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A ground-based dataset and diffusion model for on-orbit low-light image enhancement

Key words: Satellite capture; Low-light image enhancement (LLIE); Data collection; Diffusion model; Fused attention

Corresponding author: Lu WANG
E-mail: wanglu21@njust.edu.cn
ORCID: https://orcid.org/0000-0001-8147-1581

Motivation

1. Variable illumination in space, especially when satellites enter Earth's shadow, severely degrades image quality, making it hard to extract key features for downstream tasks like pose estimation and visual measurement.
2. The lack of specialized datasets for on-orbit LLIE tasks limits the performance of deep learning (DL) models, which relies heavily on high-quality data reflecting real-world scenarios.
3. Precise recovery of structural and texture details in satellite images under extreme low light is critical for supporting space situation awareness and autonomous on-orbit servicing.

Main idea

1. Build the first dataset for on-orbit LLIE using a hardware-in-the-loop (HIL) testbed. A pose-stratified sampling strategy is designed based on a physics engine to cover diverse viewpoints safely and efficiently.
2. Apply a diffusion model to on-orbit low-light image enhancement, leveraging its stable training and ability to generate artifact-free, detail-rich results compared to generative adversarial networks and traditional convolutional neural networks.
3. Further improve enhancement quality by introducing fused attention guidance (FAG), which explicitly extracts and integrates illumination and structural cues to guide the enhancement process.

Method

1. Use PyBullet to build a collision-free workspace by modeling robot and satellite geometry, generating candidate poses with quasi-Monte Carlo sampling, and verifying trajectories to safely simulate satellite motion.

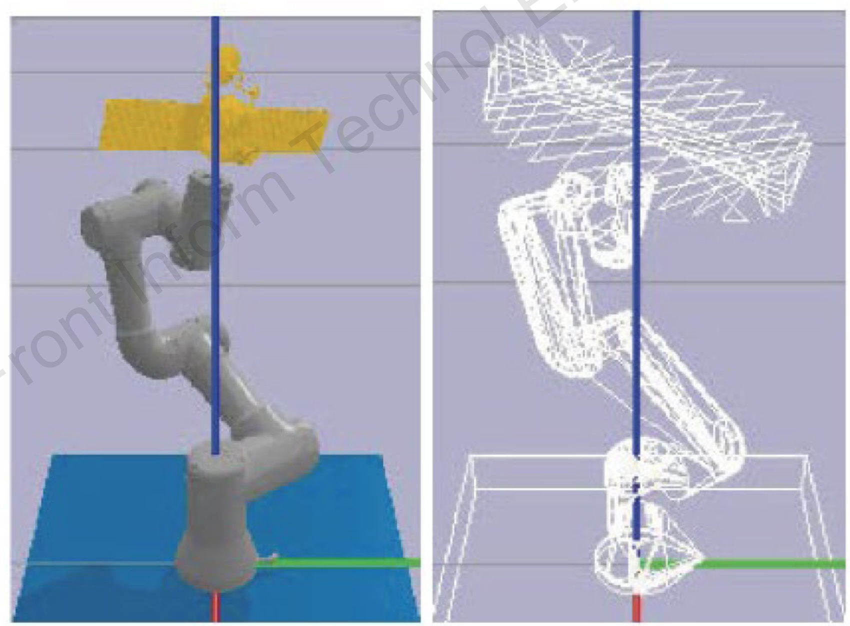


Fig. 1 Virtual environment in PyBullet: visual rendering (left) and collision mesh (right) of the robot model

Method (Cont'd)

2. Divide the collision-free workspace into spherical coordinate bins and apply stratified sampling to ensure a uniform pose distribution with fewer samples.

