

Problem and Contribution

Goal: How to overcome the problem of local over-smoothing or amplified artifacts caused by fixed spatial operations when performing low-light image enhancement under unsupervised conditions.

Idea: Inspired by natural swarm intelligence (e.g., the self-organizing behavior of birds and fish), we treat each pixel in the image as an adaptive agent. By designing a dynamic, locally interactive neighborhood mechanism coupled with a distributed reinforcement learning framework, these pixel “agents” autonomously negotiate and adjust their intensity values. This enables the emergence of an organic, context-aware enhancement at the global level, simultaneously restoring fine textures and maintaining overall illumination consistency.

Contributions:

- Drawing inspiration from the dynamic behaviors of biological swarms, we have developed an image enhancement method based on swarm dynamics, offering fresh ideas and insights.
- We optimize the dynamic system using a decentralized multi-agent approach, enabling more flexible, adaptive interactions between agents and improving the overall efficiency of the system.

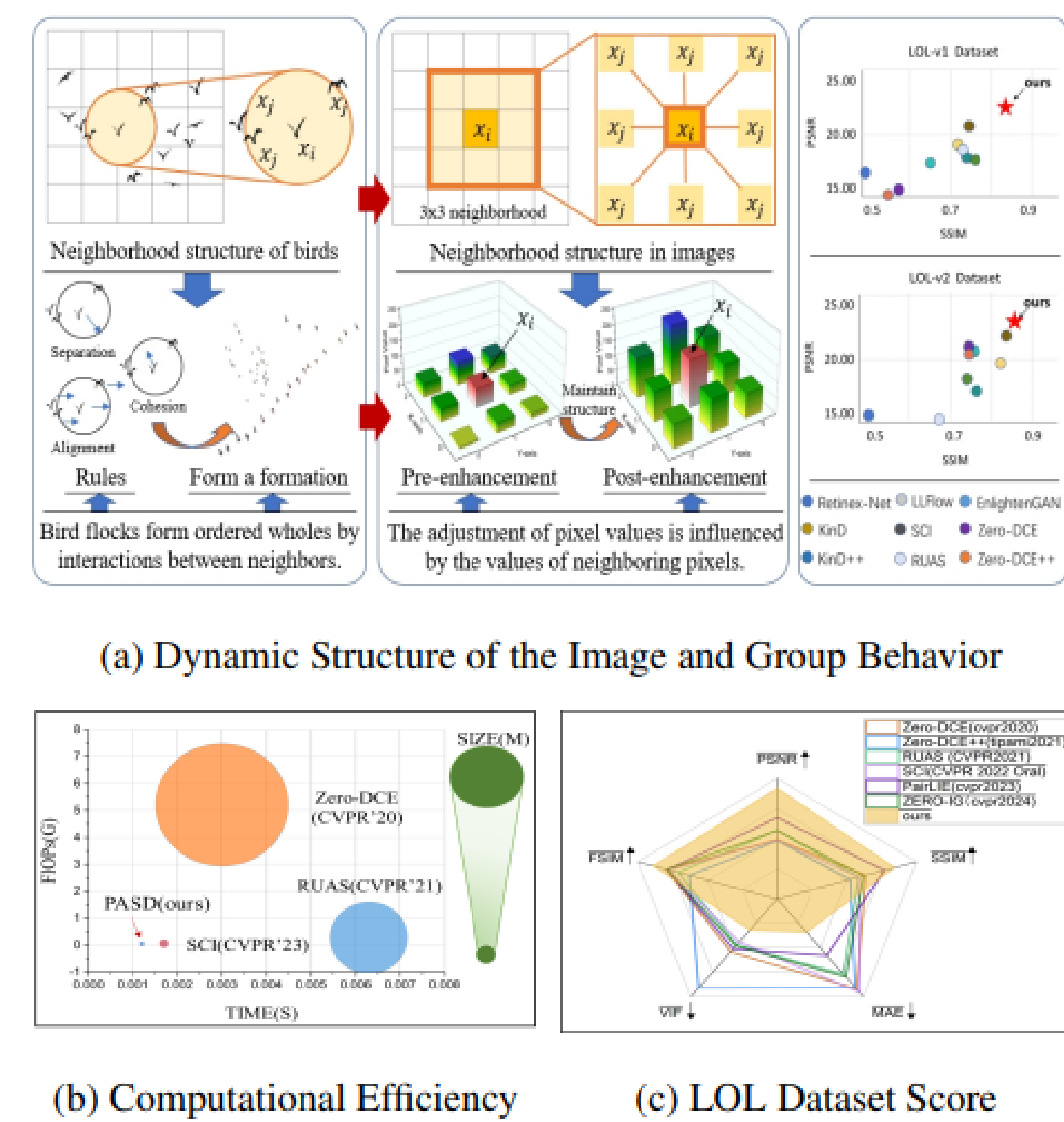


Figure 1. (a) We draw inspiration from the dynamic interactions observed in natural collective behaviors and use dynamic interactions between neighbors for image enhancement. (b) and (c) demonstrate the effectiveness of our approach.

