End-to-End Unified Network for Solving Reflection and Reflective Flare Artifacts

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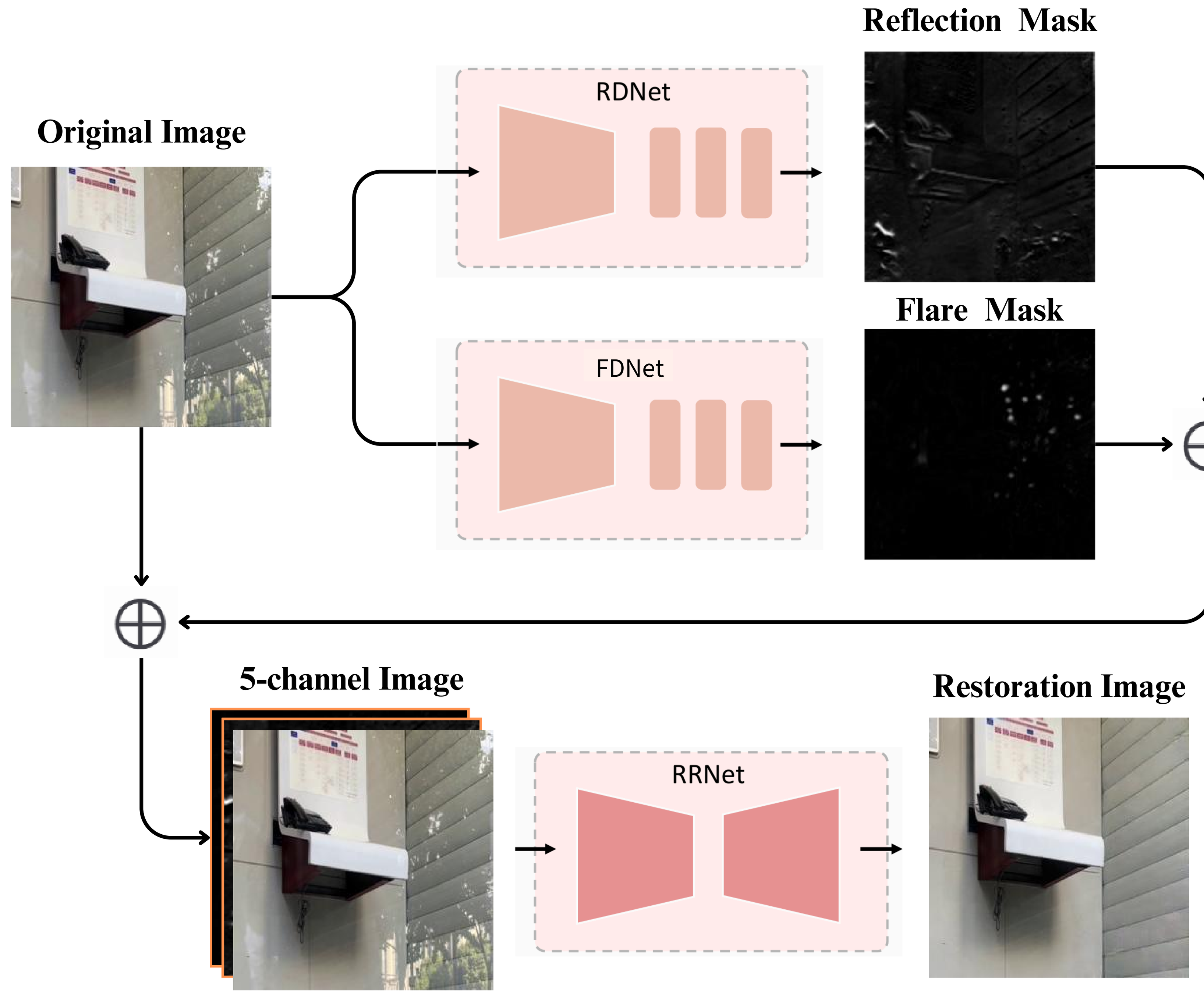
Introduction

