

# Improving Aerial Instance Segmentation in the Dark with Self-Supervised Low Light Enhancement (Student Abstract)

Prateek Garg,<sup>1</sup> Murari Mandal,<sup>2</sup> Pratik Narang<sup>3</sup>

<sup>1</sup>Department of Electrical and Electronics Engineering, BITS Pilani, Pilani, Rajasthan, India

<sup>2</sup>Department of Computer Science and Engineering, IIIT Kota, Kota, Rajasthan, India

<sup>3</sup>Department of Computer Science and Information Systems, BITS Pilani, Pilani, Rajasthan, India  
f20180412@pilani.bits-pilani.ac.in, murarimandal.cv@gmail.com, pratik.narang@pilani.bits-pilani.ac.in

## Abstract

Low light conditions in aerial images adversely affect the performance of several vision based applications. There is a need for methods that can efficiently remove the low light attributes and assist in the performance of key vision tasks. In this work, we propose a new method that is capable of enhancing the low light image in a self-supervised fashion, and sequentially apply detection and segmentation tasks in an end-to-end manner. The proposed method occupies a very small overhead in terms of memory and computational power over the original algorithm and delivers superior results. Additionally, we propose the generation of a new low light aerial dataset using GANs, which can be used to evaluate vision based networks for similar adverse conditions.

## Introduction

Most of the computer vision methods are biased towards highly clean and sanitised dataset, which is hardly the scenario in most practical settings. The data on which these methods are trained lack substantially in adverse aspects such as low lighting conditions and unwanted noise, which demand immediate attention if the methods are to be utilised in real-time. Moreover, the methods which are being developed do not include any distinctive mechanism to deal with such complications, hence supplementing the underlying problem.

Amongst many adverse problems, low light conditions in aerial imagery is a prominent one. Low light is an inevitable part of aerial images, since they may be captured with insufficient light due to extreme weather constraints, night time, poor capturing techniques, low contrast conditions, inept position of ground objects etc. This makes it very difficult to accommodate key UAV applications such as remote sensing and urban surveillance, problems which cannot endure poor prediction results and demand robust solutions.

In this study, we propose a novel network capable of performing simultaneous low light enhancement coupled with instance segmentation on the aerial images. The entire architecture is an end-to-end trainable CNN and delivers an increased quality of predictions. The overall contributions of this study are: (1) We propose a self-supervised light enhancement network capable of performing instance segmentation

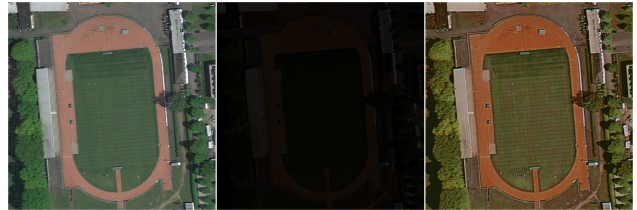


Figure 1: Low light aerial dataset generation. Left-original image; Middle-low light image generated using GAN; Right-enhanced low light image using light enhancement module.

on low light aerial images. (2) We generate a new low light aerial image dataset having annotations for instance segmentation. (3) We demonstrate the effectiveness of our proposed network on the low light aerial dataset both qualitatively and quantitatively, thus laying the groundwork for future research.

## Dataset Generation

To the best of our knowledge, no dataset provides low light aerial images along with annotations for instance segmentation. To validate our proposed method, we generate a low light aerial image dataset using iSAID (Waqas Zamir et al. 2019), LOW-Light dataset (LOL) (Wei et al. 2018) and GANs. The iSAID (outdoor, aerial) and LOL (indoor, terrestrial) datasets belong to different domains and lack one-to-one mapping between them. To efficiently translate the low light attribute from LOL to iSAID, we train them on the CycleGAN (Zhu et al. 2017) architecture, which is based on cycle consistency loss. We generate 18528 low light aerial images for the training set. All generated images are superior in quality and match with real-time low light conditions (Figure 1).

## Proposed Method

The network is a two-phase architecture. The first phase deals with the brightness reconstruction of the image in a self-supervised manner, whereas the second phase is associated with the computer vision task of segmentation and detection.

**1. Self-Supervised Low Light Enhancement.** A self-supervised CNN module is used in this phase to eliminate the need of ground truth clear images or paired training data. This reduces the computational complexity of the network and

