NTIRE 2021 Challenge on Image Deblurring Track 2. JPEG artifacts - Blur Attack -

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1. Team details

• Team name

- Blur Attack

• Team leader name

- Jaeyeob Kim

• Team leader address, phone number, and email

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• Rest of the team members

- Jechang Jeong

• Team website URL (if any) : None

• Affiliation

- Image Communication & Signal Processing Laboratory, Hanyang University, Seoul, Korea

• Affiliation of the team and/or team members with NTIRE 2021 sponsors (check the workshop website) : None

• User names and entries on the NTIRE 2021 Codalab competitions (development/ validation and testing phases)

- YeobKim, jimmy_jeong

• Best scoring entries of the team during development/validation phase

- Track2 : PSNR 27.00 / SSIM 0.7670

• Link to the codes/executables of the solution(s)

- Github : https://github.com/YeobKim/EACD

• Link to the restoration results of all frames

- CodaLab : https://competitions.codalab.org/competitions/28074#participate-submit_results

2. Contribution details

• Title of the contribution

- EACD : Deblurring Network Using Edge Module, ASPP Channel Attention and Dual Network

• General method description

• Description of the particularities of the solutions deployed for each of the challenge competitions or tracks

• References

[1] J. Pan et al., "Learning Dual Convolutional Neural Networks for Low-Level Vision," *IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, pp. 3070-3079, Jun. 2018.

[2] Y. Zhang, Y. Tian, Y. Kong, B. Zhong and Y. Fu, "Residual Dense Network for Image Super-Resolution", *IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, Feb. 2018.

[3] Y. Zhang, Y. Tian, Y. Kong, B. Zhong and Y. Fu, "Image Super-Resolution Using Very Deep Residual Channel Attention Networks," *IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, pp. 2472-2481, Jul. 2018.

[4] L. Chen, G. Papandreou, F. Schroff and H. Adam, "Rethinking Atrous Convolution for Semantic Image Segmentation," *IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, Jun. 2017.

[5] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising," *IEEE Conference on Computer Vision and Pattern Recognition(CVPR)*, vol. 26, no. 7, pp. 3142-3155, Feb. 2017.

• Representative image / diagram of the method(s)

