Illumination Adaptive Transformer

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Abstract. Challenging illumination conditions (low light, underexposure and overexposure) in the real world not only cast an unpleasant visual appearance but also taint the computer vision tasks. Existing light adaptive methods often deal with each condition individually. What is more, most of them often operate on a RAW image or over-simplify the camera image signal processing (ISP) pipeline. By decomposing the light transformation pipeline into local and global ISP components, we propose a lightweight fast Illumination Adaptive Transformer (IAT) which comprises two transformer-style branches: local estimation branch and global ISP branch. While the local branch estimates the pixel-wise local components relevant to illumination, the global branch defines learnable queries that attend the whole image to decode the parameters. Our IAT could also conduct both object detection and semantic segmentation under various light conditions. We have extensively evaluated IAT on multiple real-world datasets on 2 low-level tasks and 3 high-level tasks. With only 90k parameters and 0.004s processing speed (excluding high-level module), our IAT has consistently achieved superior performance over SOTA. Code is available at https://github.com/cuiziteng/Illumination-Adaptive-Transformer

Keywords: Lightness Adaptation · Transformer · Low Light Vision

1 Introduction

Computer vision has witnessed great success on well-taken images and videos. However, the varying light condition in the real world poses challenges on both visual appearance and downstream computer vision tasks (e.g., semantic segmentation and object detection). Images under inadequate illumination (Fig1) suffer from limited photon counts and undesirable in-camera noise. On the other hand, outdoor scenes are often exposed to strong light such as direct sunlight, making image saturated due to the limited range of sensors and non-linearity in the camera image pipeline. To make it worse, both the under and over exposure may exist together, i.e. spatial-variant illumination cast by shadow could make the contrast ratio to be 1000:1 or higher.
Multiple techniques such as low-light enhancement \cite{37,59,25,47,52,48,24,73,35,62}, exposure correction \cite{69,1} have been proposed to adapt to the difficult light condition. Low-light enhancement methods restore the details while suppressing the accompanying noises. Exposure correction focus on adjusting the under and over exposure condition to reconstruct a clear image against strong illumination changes. While the fore-mentioned algorithms focus on improving human oriented visual perceptual, there are also several methods that integrate the enhancement into the high-level tasks such as object detection to boost the robustness against low light \cite{46,16,43,52} and over-exposure conditions \cite{49}. In this paper, we aim to propose a unified lightweight framework to solve these low-level and high-level tasks in the real world.

A shown in in Fig.1, left hand side RGB images in Fig.1 suffers non-perfect illumination. However, the intensity of these images is not linearly proportion to the actual scene irradiance due to the image signal processor (ISP) pipeline in the camera. Since it is not straightforward to transfer these images to the normal-lit RGB ones, existing methods either directly operate on RAW images \cite{9,8} or over-simplify the ISP pipeline with gamma correction \cite{48} etc.

In this work, we analyze a pipeline that transfers the input RGB image through an inverse ISP to RAW and then converts the adapted normal-lit RAW image into target RGB. It shows that this pipeline could be decomposed into a combination of pixel-wise local components and global ISP components. Based on the analysis, we propose a Illumination Adaptive Transformer (IAT), shown in Fig.1 which also consists of two transformer-style branches. Both branches are designed to be lightweight to estimate the factors for generating the adapted RGB images. The local branch estimates the pixel-wise local components relevant to illumination, wherein the input resolution is maintained to preserve the informative details. The global branch estimates global ISP parameters by designing the learnable queries to attend the whole image. Furthermore, via attaching a high-level task module, we could jointly optimize our IAT for object detection and semantic segmentation under challenging light conditions.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig1.png}
\caption{Nature lay hid in Night, apply our IAT, and all was light.}
\end{figure}
Extensive experiments are conducted on several real-world datasets, i.e., LOL [65] and FiveK [6] for low-level tasks, and EXDark [46], ACDC [56] and TYO-L [29] for high-level tasks. Results show that our IAT can achieve state-of-the-art performance across a range of tasks. More importantly, our IAT only contains 0.09M model parameters, which is 100× smaller than current SOTA models (e.g., 14.14M for MAXIM [62]). Besides, its average inference time on LOL benchmark [65] only require 0.004s per image, while the SOTA methods often take 1s per image.