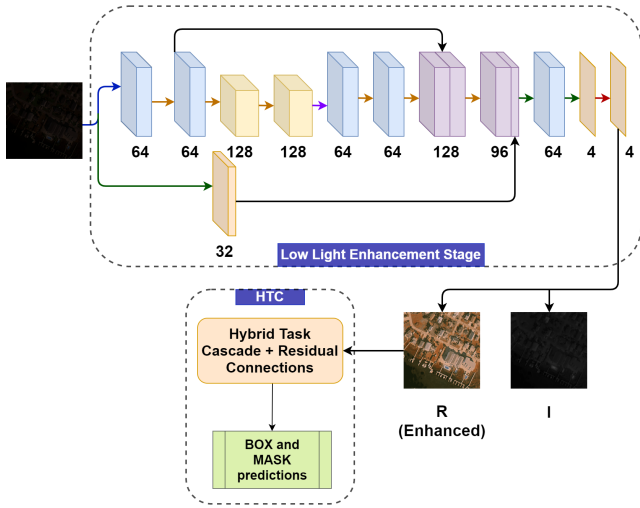


Figure 2: The architectural representation of the proposed method. (Magnify for minor details in the images)

makes the training process more generalisable. The method utilises the approach proposed by Zhang et al. (Zhang et al. 2020) based on the Maximum Entropy-based Retinex Model. The light enhancement task is based on the assumption that the histogram distribution of the maximum channel of the enhanced image should validate and follow the histogram distribution of the maximum channel of the low light image after it has been histogram equalised. This attribute eliminates the requirement of paired examples, and thus, the loss is constructed using low light image tensors only. The following equation (Eq. 1) generalises the aforementioned concept.

$$Z = \|S - R \cdot I\| + \lambda_1 \left\| \max_{c \in R, G, B} R^c - F \left( \max_{c \in R, G, B} S^c \right) \right\| \quad (1)$$

$$+ \lambda_2 \|\Delta I \cdot \lambda \exp(-\lambda_3 \Delta R)\| + \lambda_4 \|\Delta R\|$$

where  $S$  represents the low light image,  $R$  and  $I$  represent the reflectance and illuminance of the image, and  $\lambda_i$  are the weight parameters. This composite equation can be solved by a deep learning network which can fragment the given image into illuminance and reflectance and employ this equation as its loss function. The deep learning network utilised is shown in Figure 2, which is a very elementary CNN structure apt for our usage, since it is fast, efficient and lightweight (2 MB). In the network, the upsampling and downsampling convolutions help in reducing noise but make the image tensors blurry. This flaw can be rectified by using extra convolutions post the sampling operations that can aid in the correct reconstruction of the target image.

**2. Instance Segmentation Network.** To perform instance segmentation on the enhanced image, we utilise Hybrid Task Cascade (Chen et al. 2019) along with some novel improvements that boost the prediction accuracy. We implement residual connection in the mask pipeline of HTC, which allows an efficient flow of the computed mask features in the pipeline. These connections help in retaining the mask features of tiny objects (which are abundant in aerial images) deduced in the initial stages throughout the final stages as well.

Method	Type	AP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>S</sub>	AP <sub>M</sub>
Original HTC	Box	38	55.9	42.1	21.1	45.9
	Segm	31.3	51.9	32.7	16.1	37.8
Proposed Method	Box	38.9	57.5	43.1	21.7	47.2
	Segm	32.2	53.8	33.9	17	39.2

Table 1: Performance on the val set of the low light aerial dataset.

The light enhancement module and HTC complement each other during the end-to-end training, and losses from both phases contribute to the global loss of the joint network. We train the network for 11 epochs on the train set of low light aerial dataset and obtain good results (Table 1) on the val set. Addition of a light enhancing module considerably boosts the prediction scores of the instance segmentation network.

## Conclusion

In this abstract, we propose a new method for robust feature extraction from low light aerial images. Our method efficiently restores the brightness in the image and then performs instance segmentation on the enhanced image. The light enhancement module, adept in brightness reconstruction, is self-supervised and incurs a very minor computational cost. The instance segmentation algorithm is further improved by using residual connections, which aid in dense information flow in the network. In addition, we also generate a synthetic dataset consisting of low light aerial images and annotations for performing instance segmentation in adverse conditions.

## Acknowledgements

This work is supported by BITS Additional Competitive Research Grant (PLN/AD/2018-19/5).

## References

- Chen, K.; Pang, J.; Wang, J.; Xiong, Y.; Li, X.; Sun, S.; Feng, W.; Liu, Z.; Shi, J.; Ouyang, W.; et al. 2019. Hybrid task cascade for instance segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 4974–4983.
- Waqas Zamir, S.; Arora, A.; Gupta, A.; Khan, S.; Sun, G.; Shahbaz Khan, F.; Zhu, F.; Shao, L.; Xia, G.-S.; and Bai, X. 2019. isaid: A large-scale dataset for instance segmentation in aerial images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 28–37.
- Wei, C.; Wang, W.; Yang, W.; and Liu, J. 2018. Deep Retinex Decomposition for Low-Light Enhancement. In *British Machine Vision Conference*.
- Zhang, Y.; Di, X.; Zhang, B.; and Wang, C. 2020. Self-supervised Image Enhancement Network: Training with Low Light Images Only. *arXiv arXiv-2002*.
- Zhu, J.-Y.; Park, T.; Isola, P.; and Efros, A. A. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, 2223–2232.