Automatical Enhancement and Denoising of Extremely Low-light Images

Yuda Song,[1] Yunfang Zhu,[2] and Xin Du,[1,*]
[1] Department of Information Science and Electronic Engineering, Zhejiang University, Hangzhou 310027, China
[2] Department of Computer Science, Zhejiang Gongshang University, Hangzhou 310027, China
[*]E-mail: duxin@zju.edu.cn

Abstract

Deep convolutional neural networks (DCNN) based methodologies have achieved remarkable performance on various low-level vision tasks recently. Restoring images captured at night is one of the trickiest low-level vision tasks due to its high-level noise and low-level intensity. We propose a DCNN-based methodology, Illumination and Noise Separation Network (INSNet), which performs both denoising and enhancement on these extremely low-light images. INSNet fully utilizes global-ware features and local-ware features using the modified network structure and image sampling scheme. Compared to well-designed complex neural networks, our proposed methodology only needs to add a bypass network to the existing network. However, it can boost the quality of recovered images dramatically but only increase the computational cost by less than 0.1%. Even without any manual settings, INSNet can stably restore the extremely low-light images to desired high-quality images.

Method

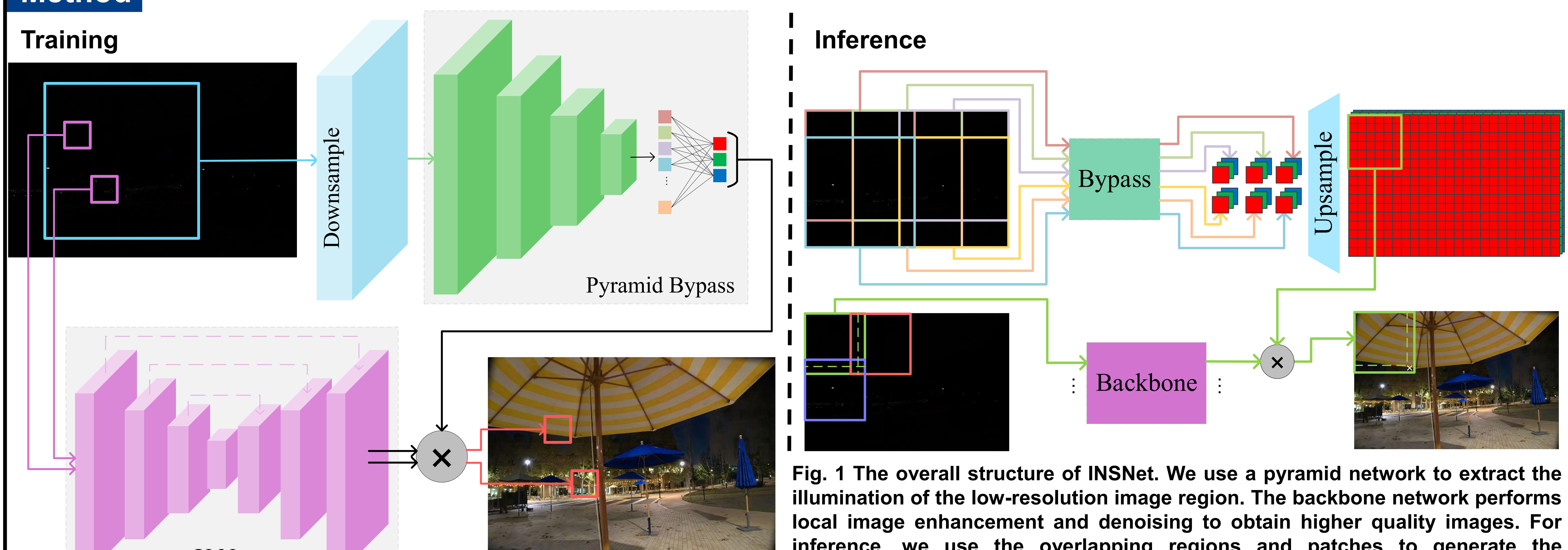
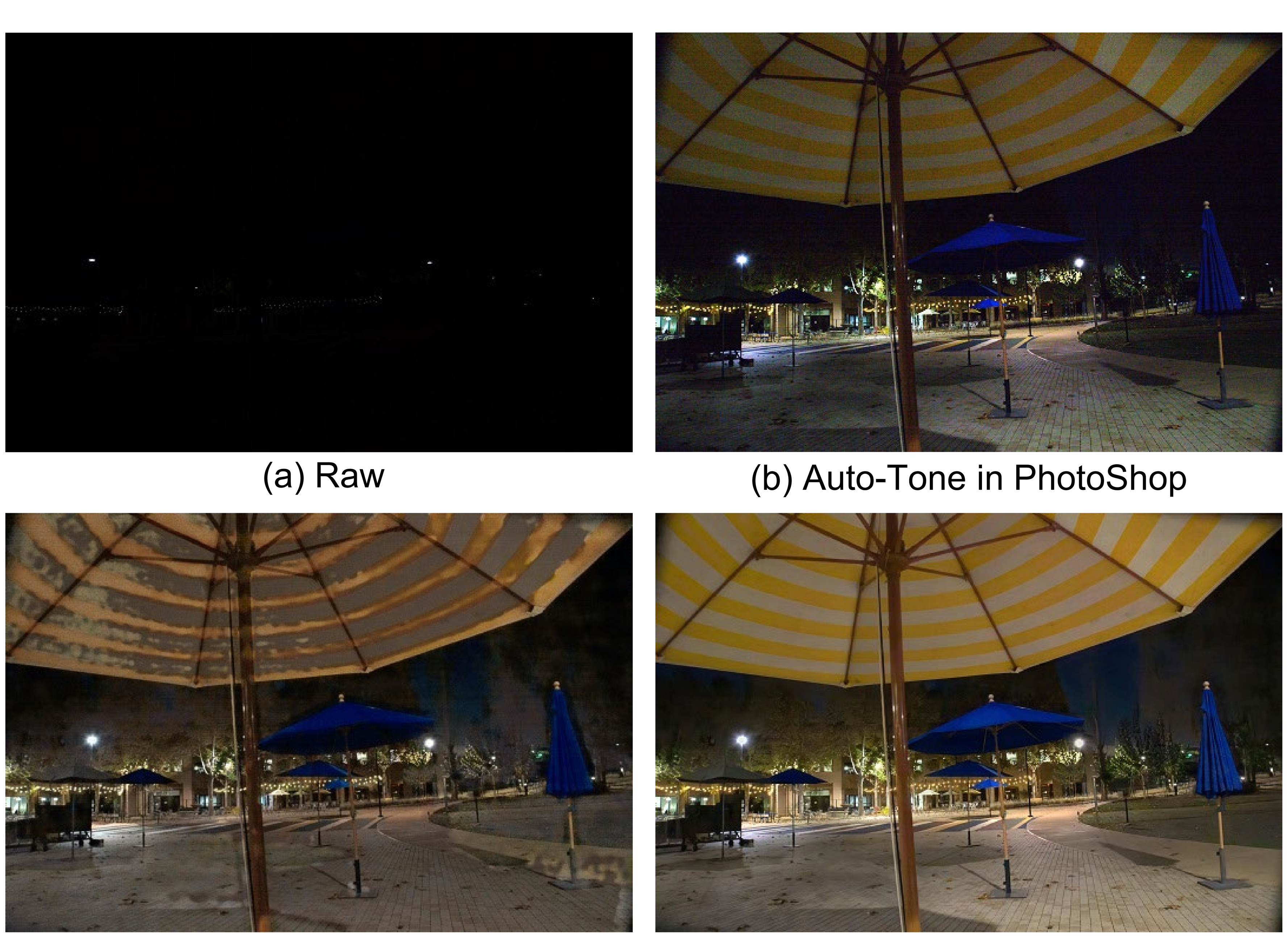