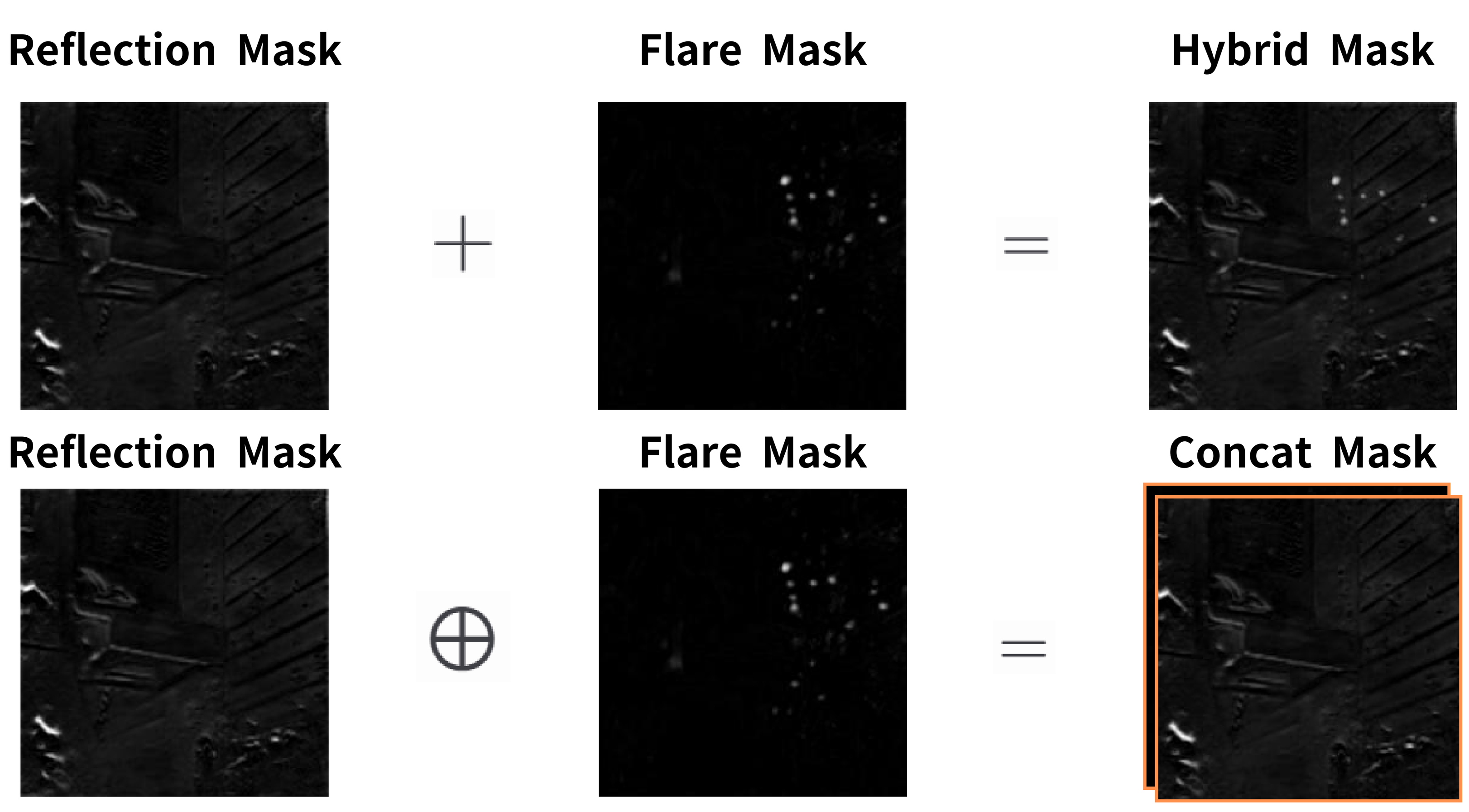
The motivation behind this study stems from the significant impact that reflections and flare can have on image quality, often leading to errors or misjudgments in computer vision tasks. These distortions are particularly problematic in real-world applications, where accurate image analysis is crucial. Building upon the two-stage method proposed in the RRW paper, we developed a specialized mask computation technique tailored to address reflective flare. In addition, we introduced an FDNet module to predict areas in the image that are likely affected by flare. Our innovation lies in successfully predicting and correcting these problematic regions using a simpler architecture, which not only reduces computational complexity but also delivers impressive final restoration results.