Our contribution could be summarized as follow:

– We have proposed a fast light-weight framework, Illumination Adaptive Transformer (IAT), to handle challenging light conditions in the real world.
– We have proposed a novel transformer-style structure to estimate global ISP parameters to fuse the RGB target image, wherein the learnable quires are utilized to attend the whole image.
– Extensive experiments on several real-world datasets on 2 low-level tasks and 3 high-level tasks show the superior performance of IAT over SOTA methods. IAT is light-weight and mobile-friendly with only 0.09M model parameters and 0.004s processing time per image. We will release the source code upon publication.

2 Related Works

2.1 Enhancement against Challenging Light Condition

Low-light Enhancement. Earlier low-light image enhancement solutions use RetiNex theory [37] based methods and histogram equalization [22,59] based methods. Since LLNet [47] first utilize a deep-autoencoder structure, deep-learning based methods [48,73,21,41,64,62,20] have been widely used in this task and gain SOTA results on the benchmark enhancement datasets [6,65].

Image enhancement is also relevant to multi-illuminant estimation that corrects the undesired color cast by light. Assuming illumination varies smoothly across the image, the spatially varying illuminants could be estimated [19,37]. Making use of the local information, [21,23] cluster the local features to group independent illuminants. Deep learning solutions have also gained attention. For example, Bianco et al. [3] directly apply CNN on the RAW data for the estimation of both single and multiple illumination.

Exposure Correction. Similarly to Low-light enhancement, traditional exposure correction algorithms [35,8] also use image histograms to adjust image intensities. Another strategy corrects exposure errors by adjusting the tone curve via a trained deep learning model [68,53]. Very recently, Afifi et al. [1] proposed a coarse-to-fine neural network to correct exposure of photo.

High-level Task. Existing high-level vision frameworks [7,54,12,45] are trained on large scale normal-light datasets (i.e. MS COCO [42], ImageNet [17]). Facing the challenging lighting conditions, directly taking low-light/strong-light data as
input would suffer lightness inconsistency, thus deteriorating the performance. Another solution is pre-processing the images with enhancements methods before conducting the detection or segmentation. However, due to the target inconsistency, most of the enhancement methods are designed to improve human visual perception, which may not necessarily benefit the high-level tasks.

To handle this issue, YOLO-in-the-dark built a teacher-student model to offset the gap between low-light RAW and normal-light RGB for low-light RAW object detection. MAET proposes a low-light data synthesis method and uses self-supervised learning strategy to train the object detector for low-light object detection. DB-GAN uses GAN for image normalization, then jointly trains the GAN model and object detector to handle object detection under strong light environments.

2.2 Vision Transformers

Since ViT, Transformer based model has gained superior performances in many computer vision tasks, including image classification, object detection and so on. For low-level vision tasks, transformer-based models have made much progress on several tasks, such as image super-resolution, image restoration, image colorization, image enhancement and bad weather restoration. Besides, the MLP-Mixer based method also shows MLP model’s potential on low-level vision tasks. However, directly using a transformer as an image-to-image structure would bring too much computation cost, making it hard to build a transformer model on mobile and edge devices.

3 Illumination Adaptive Transformer

3.1 Light Adaption Model

For an RGB image $I_i$ under spatial variable light $L_i$, the light adaption model maps it to target RGB image $I_t$ (under light $L_t$) that matches the real photo. Existing methods tend to follow an over-simplified model, either linear or only considering the gamma correction. However, the actual processing in camera involves more elaborated non-linear operations such as demosaicing, white balance, colour space transform, gamma correction, etc. This is called image signal processor (ISP) pipeline, which transforms original RAW images, which is linearly proportional to scene irradiance, to RGB images used in computer vision datasets and tasks. Existing illumination estimation or enhancement methods often chose to directly operate on RAW data rather than RGB images, thus inevitably limiting the application scope.

Brooks et al. shows that an invertible and bijective function $f(\cdot)$ could be defined to map data point in RAW data space to RGB space. As shown on the right hand side of Fig. 2, the input RGB image $I_i(x)$ of colour channel $c \in \{r, g, b\}$
at pixel $x$ is at first mapped to RAW space $R_i(x)$ with an inverse ISP procedure:

$$R_i(x, c) = f^{-1}(I_i(x), c). \quad (1)$$

On RAW dataspace, $R_i(x)$ of pixel $x$ is then linearly adapted to target $R_t(x)$ under target light $L_t$ following von Kries coefficient law [4]:

$$R_t(x, c) = \frac{L_t(x, c)}{L_i(x, c)}R_i(x, c). \quad (2)$$

Based on [5,13,16], our ISP pipeline follows the following order: demosacing, white balance, colour space transformation and gamma correction. Therefore, the ISP function $f$ could be further decomposed into

$$f(\cdot, c_i) = \sum_{c_j} k_{c_i,c_j}(D(\cdot))^{\gamma}, c_i, c_j \in \{r, g, b\}, \quad (3)$$

where $D(\cdot)$ represents the transformation of demosacing and some denoising operations. The $W$ represents the colour transfer matrix that combines camera colour space transformation and white balance operation. $\gamma$ represents gamma value in gamma correction.

