



INTRODUCTION

1. We are the first to construct a large-scale high-quality dataset with 3 groups of different film style and a total of 5,285 high-quality images, called FilmSet.
2. To learn the features in FilmSet properly, we present FilmNet, a novel multi-frequency framework based on Laplacian Pyramid for simulating film styles and subsequently retouching normal photos.

DATASET

We develop FilmSet. We have three styles in total: Cinema, Classical Negative and Velvia, each style contains 5285 images.



Figure 1: Visual samples of FilmSet.

RESULT

Method	Cinema			ClassNeg			Velvia		
	PSNR↑	SSIM↑	ΔE↓	PSNR↑	SSIM↑	ΔE↓	PSNR↑	SSIM↑	ΔE↓
HDRNet	35.18	0.990	2.81	35.41	0.988	2.19	34.37	0.975	3.56
DPE	3.98	0.358	47.58	3.79	0.320	49.66	3.48	0.313	52.12
UPE	22.81	0.946	4.22	22.50	0.936	4.97	22.23	0.893	5.00
DeepLPF	36.34	36.34	1.96	33.40	0.978	2.43	34.06	0.956	2.24
3D-LUT	35.49	0.990	1.86	33.82	0.989	1.83	34.07	0.976	2.40
STAR-DCE	28.12	0.949	6.91	25.54	0.945	7.98	34.06	0.956	2.24
LPTN	36.55	0.985	2.12	34.22	0.972	2.72	33.19	0.948	3.32
SepLUT	35.82	0.986	2.42	34.10	0.982	2.34	32.88	0.964	3.60
Ours	40.07	0.993	1.61	38.89	0.992	1.47	37.60	0.981	2.05

Table 1: Quantitative comparisons on the FilmSet dataset of different image enhancement methods. The top result is highlighted in red.

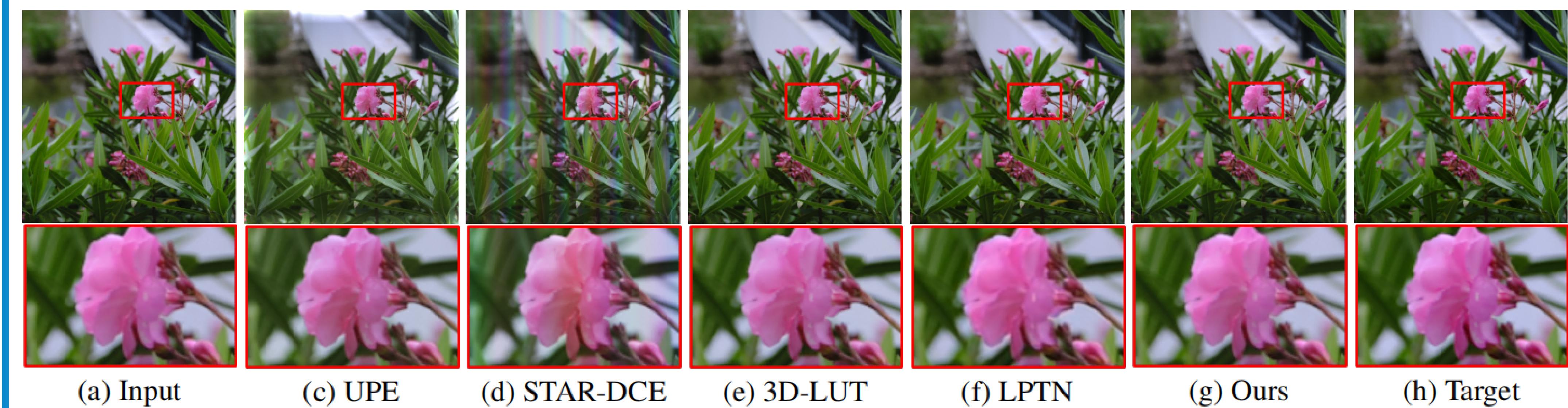


Figure 3: Visual comparison of different methods for image enhancement on the FilmSet dataset. Our results (g) are visually better in color tone and details.

METHODOLOGY

Following the core idea of multi-frequency optimization, initially, our network splits the input picture into two distinct areas using Laplacian Pyramid (LP): two high-frequency regions representing textures and edges, and a colored low-frequency region. The 512×512 input image is downsampled to 128×128 and sent into the Nonlinear Stylization Remapping (NSR) block to precisely adjust the color details, which substantially increases computing efficiency. The high-frequency sections are input individually into a cascade network, and a mask is learned and expanded, which saves our computation volume and enables us to optimize the high-frequency regions more effectively. Finally, these three images are recombined into a single picture I_{out} , downsampled to a Low-Resolution (LR) image I_{LR} and fed into Triple Trilinear Regulator (TTR) alongside the I_{out} , and the weights of the TTR are adjusted using a CNN to produce the final film output. Each node in our network has lightweight parameters, resulting in a more efficient calculation. The overall framework of FilmNet can be seen in Figure 2.

