Thanks for participating challenge at MIPI workshop. This template is provided to collect necessary information for preparing the challenge report. Every participants will be invited to co-author the report to be publised on ECCV Workshop proceedings.

Please address all the contents in this factsheet. We will decide the final ranking and award according to the metrics, reproducibility, and methods details. If the methods are not clearly described or not reproducible, we may ignore the results of submissions. Participants are also recommended to submit paper to the MIPI workshop.

We acknowledge the templates from NTIRE2020 Challenge.

1 Submission Guidelines

1.1 Submission Number Limits

A team is allowed to have up to three accounts of the Codalab to submit results. You can also submit different (up to three) factsheets if the methods are significantly different. For each account, we will take the latest submission as the final score.

1.2 Submission Contents

Participants should first submit their results to Codalab platform to be evaluated, and email all the materials to challenge organizer: mipi.challenge@gmail.com

The email should contain (1) details, (2) final factsheet, and (3) link to codes or executables. You should be using the following format. Title: TRACK_NAME – (TEAM_NAME). Replace the TRACK_NAME and TEAM_NAME with the track you are participating and your team name. Contents should include:

- the challenge name and track number
- team name
- team leader's name, affiliation and email address (primary contact)
- rest of the team members and affiliations
- team members related to organizers or sponsors (if any)
- team name and user names on CodaLab competitions
- fact sheet attached.
- executable/source code attached or download links. The executable/source code should include trained models or necessary parameters so that we could run it and reproduce results. There should be a README or descriptions that explains how to execute the executable/code.

2 Team and Members

- Team name
  GoodGame
- Team leader name
  Jian Wang
- Team leader's affiliation, and email address
  Snap Inc., jwang4@snapchat.com
- Rest of the team members and affiliations
  Yuqi Miao, Tongji University, Baiang Li, Hefei University of Technology, Gang Wei, Tongji University
- Team website URL (if any)

- Team members related to organizers or sponsors (if any)

- Which tracks are you participating?
MIPI-challenge@The nighttime flare removal track

- User names and entries on UDC Codalab tracks/competitions (development/validation and testing phases)
Yuqi0827,7(validation) and 5(test)

- Best scoring entries of the team during development/validation phase
Val: best scoring entry 6, score: 0.2615744211 test: best scoring entry 2, score: 0.1813

- Link to the codes/executables of the solution(s):This Link

3 General Descriptions

- Title of the contribution
Efficient Transformer for Flare Removal

- General method description
Numerous prior studies [1,2,3] in the area of image restoration have leveraged Transformer-based methodologies, such as Uformer[2], Restormer[1], and SwinIR[3], showcasing significant advancements in the field.In this challenge, we tested many models based on the Transformer architecture. After comparison, we finally used a model similar to the Restormer architecture for flare removal.In the model, we use a Flare-Aware Transformer Block to capture the Flare in the image, and the composition structure is similar to that of Restormer.Residual connections are also used in the model, so that the model only needs to learn the changes in the flare and does not need to reconstruct the entire image. The model is also efficient enough to infer large-resolution images.

- Description of the particularities of the solutions deployed for each of the challenge competitions or tracks
The experiments of this paper are mainly used to flare removal in night images to obtain higher quality night images. There may be limitations in flare removal in the daytime.

- References
[1] Syed Waqas Zamir, Aditya Arora, Salman Khan, Munawar Hayat, Fahad Shahbaz Khan and Ming-Hsuan Yang. Restormer: Efficient transformer for high-resolution image restoration, 2022.
[2] Zhendong Wang, Xiaodong Cun, Jianmin Bao, Wengang Zhou, Jianzhuang Liu and Houqiang Li. Uformer: A General U-Shaped Transformer for Image Restoration, 2021.
[3] Jingyun Liang, Jiezhang Cao, Guolei Sun, Kai Zhang, Luc Van Gool and Radu Timofte. SwinIR: Image Restoration Using Swin Transformer, 2021.