The target RGB image $I_t(x, c_i)$ of channel $c_i$ then becomes:

$$I_t(x, c_i) = \sum_{c_j} k_{c_i,c_j} D(M_{c_i}(x)L_t(x)f^{-1}(I_i(x, c_i))))^{\gamma}$$

$$= \sum_{c_j} W_{c_i,c_j}(M_{c_i}(x)I_i(x, c_i) + A_{c_i}(x))^{\gamma} \quad (5)$$

We simplify the complex and non-linear transformation of Eq.[1] and $D(\cdot)$ into a combination of multiplier factor $M(x)$ and additive $A(x)$. The spatial distribution of light $L$ is widely assumed to be varying smoothly without abrupt changes between adjacent locations [37,19]. Since the pixel-wise factors $M(x)$ and $A(x)$ depend on local information of $L_t(x)$ and $L_i(x)$ and global configuration of ISP procedure, the pixel value $M(x)$ and $A(x)$ should also vary smoothly across the space, leaving a small degree of freedom on spatial distribution.

### 3.2 Model Structure

Given an input RGB image $I_i \in \mathbb{R}^{H \times W \times 3}$ under light condition $L_i$, where $H \times W$ denotes the size dimension and 3 denotes the channel dimension ($\{r, g, b\}$). As shown in Fig.2, we propose our Illumination Adaptive Transformer (IAT) to transfer the input RGB image $I_i$ to a target RGB $I_t \in \mathbb{R}^{H \times W \times 3}$ under the proper uniform light $L_t$. By incorporating the downstream detection or segmentation module [75,12], our IAT could also achieve high-level vision tasks under different illumination environments.

According to the discussion above, the complex pipeline, as shown in Fig.2 that transfers RGB image $I_i$ to RGB image $I_t$, could be simplified into Eq.[5].

The
Structure of our Illumination Adaptive Transformer (IAT), the black line refers to the parameters generation while the yellow line refers to image processing. The light adaption pipeline is shown on the right hand side.

non-linear operations are decomposed into local pixel-wise components $M, A \in \mathbb{R}^{H \times W \times 3}$ and global ISP components $W \in \mathbb{R}^{3 \times 3}$, $\gamma \in \mathbb{R}^{1 \times 1}$. Thus, we design two transformers style branches: local branch and global ISP branch to estimate the local pixel-wise components and global ISP components respectively.

As shown in Fig. 2, our ISP obtains the target RGB image $I_t$ via

$$I_t = ((\text{concat}(I_i \odot M + A))W)^\gamma.$$  

concat is an operation concatenates $I_i \odot M + A$ into $HW$ matrix. The exponential operations here is also point wise.

**Local Branch.** In the local branch, we focus on estimating the local components $M, A$ to correct the effect of illumination following Eq.5. Instead of adopting a U-Net [55] style structure, which downsamples the images first before upsampling them, we aim to maintain the input resolution through the local branch to preserve the informative details. Therefore, we propose a novel transformer-style architecture for the local branch. Compared to the popular U-Net [55] style structure, our structure could also deal with arbitrary resolution images without resizing them.

At first, we expand the channel dimension via a $3 \times 3$ convolution and pass them to two independent branches stacked by Pixel-wise Enhancement Module (PEM). Since $M$ and $A$ should vary smoothly on the spatial domain as discussed in Section 3.1 in our Pixel-wise Enhancement Module (PEM), we replace self-attention with depth-wise convolution as suggested in the previous works [26,40,39]. As shown in Fig. 3(a), our PEM first encode the position information by $3 \times 3$ depth-wise convolution before enhancing local details with PWConv-DWConv-PWConv. Finally, we adopt two $1 \times 1$ convolutions to enhance token representation individually. Specially, we design Colour Normalization to replace Layer Normalization [2]. It learns to scale $a$ and bias $b$ via two learnable parameters, and fuses the channels via the learnable matrix, which is initiated as an
identity matrix. Besides, we adopt Layer Scale \[ \frac{1}{k_1/k_2} \] for better convergence, which multiplies the features by a small number \( k_1/k_2 \).