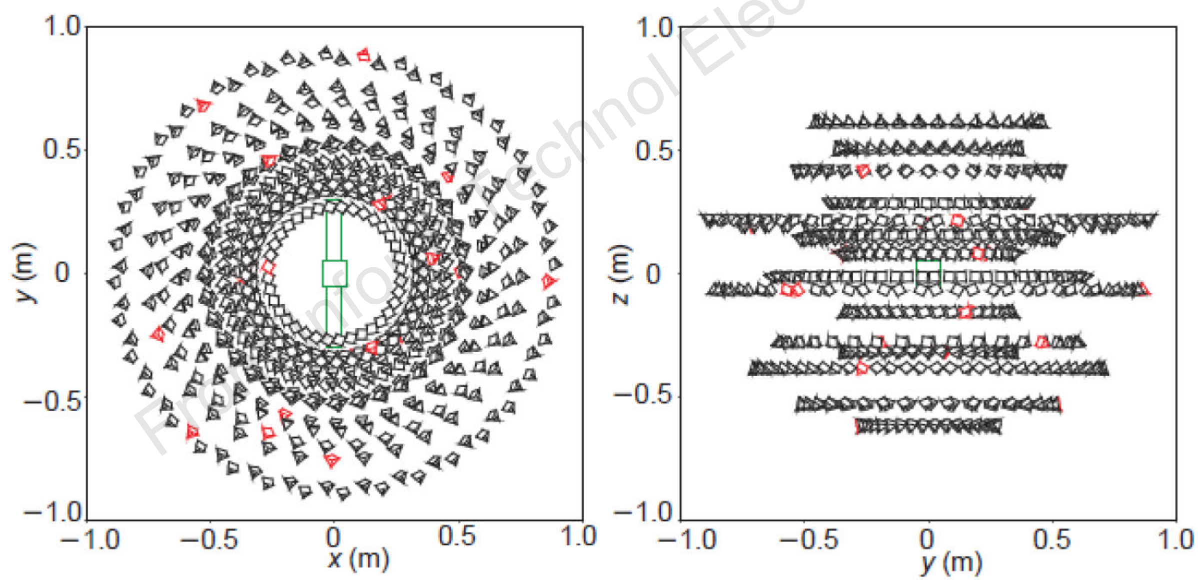
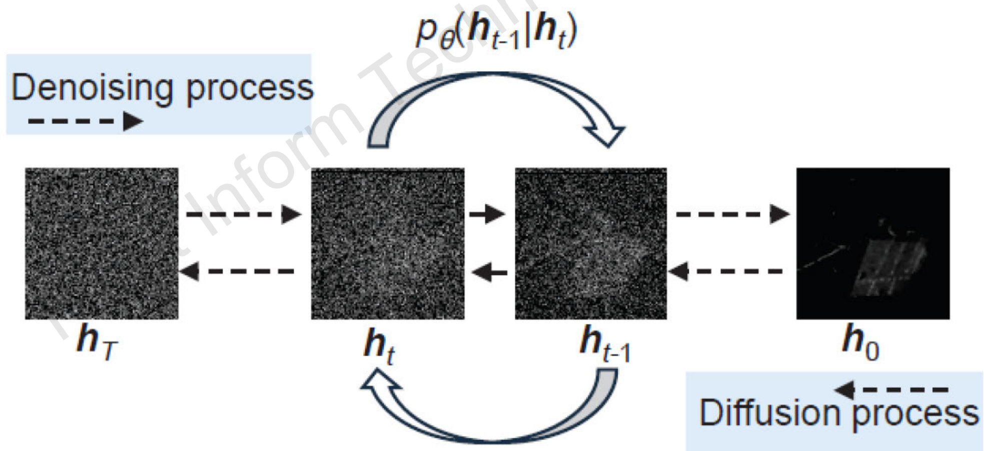


Fig. 2 Visualization of camera poses for images of our dataset in the 3D space. The black camera pyramids stand for the training set and red camera pyramids stand for the test set

Method (Cont'd)

3. With the diffusion model, Gaussian noise is progressively added to high-light images in the forward process; UNet is trained to model the reverse diffusion process, recovering clean high-light images from noisy observations.



$$q(\boldsymbol{h}_t|\boldsymbol{h}_{t-1}) = \mathcal{N}(\boldsymbol{h}_t; \sqrt{1-\beta_t}\,\boldsymbol{h}_{t-1}, \beta_t \boldsymbol{I})$$

Fig. 3 Diffusion model process

Method (Cont'd)

4. With FAG combining hue/saturation/intensity (HSI) color space and high-frequency filtering to enhance dark region details and textures, the network is guided to focus on structural and lighting restoration.