Data Processing

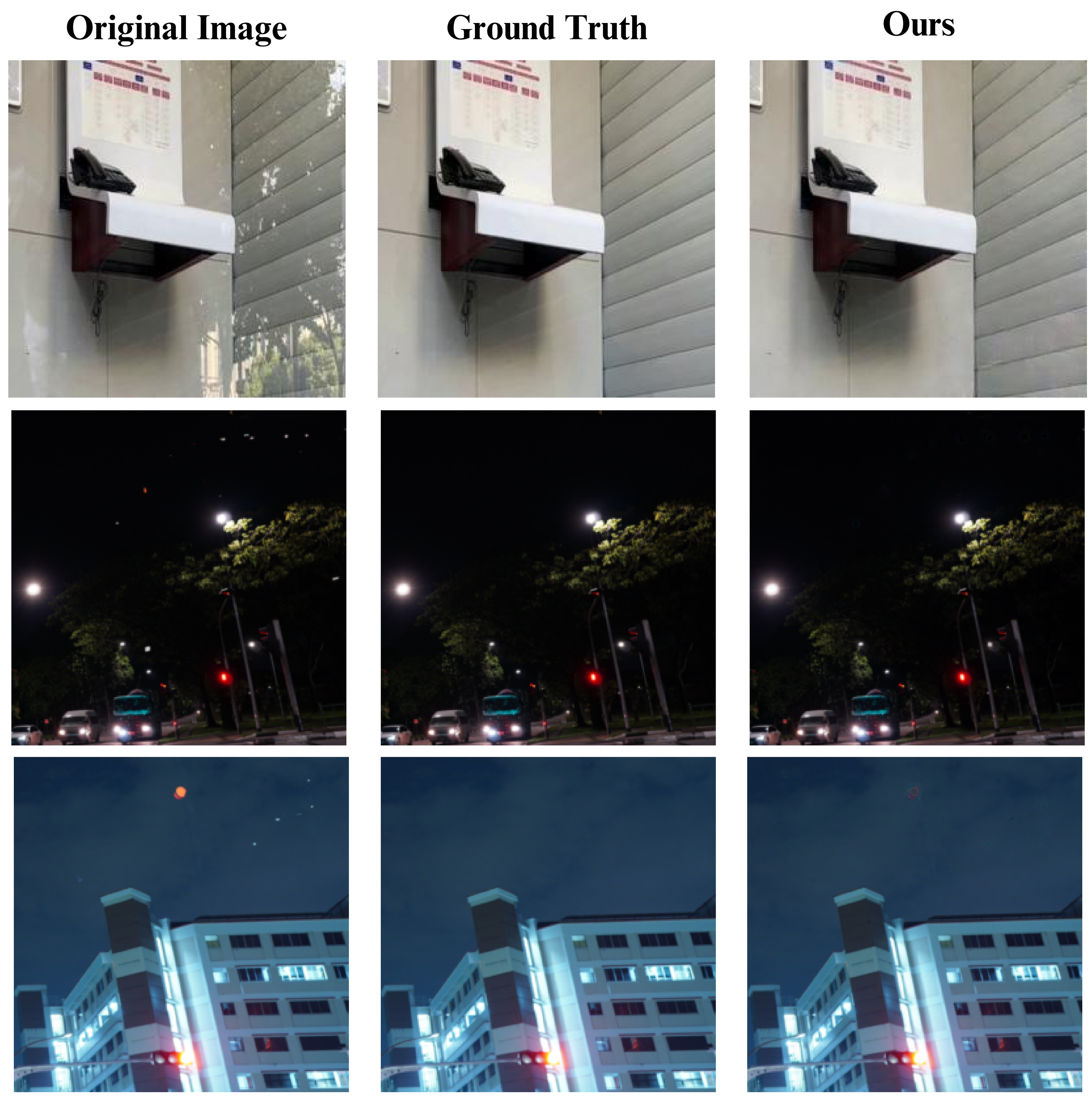


Method

In the RRNet stage, we compared the difference between concatenating two masks and applying a logical OR operation on them. We found that using the concatenation method to combine the two masks led to better training performance.



Result



Experiment

We also experimented with modifying the model's loss functions by incorporating SSIM as an additional loss into RRNet and adding Charbonnier Loss to FDNet and RDNet. The results show that the best performance is achieved when SSIM is added to RRNet and Charbonnier Loss is only included in FDNet.

Methods	*Nature* (20)		*Real* (20)		*SIR*^{2} (500)		*Flare* (40)	
	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑
Input Image	20.9327	0.8381	19.6094	0.8178	22.9191	0.8848	38.1243	0.9900
SOTA_reflection	25.9034	0.8858	**25.2290**	0.8178	**25.3431**	**0.9101**	27.9571	0.8800
SOTA_flare	-	-	-	-	-	-	**48.4100**	**0.9940**
Ours	23.7315	0.8888	20.2960	0.8171	22.4983	0.8798	39.0346	0.9785
Ours w/ SSIM	26.7691	0.8961	20.6014	0.8195	22.5533	0.8788	41.4758	0.9886
Ours w/ SSIM and RD_Char	**26.9125**	**0.9040**	20.7674	**0.8229**	22.9589	0.8842	39.0107	0.9837
Ours w/ SSIM, RD_Char and FD_Char	25.645	0.8929	19.8065	0.8127	21.6584	0.8696	33.2435	0.9715

$$\mathcal{L}_{FDNet} = \|M_{FD\_local} - \hat{M}_{FD\_local}\|_1 + \gamma_{FD} * TVLoss(\hat{M}_{FD\_Local}) \quad (1)$$

$$\mathcal{L}_{RDNet} = \|M_{RD\_local} - \hat{M}_{RD\_local}\|_1 + \gamma_{RD} * TVLoss(\hat{M}_{RD\_Local}) \quad (2)$$

$$\mathcal{L}_{RRNet} = \|T - \hat{T}\|_1 + \gamma_{RR} * \|VGG(T) - VGG(\hat{T})\|_1 + \gamma_{other} * OTHER \quad (3)$$

$$\mathcal{L} = \mathcal{L}_{FDNet} + \mathcal{L}_{RDNet} + \mathcal{L}_{RRNet} \quad (4)$$

Conclusion

- We propose an end-to-end unified network designed to tackle both reflection removal and reflective flare removal.
- While addressing both problems simultaneously, our results on the Nature dataset still outperform those of the original study.
- We experimented with adding SSIM loss to RRNet and achieved better PSNR performance.