We stack 3 PEMs in each branch and then connect the output features with the input features through element-wise addition. This skip connection \[27\] helps maintain the original image details. Finally, we decrease the channel dimension by a \(3\times3\) convolutions and adopt ReLU/Tanh function to generate the local components \( M/A \) in Eq. 5.

**Global ISP Branch.** Global ISP branch accounts for part of the ISP pipeline \[28,32,34,5\] (i.e. gamma correction, colour matrix transform, white balance) when transferring the target RGB image \( I_t \). Specifically, the value of each pixel in the target image is determined by a global operation defined in Eq. 5.

Inspired by Detection Transformer DETR \[7\] that uses object queries to decode the position and labels, we also design global component queries to decode and predict the \( W, \gamma \) and then apply it to generate RGB image \( I_t \). This transformer structure allows capturing global interactions between context and individual pixels. As shown in Fig. 2, we first stack two convolutions as a lightweight encoder, which encodes the features in a high dimension with lower resolution. Then the features are passed to the Global Prediction Module (GPM), for effective global modeling. As shown in Fig. 3(b), different from DETR, our global component queries \( Q \) are initialized as zeros without extra multi-head self-attention. \( Q \) is global component learnable embedding that attends keys \( K \) and values \( V \) generated from encoded features. The positional encoding for \( K \) and \( V \) is from a depth-wise convolution, which is friendly with different input resolutions. After FFN with two linear layers \[18\], we add two extra parameters with special initialization to output colour matrix and gamma. Such initialization makes sure the colour matrix is identity matrix \( W \) and the gamma value \( g \) is one in the beginning, thus contributing to stable training.

### 3.3 High-level Vision

As shown in Fig. 4, by passing \( I_t \) to the attached downstream task module, our IAT could conduct object detection and semantic segmentation. During train-
Fig. 4. IAT for high-level vision.

ing, we aim to minimise the downstream framework’s loss function (i.e. object detection loss $L_{obj}$ between prediction $\hat{t}$ and ground truth $t$) by jointly optimising the whole network’s parameters (see Eq. [7]). Compared to the subsequent high-level module, the time-complexity and model storage of our IAT main structure could be ignored (i.e. IAT main structure v.s. YOLO-V3 [54], 417KB v.s. 237MB).

$$\min_{i \in I, d \in D} L_{obj}(\hat{t}, t)$$

$$I_t(x) = I(I_t(x)), \hat{t} = D(I_t(x))$$

4 Experiments

We evaluate our proposed IAT model on benchmark datasets and experimental settings for both low-level and high-level vision tasks under different illumination conditions. Three low-level vision tasks include: (a) image enhancement (LOL [65]), (b) image enhancement (MIT-Adobe FiveK [6]), (c) exposure correction [1]. Three high-level vision tasks include: (d) low-light object detection (e) low-light semantic segmentation (f) various-light object detection. The PEM number in local branch to generate $M$ and $A$ are both set to 3, while the channel number in PEM is set to 16.

For all low-level vision experiments: \{(a), (b), (c)\}, the IAT model are trained on a single GeForce RTX 3090 GPU with batch size 8. We use Adam optimizer to train our IAT model while the initial learning rate and weight decay are separately set to $2e^{-4}$ and $1e^{-4}$. A cosine learning schedule has also been adopted to avoid overfitting. For data augmentation, horizontal and vertical flips have been used to acquire better results.
4.1 Image Enhancement Results

For (a) and (b) image enhancement task, we evaluate our IAT framework on two benchmark real-world datasets: LOL [65] and MIT-Adobe FiveK [6].

LOL [65] is a small dataset consisting of 789 paired normal-light images and low-light images. 689 images are used for training and the other 100 images are for testing. The loss function between input image $I_i$ and target image $I_t$ for LOL dataset training is a mixed loss function [63] which consists of smooth L1 loss and VGG loss [33]. As shown in Eq. 8 $\lambda$ is a weight parameter which set to 0.04 in our experiments. In both training and testing, the image resolution is maintained at 600 × 400. We compare our method with SOTA low light enhancement methods [25,65,48,73,24,67,72,62,35]. For image quality analysis, we evaluate three metrics: peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM) and NIQE [50]. To analyse the computational complexity, we also report three metrics: FLOPs, model parameters and test time shown in the last column of Table 1. We have listed different model’s test time on their corresponding code platform (M means Matlab, T means TensorFlow, P means PyTorch). As shown in Table 1, IAT(local) means only using the local network to train the model and IAT means using the whole framework. We could see that our IAT gains SOTA result on both image quality and computational complexity.

