

LVRNet: Lightweight Image Restoration for Aerial Images under Low Visibility (Student Abstract)

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Abstract

Learning to recover clear images from images having a combination of degrading factors is a challenging task. That being said, autonomous surveillance in low visibility conditions caused by high pollution/smoke, poor air quality index, low light, atmospheric scattering and haze during a blizzard, etc, becomes even more important to prevent accidents. It is thus crucial to form a solution that can not only result in a high-quality image but also which is efficient enough to be deployed for everyday use. However, the lack of proper datasets available to tackle this task limits the performance of the previous methods proposed. To this end, we generate the LowVis-AFO dataset, containing 3647 paired dark-hazy and clear images. We also introduce a new lightweight deep learning model called Low-Visibility Restoration Network (LVRNet). It outperforms previous image restoration methods with low latency, achieving a PSNR value of 25.744 and an SSIM of 0.905, hence making our approach scalable and ready for practical use.

Introduction

Image enhancement and restoration have been a critical area of research using both traditional digital image processing techniques, and the recent deep learning frameworks. In this study, we perform recovery of the clear image from the hazy version while performing low-light image enhancement using a single convolutional network, which could further be applied to tasks such as search and rescue operations using object detection.

We observed that, on most benchmark datasets, deep learning-based methods often outperform traditional methods significantly. However, there are still challenges that the researchers have to tackle for image restoration. Publicly available datasets containing a variety of degrading factors that model real-world scenarios are few in number. From the

perspective of computational complexity, recent deep learning methods are computationally expensive, and thus they can't be deployed on edge devices. Moreover, image restoration has been a long-standing ill-posed research problem, as there are infinite mappings between the degraded and the clear image. In this work, we focus on developing an end-to-end lightweight deep learning solution for the task of image restoration. Our major contributions are (1) Taking inspiration from Non-linear Activation Free Network (NAFNet) (Chen et al. 2022) and Level Attention Network (Zhang et al. 2021a), we propose a novel algorithm - Low-Visibility Restoration Network (LVRNet), that can effectively recover high-quality images from degraded images taken in poor visual conditions. (2) Due to the lack of available datasets that exhibit a combination of adverse effects, we generate a new dataset, namely LowVis-AFO (abbreviation for Low-Visibility Aerial Floating Objects dataset), consisting of a combination of low-light and hazy images. (3) Benchmarking experiments have been provided on the LowVis-AFO dataset. Along with that, LVRNet surpasses the results obtained using previous image restoration techniques by a significant margin.

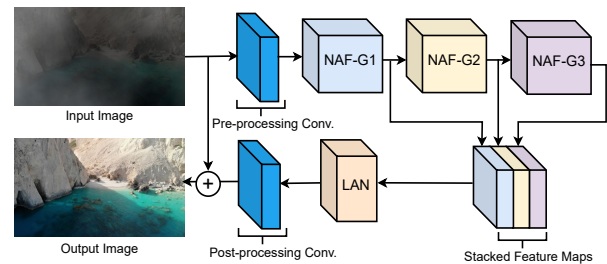


Figure 1: Model architecture of the proposed LVRNet.

Dataset Generation

Due to the lack of available datasets that meet our requirements, we generate a new one called LowVis-AFO using the AFO dataset (Gasienica-Józkowy, Knapik, and Cyganek 2021). Haze effect is added by using `imgaug`, a well-known python library. Severity of the fog was selected randomly from a set of discrete values $\{3, 4, 5\}$. To add low-light,

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[†]This work is supported by NRIDA Research Grant NRRDA-P017(23)/2021-Dir(P-II) under Project “AI-enabled drone-based remote health assessment of PMGSY roads” and ARTPARK’s Student Innovation Grant Program.

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Method	PSNR	SSIM
Star-DCE (Zhang et al. 2021b)	16.651	0.539
FFANet(Cho et al. 2021)	15.050	0.582
MSBDN-DFF(Hang et al. 2020)	16.686	0.689
LVRNet (Ours)	25.744	0.905

Table 1: Quantitative comparison: Best results have been highlighted in bold.

we follow the pipeline introduced (Cui et al. 2021) which parametrically models the low light-degrading transformation by observing the image signal processing (ISP) pipeline between the sensor measurement system and the final image. Finding a unique solution for such a combination has not been explored to date. Examples of generated images have been included in Figure 2.

Proposed Method

The network consists of two major components, first is K NAF-groups ($K=3$) and the second is the level attention net (LAN) as shown in Figure 1. Each group consists of N NAF Blocks (Chen et al. 2022) ($N=16$) with a skip connection at the end. After being concatenated, the output of each group is passed to LAN to find the significance of feature maps obtained, and post-processed using two convolutional layers. This is accompanied by a long skip connection for global residual learning.

NAF-Block NAF Block is a novel convolutional building block of NAFNet (Chen et al. 2022). To avoid over-complexity in the architecture, this block avoids using any activation functions.

Level Attention Network LAN (Zhang et al. 2021a) learns attention weights for features obtained at different levels. In LAN, each feature map is reshaped to a 2D matrix of the size $K \times HWC$, where K, H, W , and C are the no. of NAF Groups, height, width, and no. of channels of the feature maps respectively. It’s correlation matrix is found by multiplying it with its transpose. Finally, we multiply the 2D matrix with this correlation matrix and reshape it to $K \times H \times W \times C$ tensor. Inspired by residual learning, this tensor is substituted for residual and is added to the original concatenated feature maps. The resultant features are then reshaped to $H \times W \times KC$. Result is passed through 1×1 convolution operation to get the $H \times W \times C$ feature map.

Loss Functions

Four loss functions, namely, reconstruction loss, perceptual loss, edge loss, and FFT loss(Cho et al. 2021) have been used. The total loss L is defined in Equation 1, where $\lambda_1 = 0.04$, $\lambda_2 = 1$ and $\lambda_3 = 0.01$.

$$L = L_s + \lambda_1 L_p + \lambda_2 L_e + \lambda_3 L_f \quad (1)$$

Table 1 presents the results of our model on LowVis-AFO. Previous methods were trained on the new dataset and

tested. Clearly, our network gives better results than previous works.



Figure 2: Example images of the generated dataset.

Conclusion

In this work, we have presented Low-Visibility Restoration Network (LVRNet), a new lightweight deep learning architecture for image restoration. We also introduce a new dataset, LowVis-AFO, that includes a diverse combination of synthetic darkness and haze. We surpass the results obtained using the previous image restoration network by a significant margin. We believe that our work will motivate more research work, focused on dealing with a combination of adverse effects such as haze, rain, snowfall, etc. rather than considering a single factor. In our future work, we plan to extend LVRNet for image restoration tasks where more factors, that negatively impact the image quality, are taken into account.

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