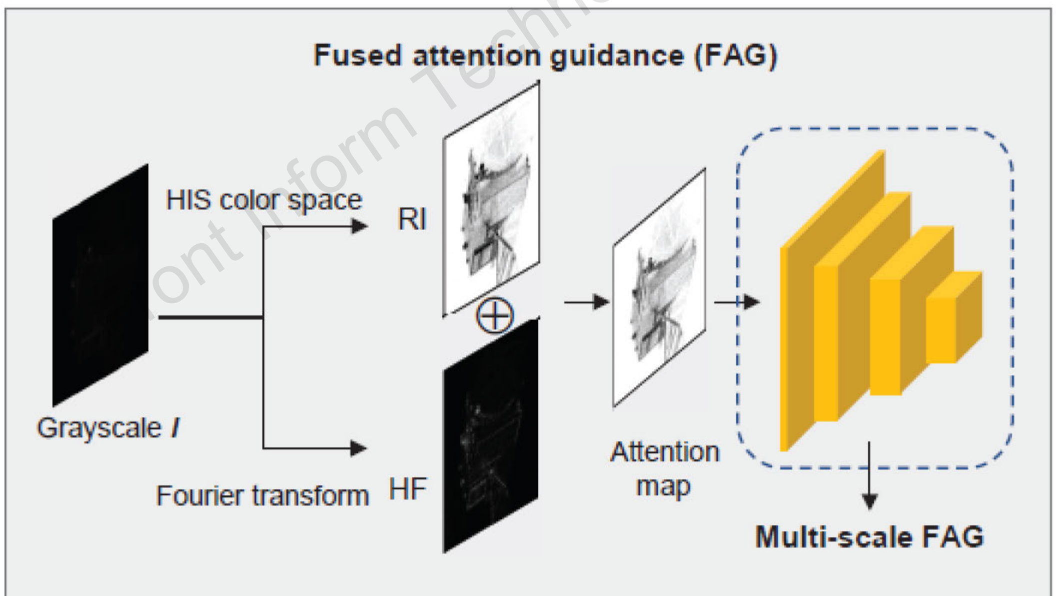


Fig. 4 FAG

Major results

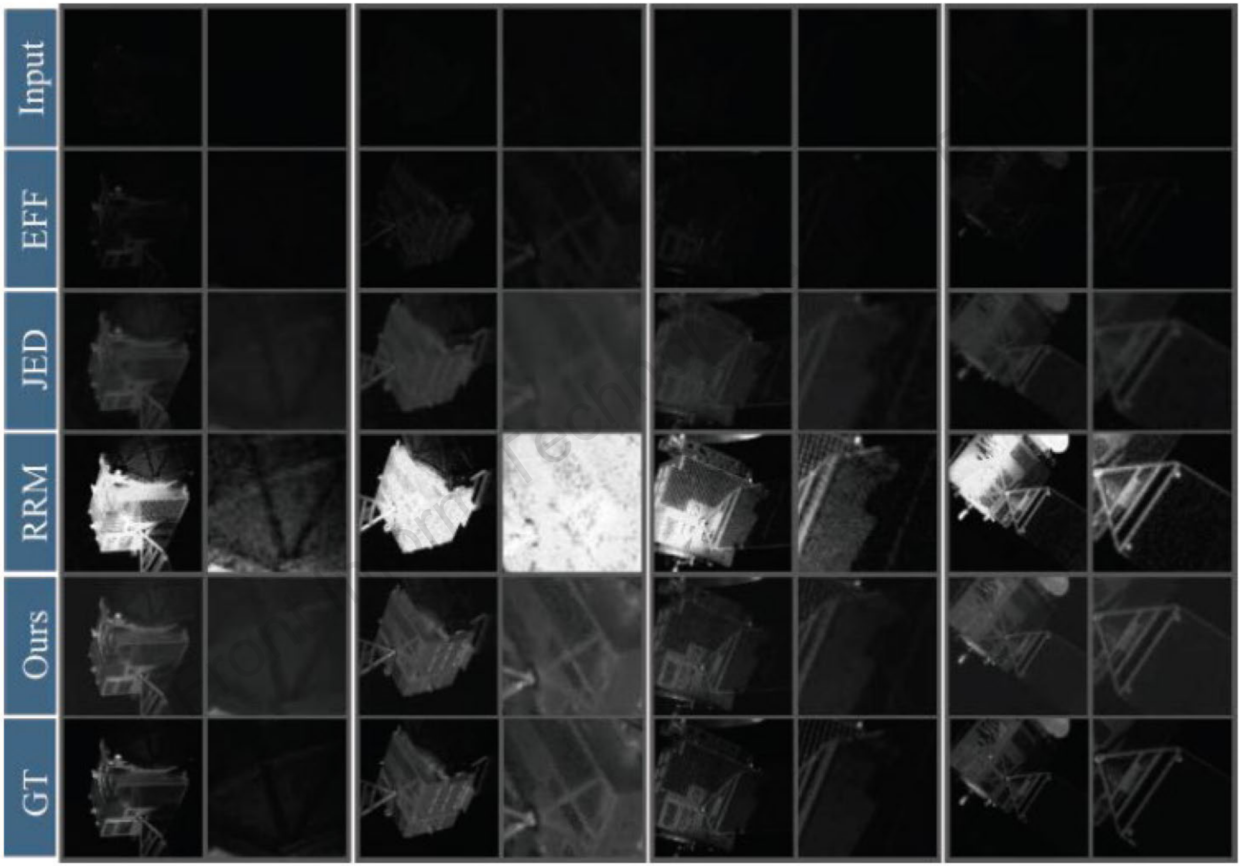


Fig. 5 Visual comparison of the enhanced results and enlarged local details between our method and traditional methods

Major results

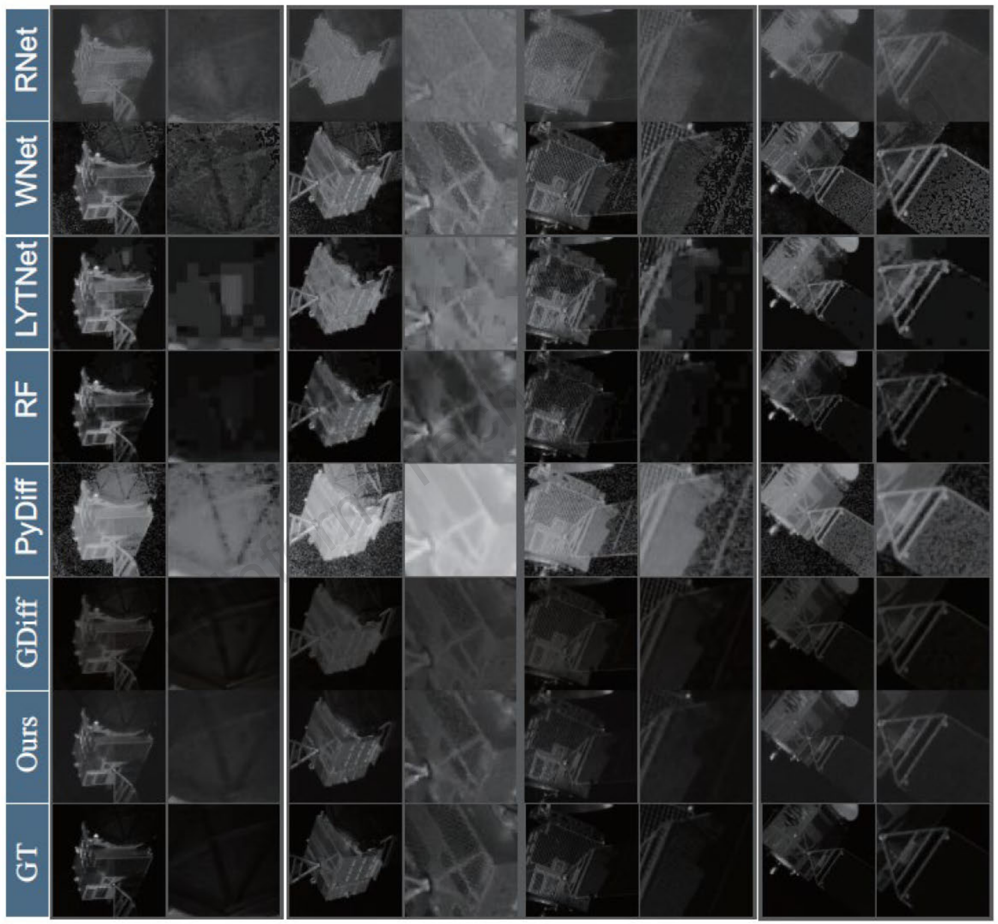


Fig. 6 Visual comparison of the enhanced results and enlarged local details with different DL methods

Major results

Table 1 Comparison of IQA metrics between our method and previous methods

IQA metric	Traditional method			DL method						
	EFF CAIP'17	JED ISCAS'18	RRM TIP'18	RNet BMVC'18	PyDiff IJCAI'23	WNet PG'23	GDiff ICCV'23	RF NIPS'23	LYTNet arXiv'24	Ours
PSNR↑	19.21	24.25	9.284	15.05	10.51	18.03	17.47	23.83	18.31	**25.14**
SSIM↑	0.5499	0.5958	0.3697	0.3368	0.2601	0.4413	0.3487	**0.7602**	0.5503	0.6107
FSIM↑	0.8263	0.8043	0.6231	0.8292	0.6689	0.7677	0.6610	0.8899	0.8144	**0.9102**
LPIPS↓	0.2159	0.3072	0.5062	0.3278	0.5192	0.3578	0.4987	0.2043	0.3496	**0.0951**