$$L_{mix}(I_1, I_2) = L_{smoothL1}(I_1, I_2) + \lambda \cdot L_{vgg}(I_1, I_2)$$

$$L_{smoothL1}(I_1, I_2) = \begin{cases} 0.5 \cdot (I_1 - I_2)^2, & |I_1 - I_2| < 0 \\ |I_1 - I_2| - 0.5, & otherwise \end{cases}$$ (8)

MIT-Adobe FiveK [6] dataset contains 5000 images, each of which was manually enhanced by five different experts (A/B/C/D/E). Following the previous settings [64,51], we only use experts C’s adjusted images as ground truth images. For MIT-Adobe FiveK [6] dataset training, we use a single L1 loss function to optimize IAT model. We compare our method with SOTA enhancement methods [30,55,14,31,64,63,51,74] on FiveK dataset, then report image quality results (PSNR, SSIM) and model parameters in Table 2. Our IAT also gain satisfactory result in both quality and efficiency. Qualitative results of LOL [65] and FiveK [6] has been shown in Fig 5, more results are in supplementary.

4.2 Exposure Correction Results

For the (c) exposure correction task, we evaluate IAT on the benchmark dataset proposed by [1]. The dataset contains 24,330 8-bit sRGB images, divided into 17,675 training images, 750 validation images, and 5905 test images. Images in [1] are adjusted by MIT-Adobe FiveK [6] dataset with 5 different exposure values (EV), ranging from under-exposure to over-exposure condition. Same as [6], test set has 5 different experts’ adjust results (A/B/C/D/E). Following the setting of [1], the training images are cropped to 512 × 512 patches and the test image is resized to have a maximum dimension of 512 pixels. we compare the test images
Table 1. Experimental results on LOL [65] dataset, best and second best results are marked in red and blue respectively, noted here [25] is non-deep learning method and [24] is self-supervised learning method.

| Method           | PSNR↑ | SSIM↑ | NIQE↓ | FLOPs(G)↓ | #Params.(M)↓ | test time(s)↓ |
|------------------|-------|-------|-------|-----------|-------------|--------------|
| LIME* [25]       | 14.92 | 0.516 | 5.77  | -         | 3.241 (M)   |              |
| Zero-DCE* [24]   | 14.83 | 0.531 | 8.22  | 2.53      | 0.08        | 0.002 (P)    |
| RetiNexNet [65]  | 16.77 | 0.562 | 8.89  | 136.01    | 0.84        | 0.841 (T)    |
| MBLLEN [48]      | 17.90 | 0.702 | 7.82  | 19.95     | 20.47       | 2.981 (T)    |
| DRBN [67]        | 20.13 | 0.820 | 5.11  | 37.79     | 0.58        | 1.210 (P)    |
| KIND [72]        | 20.86 | 0.810 | 5.15  | 29.15     | 8.16        | 0.138 (T)    |
| KIND++ [72]      | 21.30 | 0.822 | 3.88  | -         | 8.28        | 1.033 (T)    |
| RCT [45]         | 22.67 | 0.788 | -     | -         | -           | -            |
| MAXIM [62]       | 23.43 | 0.863 | -     | 216.00    | 14.14       | -            |
| IAT (local)      | 20.30 | 0.789 | 4.03  | 1.31      | 0.02        | 0.002 (P)    |
| IAT              | 23.50 | 0.824 | 3.08  | 1.44      | 0.09        | 0.004 (P)    |

Table 2. Experimental results on MIT-Adobe FiveK [6] dataset.

| Metric | White-Box [30] | U-Net [55] | DPE [14] | DPED [31] | D-UPE [64] | D-LPF [51] | STAR [74] | IAT |
|--------|----------------|------------|----------|-----------|------------|------------|-----------|-----|
| PSNR↑  | 18.57          | 21.57      | 23.80    | 21.76     | 23.04      | 23.63      | 24.50     | 24.88 |
| SSIM↑  | 0.701          | 0.843      | 0.880    | 0.871     | 0.893      | 0.875      | 0.893     | 0.905 |
| #Params.↓| -              | 1.3M       | 3.3M     | -         | 1.03M      | 0.83M      | 0.02M     | 0.00M |

with all five experts’ results. Here we use the mixed loss function (Eq. 8) for exposure correction training.