Fig. 1 The overall structure of INSNet. We use a pyramid network to extract the illumination of the low-resolution image region. The backbone network performs local image enhancement and denoising to obtain higher quality images. For inference, we use the overlapping regions and patches to generate the illumination map and enhanced image.

We use an encoder network to encode the thumbnail to obtain an illumination vector. Then the illumination information is fused into the backbone network using channel attention to improve image enhancement and denoising performance. When training, ensure that the sizes of the input image patch and the input thumbnail are close for balancing the training of the bypass network and the backbone network. When inference, we crop the image into overlapping regions to produce the vectors to form an extremely low-resolution illumination map that is upsampled to a high-resolution illumination map. Furthermore, we collect some high-quality, high-resolution night photos as additional long-exposure images to improve image quality. We use Brightness Transform Function (BTF) and add noise to the images using a realistic noise model to generate short-exposure images.

Comparison



(a) Raw (b) Auto-Tone in PhotoShop (c) U-Net (d) ours

Fig. 2 An extremely low-light image (a) and the enhanced image using different methods (b)-(d). Our result has more natural colors, lower-level noise, and fewer artifacts.

Experiment

TABLE I EFFICIENCY EVALUATION ON A FIXED-SIZE IMAGE.

Method	Image	Thumbnail	Params (M)	FLOPs (T)
U-Net	2560 × 2560	×	31.03	5.469
ours	2560 × 2560	160 × 160	42.21	5.471

TABLE II ENHANCEMENT RESULTS (PSNR / SSIM) ON THE SID DATASET.

Method	Blind / Non-blind	Process on	PSNR	SSIM
U-Net	Non-blind	RAW	28.60	0.768
ours	Non-blind	RAW	**29.10**	**0.775**
U-Net	Non-blind	sRGB	28.02	0.754
ours	Non-blind	sRGB	**28.51**	**0.767**
U-Net	Blind	RAW	22.60	0.712
ours	Blind	RAW	**25.41**	**0.744**
U-Net	Blind	sRGB	21.64	0.655
ours	Blind	sRGB	**24.73**	**0.734**
U-Net	Blind	sRGB*	18.08	0.589
ours	Blind	sRGB*	**21.56**	**0.660**