The upward arrow indicates that a higher value is better, while the downward arrow indicates that a lower value is better. The optimal values are in bold and the suboptimal values are underlined. RNet: RetinexNet; WNet: WaveNet; RF: Retinexformer

Major results (Cont'd)

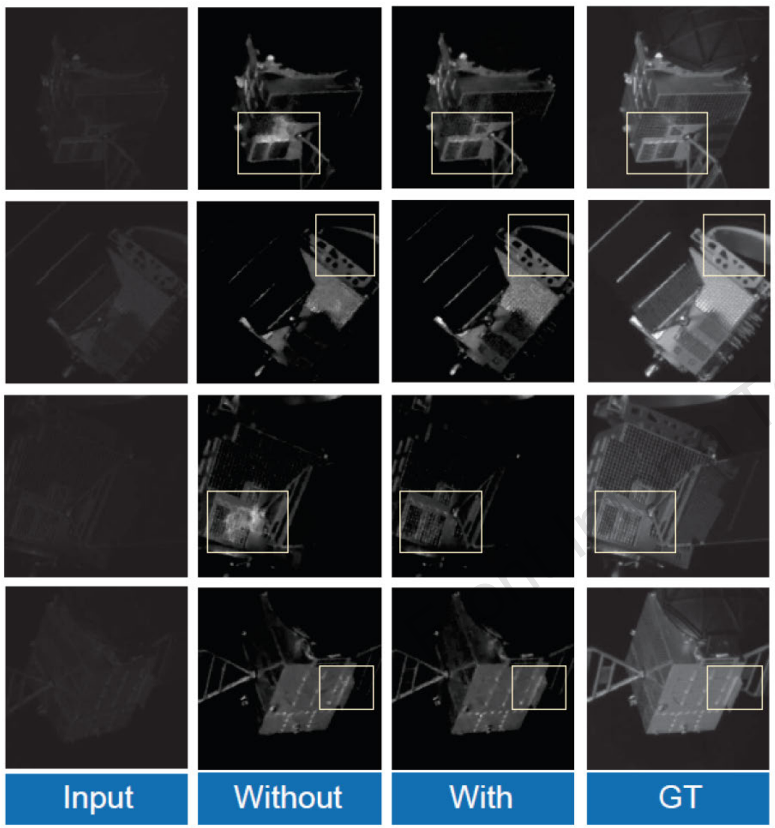


Fig. 7 Visual comparison of the enhanced results and enlarged local details with different DL methods

Table 2 IQA metrics with and without FAG

IQA metric	w/o FAG	w/ FAG
PSNR↑	23.81	25.14
SSIM↑	0.5937	0.6107
FSIM↑	0.8994	0.9102
LPIPS↓	0.1206	0.0951

w/: with; w/o: without. The upward arrow indicates that a higher value is better, while the downward arrow indicates that a lower value is better

Conclusions

1. The proposed dataset acquisition method efficiently and safely collects a representative and unbiased satellite image dataset.

2. The diffusion model-based enhancement framework achieves superior low-light image enhancement compared to traditional and other deep learning methods.

3. The introduced FAG significantly improves the diffusion model's ability to restore and enhance image texture details.

Yiman Zhu is currently a PhD candidate at Nanjing University of Science and Technology. Her research focuses on computer vision and deep learning for space applications, particularly in the area of non-cooperative target perception.

Lu Wang received his PhD degree in control theory and control engineering from Nanjing University of Science and Technology, China, in 2018. He has been a Lecturer at Nanjing University of Science and Technology since 2022. His current research interests include computer vision, protocols analysis and identification, and control of robot systems.

Jingyi Yuan is currently pursuing her MS degree at Nanjing University of Science and Technology. Her research focuses on deep learning-based computer vision, with a specific focus on pose estimation of space non-cooperative targets.

Yu Guo received her BS (1984) and MS (1987) degrees in Automation, both from Huazhong University of Science and Technology, Wuhan, China, and her PhD degree in Control Science and Engineering from Nanjing University of Science and Technology. In 1987, she joined the faculty of the School of Automation, Nanjing University of Science and Technology, and is currently a professor there. Her main research interests include intelligent control, adaptive control, and robotics.