The overall framework of our approach

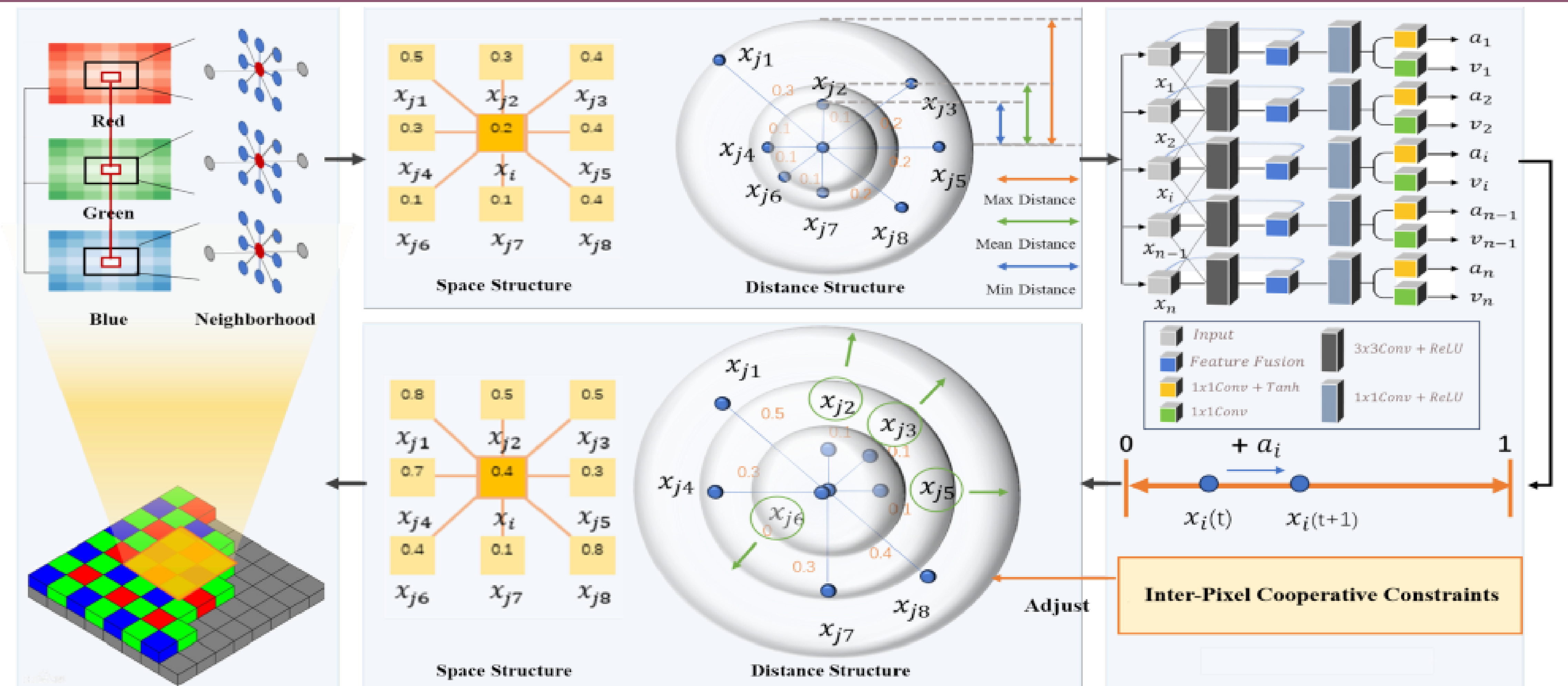


Figure 2. The overall framework of our approach. First, we define the neighborhood of each pixel and calculate the differences between pixel values within the neighborhood. Based on these differences, the pixels are assigned to different distance intervals, forming the initial distance structure. The image, containing this distance information, is then input into the model, which optimizes by calculating and adjusting each pixel's value. Using the adjusted pixel values, we adaptively compute distance and similarity constraints, updating the neighborhood's distance structure to optimize the direction of pixel adjustments. Through multiple iterations, with each update of the neighborhood constraints, the model progressively refines pixel enhancement, ultimately achieving more precise image enhancement.

Experiments & Results

Quantitative Comparisons.

Table 1. Quantitative comparison on the LOL(v1 [39] and v2 [42]) and LSRW[8] datasets in terms of PSNR \uparrow and SSIM \uparrow . The best results for unsupervised methods are bolded, respectively.