- Representative image / diagram of the method(s): See Fig 1

4 Method Description

- Total method complexity: all stages
parameters:19467408

- Which pre-trained or external methods / models have been used (for any stage, if any)

- Which additional data has been used in addition to the provided training and validation data (at any stage, if any)

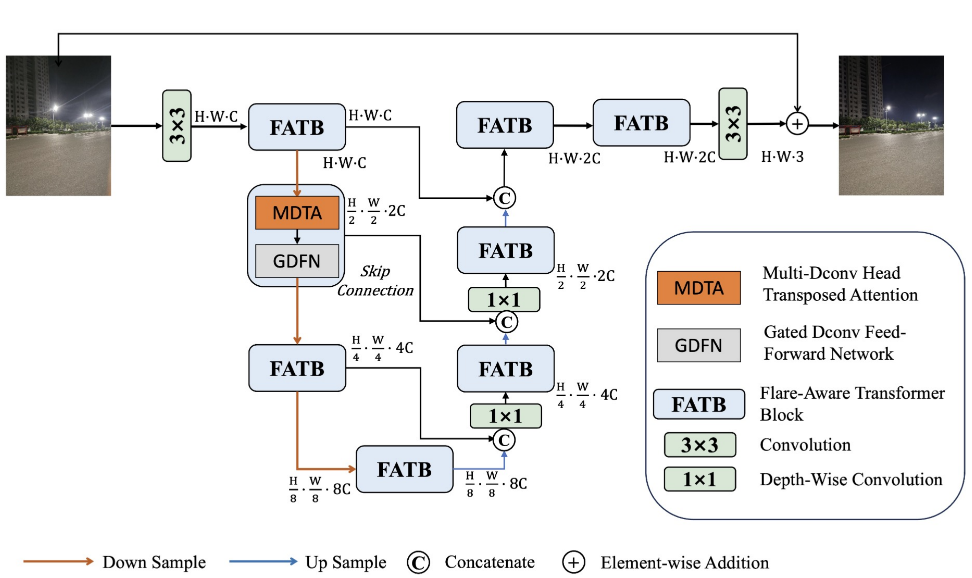

Figure 1: The structure of our proposed Efficient Transformer for Flare Removal. MDTA and GDFN is the same as Restormer[1].

- Training description
  We trained totally 300,000 iterations to take the model to convergence.Progressive learning was used during the training process, from the initial batchsize is 16 and patchsize(resize) is 128, to the final batchsize is 2 and patchsize is 384.During the training process, gradually increase the patch size of the image and reduce the batch size, so that the model can learn more details of the image.We choose `AdamW` as our optimizer, set the initial learning rate to 3×10^{-4}, and introduce a weight decay of $1e-4$. At the same time, we adopted the cosine annealing learning rate scheduler (`CosineAnnealingLR`), where $T_{\max}$ is set to 500 and the minimum learning rate is set to $1e-6$.In terms of loss, we used L1 loss, Fourier L1 loss, and Lpips loss, with Lpips loss accounting for the largest proportion.

- Testing description
  The proposed solution is implemented based on PyTorch vision 1.11.0 and on python3.8, Cuda11.3. we use RTX 3090 with 24G memory.

- Quantitative and qualitative advantages of the proposed solution
  Our solution is about 0.02 Lpips better than Uformer.

- Results of the comparison to other approaches (if any)

- Results on other standard benchmarks (if any)

- Novelty degree of the solution and if it has been previously published
  The proposed architecture solution mainly refers to Restormer[1].

5 Ensembles and fusion strategies

- Describe in detail the use of ensembles and/or fusion strategies (if any).

- What was the benefit over the single method?
  Our methods can achieve better results than Uformer.

- What were the baseline and the fused methods?
  baseline:Restormer[1]

6 Implementation Details

- including platform, required memory and parallelization requirements
  We used two RTX 3090 with 24G memory to complete the training of the model.We use parallelization.
- Training / testing time? For training, we train this model about 2 days to take it to convergence. For testing, one image takes about 1.5s on average.
- Inference time per image.
  About 0.73s on average.
- Comments on the robustness and generality of the proposed solution(s)?
  The model performs well for a single light source in the image, but the effect for multiple light sources needs to be improved.
- Comments on the efficiency of the proposed solution(s)?
  The model is efficient enough to infer images with large resolutions

7 Other details

- Plans of paper submissions to MIPI Workshop? If any, what will be the title?
  No.
- General comments, suggestions and impressions of the MIPI challenge.
  Such A Great Choice to Dive into Low Level Vision Research!