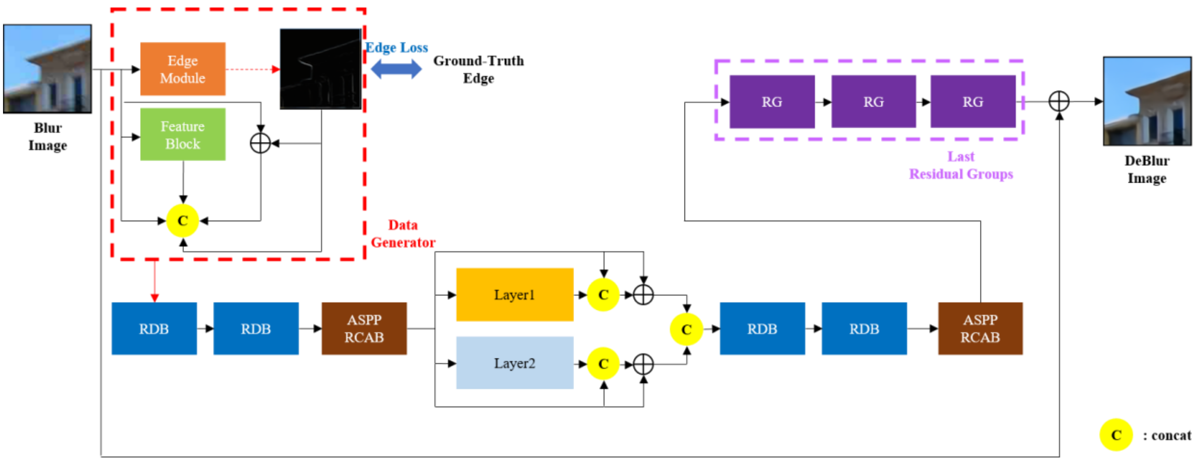

Figure 1. The structure of the proposed EACD

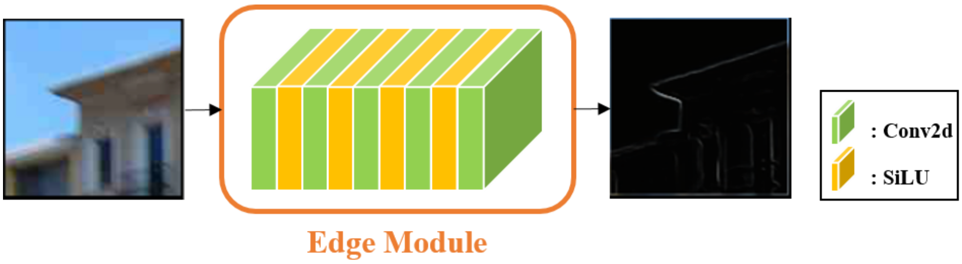

Figure 2. The structure and result of Edge Module

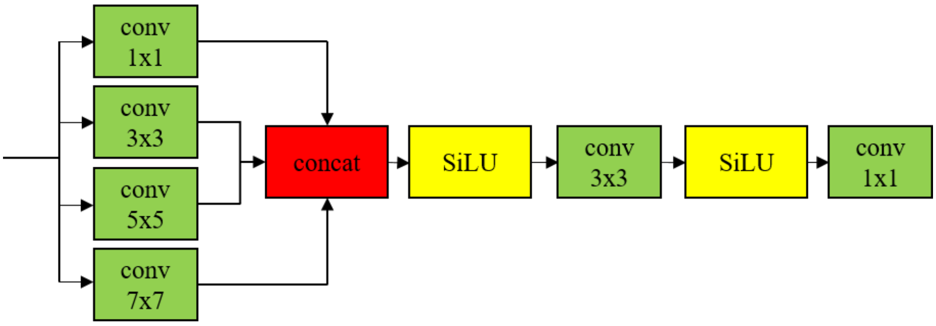

Figure 3. The structure of Feature Block

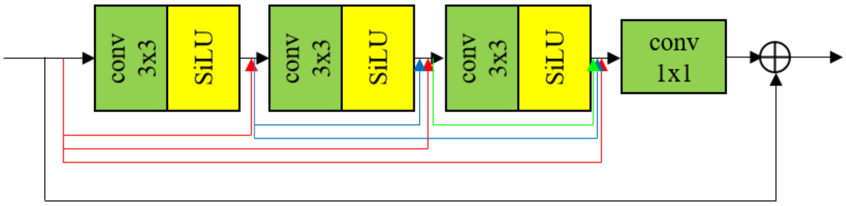

Figure 4. The structure of RDB(Residual Dense Block)

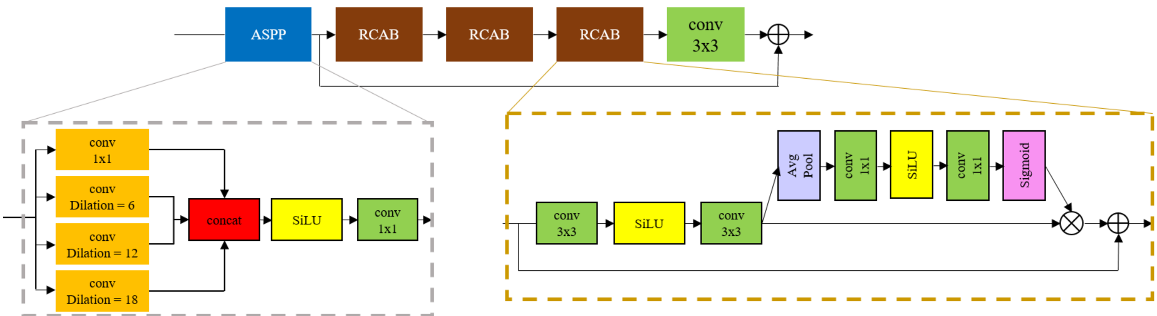

Figure 5. The structure of ASPP RCAB(Residual Channel Attention Block)