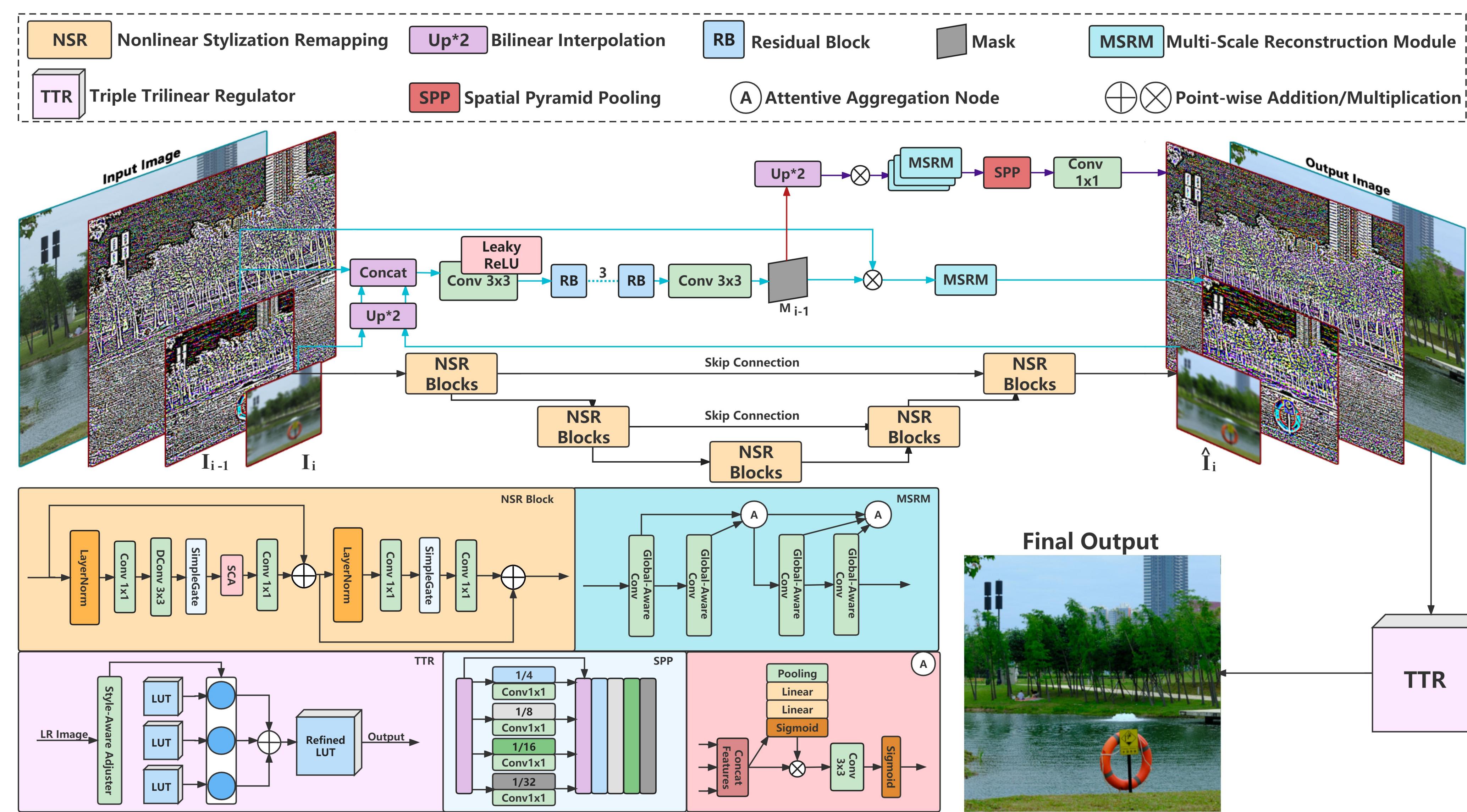


Figure 2: The general structure of our FilmNet network. Initially, the LP divides the input picture into three frequency bands and sends them to distinct networks. These pieces are combined into the output picture before being transmitted to TTR. Eventually, the TTR performs the final output processing.

In training phase, we use MSE and $SSIM$ as loss functions. Our total loss function can be written as Equation 1:

$$L_{total} = L_{MSE} + 0.4 * L_{SSIM} \quad (1)$$

REFERENCES

- [1] Jie Liang, Hui Zeng, and Lei Zhang. High-resolution photorealistic image translation in real-time: A laplacian pyramid translation network. In CVPR, 2021.

CONCLUSION

In this paper, we construct FilmSet, a large-scale and high-quality dataset of film styles. Our dataset consists of three distinct film types and over 5000 photos captured in the field in raw format. In order to learn the features of the FilmSet images more properly, we propose the FilmNet, a new framework based on Laplacian Pyramid for refining multi-frequency pictures and achieving high-quality results.

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