] He K, Zhang X, Ren S, et al. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Las Vegas, Nevada: IEEE, 2016: 770
[15] Jadhav P, Sawal M, Zagade A, et al. 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), India: IEEE, 2022: 1489

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