The evaluation result have been shown in Table. 3, our comparison methods include both traditional image processing methods (Histogram Equalization [22], LIME [25]) and deep learning methods (DPED [31], DPE [14], RetinexNet [65], Deep-UPE [64], Zero-DCE [24], MSEC [1]). Evaluation metrics are same as [1], including PSNR, SSIM and perceptual index(PI). Table. 3 shows that our IAT model has gained best result on all evaluation indexes. Also compared to the second best result MSEC [1], IAT has much fewer parameters (0.09M v.s. 7M) and less evaluation time (0.004s per image v.s. 0.5s per image). Qualitative result has been shown in Fig. 5, more results are in supplementary.

4.3 Performance of High-level Vision

For the high-level vision tasks: \{d, e, f\}, we build our code on mmdetection and mmsegmentation frameworks [11,15]. For a fair comparison, we take all the experiments in the same setting: same input size, same data augmentation methods (expand, random crop, multi-size, random flip...). All the models are initialed with COCO [42] pre-trained weight.

Low-Light Object Detection. We first evaluate the (d) low-light object detection task on the benchmark real-world dataset EXDark [46]. EXDark includes 7,363 real-world low-light images, ranging from twilight to extreme dark environment with 12 object categories. Similar to the setting of [16], we take 80% images of each category for training and the other 20% for testing. We choose both CNN-based detector YOLO-V3 [54] and transformer-based detector DETR [7] for evaluation. For YOLO-V3 [54] training, all the input images
Table 3. Experimental results on exposure correction dataset [1], note here HE and LIME [25] are non-deep learning methods. PSNR, SSIM and PI results, reported by competing works, are replicated from [1].

| Method          | Expert A | Expert B | Expert C | Expert D | Expert E | Avg | PI↓ |
|-----------------|----------|----------|----------|----------|----------|-----|-----|
| PSNR            | 16.14    | 16.29    | 16.52    | 16.63    | 17.30    | 16.58| 0.82 |
| LIME            | 11.15    | 11.83    | 11.52    | 12.64    | 13.61    | 12.15| 0.61 |
| DPE (iPhone)    | 15.13    | 16.51    | 15.91    | 16.57    | 17.25    | 16.27| 0.69 |
| DPE (Sony)      | 17.42    | 18.64    | 18.02    | 17.55    | 17.88    | 16.84| 0.76 |
| DPE (U-FiveK)   | 16.24    | 16.81    | 16.46    | 16.74    | 16.77    | 16.67| 0.55 |
| DPE (S-FiveK)   | 16.93    | 17.70    | 16.58    | 17.47    | 17.60    | 17.51| 0.67 |
| RetinexNet      | 10.76    | 11.61    | 11.13    | 11.99    | 12.67    | 11.63| 0.67 |
| Deep-UPF        | 13.16    | 13.90    | 13.69    | 14.08    | 14.50    | 13.84| 0.53 |
| Zero-DCE        | 11.64    | 12.56    | 12.06    | 12.54    | 12.58    | 12.60| 0.54 |
| MSRC [6]        | 19.16    | 20.14    | 20.20    | 19.88    | 19.89    | 19.48| 0.73 |

Table 4. Experiment results on EXDark [16] dataset, the best, second best and third best results are marked in red, blue and green respectively.

| Detector Type   | Method          | Aircraft | Bridge | Boat | Bottle | Bus Car | Cat | Chair | Copp Dog | Motorbike | People | Table Total |
|-----------------|-----------------|----------|--------|------|--------|---------|-----|-------|----------|-----------|--------|-------------|
| Baseline        | YELOV3 (YOLO)   | 79.4     | 75.5   | 58.1 | 72.4   | 86.2    | 68.0| 59.0  | 75.0     | 80.0     | 77.3   | 55.5        |
| Enhancement     | MILLEN [45]     | 82.0     | 75.5   | 59.4 | 83.4   | 67.6    | 69.1| 16.7  | 84.0     | 76.6     | 81.8   | 58.5        |
| Pre-train       | KINN [42]       | 80.1     | 77.1   | 72.1 | 85.5   | 78.9    | 68.8| 77.4  | 79.3     | 72.3     | 80.9   | 51.8        |
| Joint-train     | MAPE [15]       | 84.1     | 82.1   | 77.5 | 92.8   | 81.7    | 71.3| 79.0  | 77.8     | 77.2     | 81.1   | 47.0        |
| Joint-train     | Zero-DCE [23]   | 85.6     | 81.8   | 78.2 | 90.2   | 84.1    | 70.4| 71.4  | 77.7     | 77.2     | 80.9   | 47.2        |
| Joint-train     | IAT (Baseline)  | 53.1     | 27.0   | 50.6 | 85.8   | 61.2    | 69.6| 77.4  | 77.5     | 77.5     | 52.1   | 74.4        |
| Joint-train     | IAT (LOL)       | 59.8     | 56.9   | 59.4 | 82.5   | 58.4    | 62.4| 80.0  | 80.1     | 80.1     | 82.1   | 47.4        |
| Joint-train     | IAT (FiveK)     | 52.2     | 79.1   | 76.2 | 92.2   | 84.9    | 71.4| 72.8  | 80.1     | 81.1     | 80.1   | 47.4        |
| Joint-train     | DETR [4]        | 78.4     | 73.9   | 74.9 | 86.5   | 71.9    | 58.8| 73.1  | 74.2     | 74.2     | 74.2   | 47.2        |