Dataset		Train set	LOL-v1		LOL-v2-real		LOL-v2-syn		Nikon		Huawei	
Metrics			PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
SL	RetinexNet [39]	LOL	16.77	0.46	17.71	0.65	17.13	0.79	15.41	0.40	16.98	0.48
	KinD[45]	LOL	17.64	0.77	14.74	0.64	13.29	0.58	16.08	0.39	16.48	0.57
	LLFormer[35]	LOL	23.65	0.82	18.94	0.86	17.72	0.71	19.03	0.80	19.93	0.81
	Retinexformer[1]	LOL+	25.16	0.84	22.80	0.84	25.67	0.93	21.19	0.69	22.52	0.77
	DiffLL[12]	LOL+	26.34	0.85	28.86	0.87	22.59	0.77	19.28	0.55	18.58	0.81
UL	EnlightenGAN[14]	Mixed	17.58	0.65	18.67	0.68	16.57	0.73	17.10	0.47	17.03	0.51
	Zero-DCE[7]	Mixed	14.86	0.56	18.06	0.60	15.83	0.46	15.86	0.44	16.79	0.60
	Zero-DCE++[18]	Mixed	14.57	0.52	18.76	0.63	15.54	0.58	18.08	0.71	16.03	0.50
	SCI[22]	LOL+	14.78	0.52	17.30	0.55	16.73	0.60	15.01	0.48	15.77	0.48
	RUAS[20]	LOL	18.23	0.72	18.37	0.72	16.55	0.65	14.27	0.46	13.76	0.51
	PairLIE[4]	Mixed	19.51	0.74	19.88	0.73	18.92	0.71	17.60	0.50	19.41	0.73
	CUE[46]	Mixed	21.67	0.77	20.82	0.75	19.10	0.73	18.93	0.61	20.31	0.65
	QuadPrior[36]	CoCo	20.31	0.80	21.39	0.86	20.33	0.77	18.56	0.62	17.99	0.71
	ours	LOL	21.90	0.84	22.31	0.87	19.39	0.74	19.11	0.74	19.89	0.77

Qualitative Comparison.

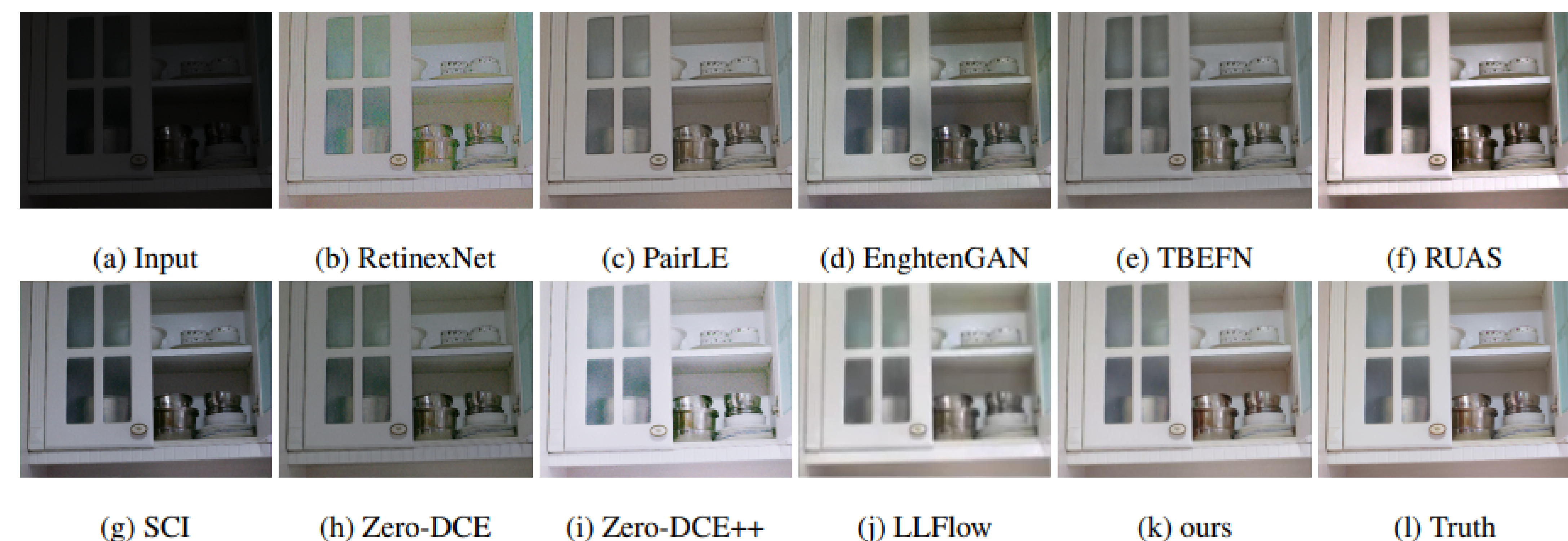


Figure 5. Visual comparison of low-light images sampled from the LOL test set.