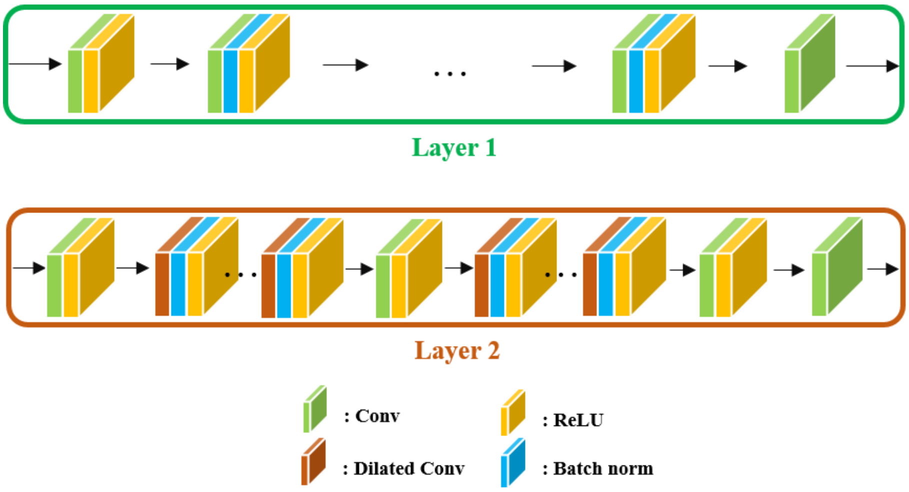

Figure 6. The structure of Dual Network

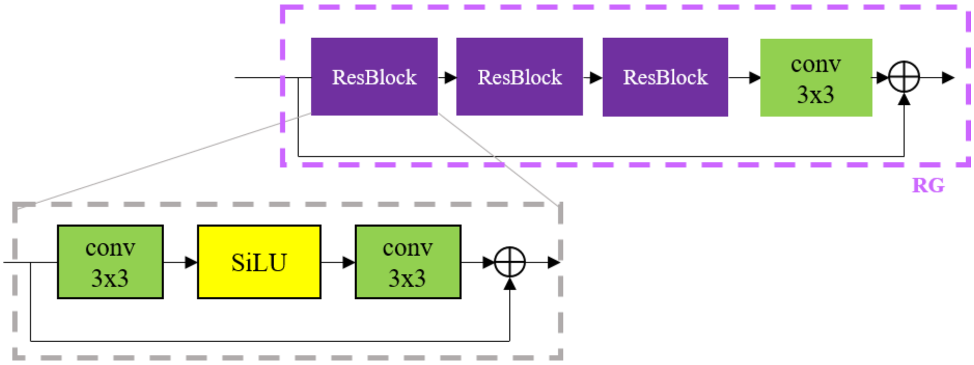

Figure 7. The structure of RG(Residual Group)

3 Global Method Description

• Total method complexity: all stages

(Model Size)

- Track 2 : JPEG Artifacts 10.893 MB

(Runtime)

- Track2 : JPEG Artifacts 0.012 seconds per image

• Which pretrained or external methods/models have been used (for any stage, if any) : None

• Which additional data has been used in addition to the provided training and validation data (at any stage, if any) : None

• Training description

- We set the batch size of the training patches to 2 for maximizing the model size and have better results, and train our proposed network for about 400 epochs in Track2. JPEG Artifacts which number of iterations is 12000 per epoch.

- We utilize the ADAM optimizer with an initial learning rate of 1e-4 .

- We use 1/10 of learning rate decay every 100 epoch. After 300 epoch, we used 1e-6 learning late.

- We use L1 Loss for Edge Loss and Blur Loss before 200 epoch. After 200 epoch, we use L1 Loss for Edge Loss and MSE Loss for Blur Loss.

- For the activation function, we used the Sigmoid Linear Units(SiLU).

- We use ARCAB for combining ASPP Block and Residual Channel Attention Block.

• Testing description

- We test the data named ʹ_9.jpg.

• Quantitative and qualitative advantages of the proposed solution

- When we have training, we extract edge information from input blur images with edge modules. And we use edge with input when we start learning. So output images has a lot of edge information compared to when edge information is not used.

- We have a short runtime of 0.012, which makes it very advantageous to apply in real-time.

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

- When we use MSE Loss for Blur Loss, PSNR increased compared to when we use L1 Loss for Blur Loss. Because MSE Loss is more sensitive than L1 Loss.

• Results on other benchmarks (if any) : None

• Novelty degree of the solution and if it has been previously published

- The proposed EACD use edge, ASPP channel attention and dual network and showed good results as real-time deblurring system.

- Not yet published.

4 Competition particularities

- We use edge informations for training. We extract edges from one network using an edge module inside network and remove blur.

5 Ensembles and fusion strategies

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

- trained flip

• What was the benefit over the single method?

- We used flip from the beginning.

• What were the baseline and the fused methods?

6 Technical details

• Language and implementation details (including platform, memory, parallelization requirements)

- Python 3.6.10 and Pytorch 1.6.0

- We use GPU memory is lesser than 8GB when training.

• Human effort required for implementation, training and validation?

- Edge Module in EACD, training environment, and test environment, as well as performed many experiments comparing loss functions, model size, a lot of blocks, etc.

• Training/testing time? Runtime at test per image.

- Training Time : 13 days
- Testing time : 0.012 seconds per image.

• The robustness and generality of the proposed solution(s). Is it easy to deploy it

to other sets?

- Yes, We have a great advantage in real-time.

• The efficiency of the proposed solution(s).

- The proposed EACD ensures deblurred images in 0.012 second per image. This is effective in real-time deblur systems such as autonomous driving due to its excellent real-time.

7 Other details

• Planned submission of a solution(s) description paper at NTIRE 2021 workshop.

• General comments and impressions of the NTIRE 2021 challenge.

- It′s very exciting experience and It is an opportunity for me to grow.

• What do you expect from a new challenge in image restoration and enhancement?

- I am looking forward to real-time image restoration in the era of autonomous driving.

• Other comments: encountered difficulties, fairness of the challenge, proposed

subcategories, proposed evaluation method(s), etc.

- PSNR measured in CodaLab was measured lower than PSNR measured by me.