Zero-DCE [23] model is initiated with their own model weight in [https://github.com/Li-Chongyi/Zero-DCE](https://github.com/Li-Chongyi/Zero-DCE).

The comparison methods include several types: (1). baseline: directly train detectors with EXDark [46] original low-light images, (2). Enhancement: train detectors with EXDark [46] images enhancement by different methods [18][73][51]. (3). Pre-train: MAET [16] changes the original pre-train COCO [42] model with low-light pre-train model. (4). Joint-train: joint training the enhancement network and detectors (details in Sec.3.3). Here we initialize IAT model with different weights in Sec.4.1 (no pretrain, pretrained on LOL dataset [65], pretrained on MIT-Adobe FiveK dataset [4]). Experiment results are reported in Table.4.

have been cropped and resized to 608 × 608 pixel size, we use SGD optimizer to train YOLO-V3 for 25 epochs with batch size 8. The initial learning rate is 1e−3, momentum and weight decay is separately set to 0.9 and 5e−4, and the learning rate is decay to one-tenth at 18 and 23 epoch. For DETR [4] training, the input images are resized with a long side of 1333 pixel size. We use Adam optimizer to train DETR for 20 epochs with batch size 2 while the initial learning rate is 1e−4. Weight decay is 1e−4 and the learning rate is decay to one-tenth at 14 and 20 epochs.
Fig. 5. Results on enhancement dataset [65,6] and exposure correction dataset [1].

Table 5. Results on ACDC [56] low-light semantic segmentation and TYO-L [29] various-light object detection.

| Dataset | Metric   | Base          | Pre-process | Joint-train |
|---------|----------|---------------|-------------|-------------|
|         |          | HE            | MBLLEN      | Deep-LPF    | IAT (none) | IAT (FiveK) | IAT (LOL) | IAT (exp) |
| ACDC    | mIoU     | 53.3          | 60.0        | 61.4        | 61.2       | 61.9       | 61.7      | -          |
| time (s)|          | 0.249         | 0.352       | 0.807       | 1.961      | 0.280      |           |            |
| TYO-L   | mAP      | 88.4          | 92.4        | 95.3        | 94.5       | 96.7       |           | 96.1       |
| time (s)|          | 0.023         | 0.105       | 0.580       | 1.023      | 0.027      |           | 0.027      |

We evaluate each class and total mean average precision (mAP) at IOU 0.5. From Table 4, we could see that directly using enhancement methods to pre-process image may be helpful to machine vision. In the joint-train fashion, initialising with pre-train weight on enhancement datasets (LOL [65], MIT-Adobe FiveK [6]) would be helpful to low-light object detection task. Some of the detection results could be seen in Fig 6, we shows the $I_t(x)$ in Eq. 7.

Low-Light Semantic Segmentation. For (c) low-light semantic segmentation task, we use benchmark real-world dataset ACDC’s [56] low-light part for model evaluation. There are total 1006 dark scene images in the ACDC dataset, including 400 for training, 106 for validation and the other 500 for testing. We use DeeplabV3+ [12] segmentation model and the input images are cropped and resized to $512 \times 512$ pixel size. The model is trained by SGD optimizer with
Fig. 6. Detection results of DETR \cite{6} on EXDark \cite{48}. (a) is the original images, (b) and (c) are images enhancement by MBLLEN \cite{48} and KinD \cite{73}. (d) and (e) are the output of IAT model ($I_t(x)$ in Eq. \ref{eq:7}), respectively initialed by LOL \cite{65} and FiveK\cite{6}.

batch size 8 for 20000 iters, initial learning rate is set to 0.04, momentum and weight decay are separately 0.9 and $5e^{-4}$.

We compare our method with three enhancement methods: Histogram Equalization \cite{22}, MBLLEN \cite{48} and DeepLPF \cite{51}, we report mIOU and test time results and total evaluation time in Table. \ref{tab:5}. From the results, we could see that our IAT framework gains SOTA results on both accuracy and speed. Some qualitative results and the generated images ($I_t(x)$) of IAT have been shown in Fig. \ref{fig:7}. In the segmentation task, the IAT module is more inclined to learn edge information rather than colour information (see (d) in Fig. \ref{fig:7}).

**Various Light Object Detection.** For (f) various light object detection tasks, we use the real-world dataset Toyota Light (TYO-L) \cite{29}. TYO-L includes 1680 images with 21 classes, each class contains 80 images under five different light conditions. We take 65 images in each class for training and the other 15 images for testing, so the total train set contains 1365 images and the test set contains 315 images. We use YOLO-V3 \cite{54} detector to train the model for 45 epochs, initial learn rate is $1e^{-3}$ and decay to one-tenth at 36 and 42 epoch, the other training setting is same as (d)'s setting.

The compare methods are the same as (e) and the experimental results have been shown in Table. \ref{tab:5}, we could see that our IAT also gains the best results on both detection accuracy and test time. For the extensive analyses, we also tried to initialise the IAT module with a weight of exposure dataset \cite{1}, but found it did not contribute to the model training (see IAT(exp) in Table. \ref{tab:5}).
Fig. 7. Segmentation results of DeepLabV3+ [12] on ACDC [56]. (a) is the original images, (b) and (c) are images enhancement by HE method and DeepLPF, (d) are the output of IAT model ($I_t(x)$ in Eq. 7), initialed by FiveK [6].

Table 6. Experiments on LOL [65] dataset (SSIM, PSNR) and EXDark [46] dataset (mAP), shows each part’s contribution of IAT.

| Local Branch | Layer Norm | Global Norm | Global Norm (matrix) | Global Norm (gamma) | PSNR↑ | SSIM↑ | mAP↑ |
|--------------|------------|-------------|----------------------|---------------------|-------|-------|-------|
| √            | √          |             |                      |                     | 18.80 | 0.762 | 75.8  |
| √            | √          |             |                      |                     | 19.61 (+0.81) | 0.776 (+0.014) | 75.8 (+0.0) |
| √            | √          |             |                      |                     | 20.01 (+1.21) | 0.786 (+0.024) | 76.3 (+0.5) |
| √            | √          | √           |                      |                     | 21.95 (+3.15) | 0.811 (+0.049) | 76.5 (+0.7) |
| √            | √          | √           |                      | √                   | 22.76 (+3.96) | 0.805 (+0.043) | 76.7 (+0.9) |
| √            | √          | √           |                      | √                   | 23.50 (+4.70) | 0.824 (+0.062) | 77.1 (+1.3) |

4.4 Ablation Analysis

Contribution of each part. To evaluate each part’s contribution in our IAT model, we make an ablation study on the low-light enhancement task of LOL [65] dataset, and the low-light object detection task of EXDark [46] dataset. We report the PSNR and SSIM results of the enhancement task and the mAP result of the detection task. We compare our normalization type with LayerNorm [2] and ResMLP’s normalization [60], and then evaluate different parts’ contributions of the global branch (predict matrix and predict gamma value). The ablation results are shown in Table 6.

Blocks & Channels Ablation. To evaluate the scalability of our IAT model, we try the different block numbers and channel numbers in the local branch. We try different PEM numbers to generate $M$ and $A$. The PSNR results on LOL [65] dataset has been shown in Table 7. It shows that keeping the same PEM number to generate $M$ and $A$ would be helpful to IAT’s performance.

Keeping the same block number to generate $M$ and $A$, we then evaluate with similar parameters to answer whether the local branch should be “short and thick” or “long and thin”. The local branch’s block number and channel...
number are respectively set to 2/24 and 4/12 for comparison. The results of PSNR, SSIM and model parameters are reported in Table 8.

### 5 Conclusion

Explicitly considering the ISP pipeline in the camera, we have proposed a novel framework IAT for challenging light conditions. Despite its superior performance on several real-world datasets for both low-level and high-level tasks, IAT is extremely lightweight with a fast speed. The lightweight and mobile-friendly IAT has the potential to become a standing plug-in tool for the computer vision community.

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