COMMUNICATION UNIVERSITY OF CHINA 中国传媒大学

超高清电视技术研究和应用国家广播电视总局重点实验室
UHDTV Research and Application Laboratory, NRTA

Gamma-enhanced Spatial Attention Network for Efficient High Dynamic Range Imaging

Fangya Li, Ruipeng Gang, Chenghua Li, Jinjing Li, Sai Ma, Chenming Liu, Yizhen Cao

State Key Laboratory of Media Convergence and Communication(CUC), Academy of Broadcasting Science, NRTA, Beijing, China

CVPR JUNE 19-24 2022 NEW ORLEANS • LOUISIANA

MOTIVATION & PROBLEM

High Dynamic Range Imaging comprises two intractable challenges:

➢ how to tackle overexposed and underexposed regions.

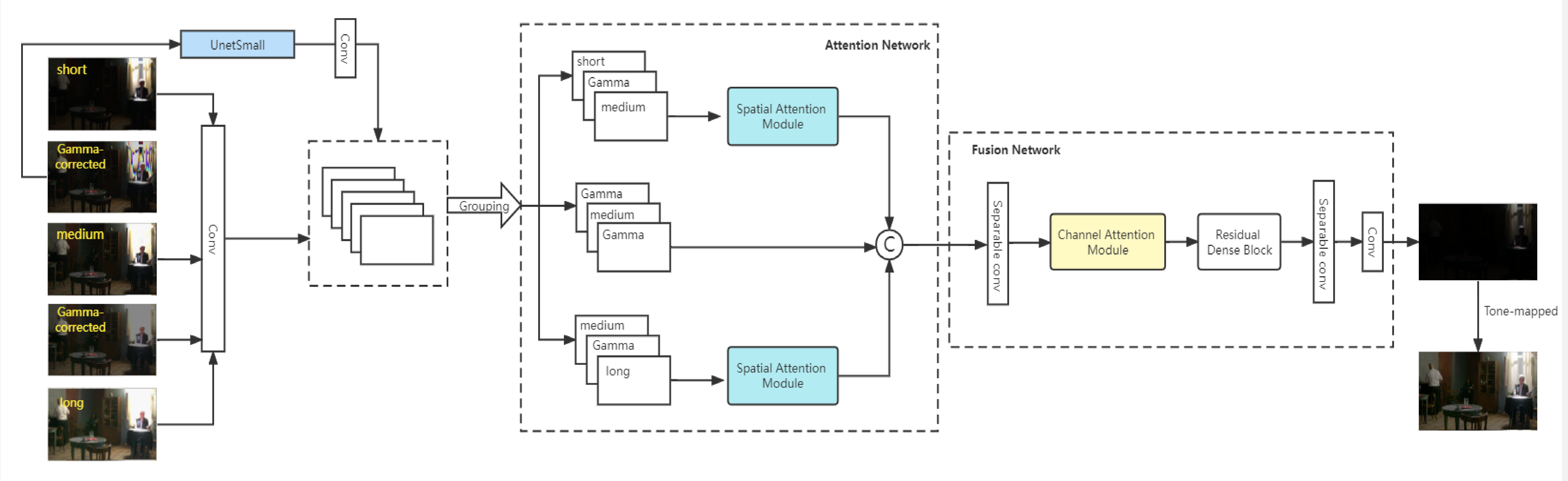
➢ how to overcome the paradox of performance and complexity trade-off.

Model	GMAcs	Param.(M)	PSNR-μ
ADNet	6249.43	280	37.22
AHDRNet	> 2000	> 100	

METHODS

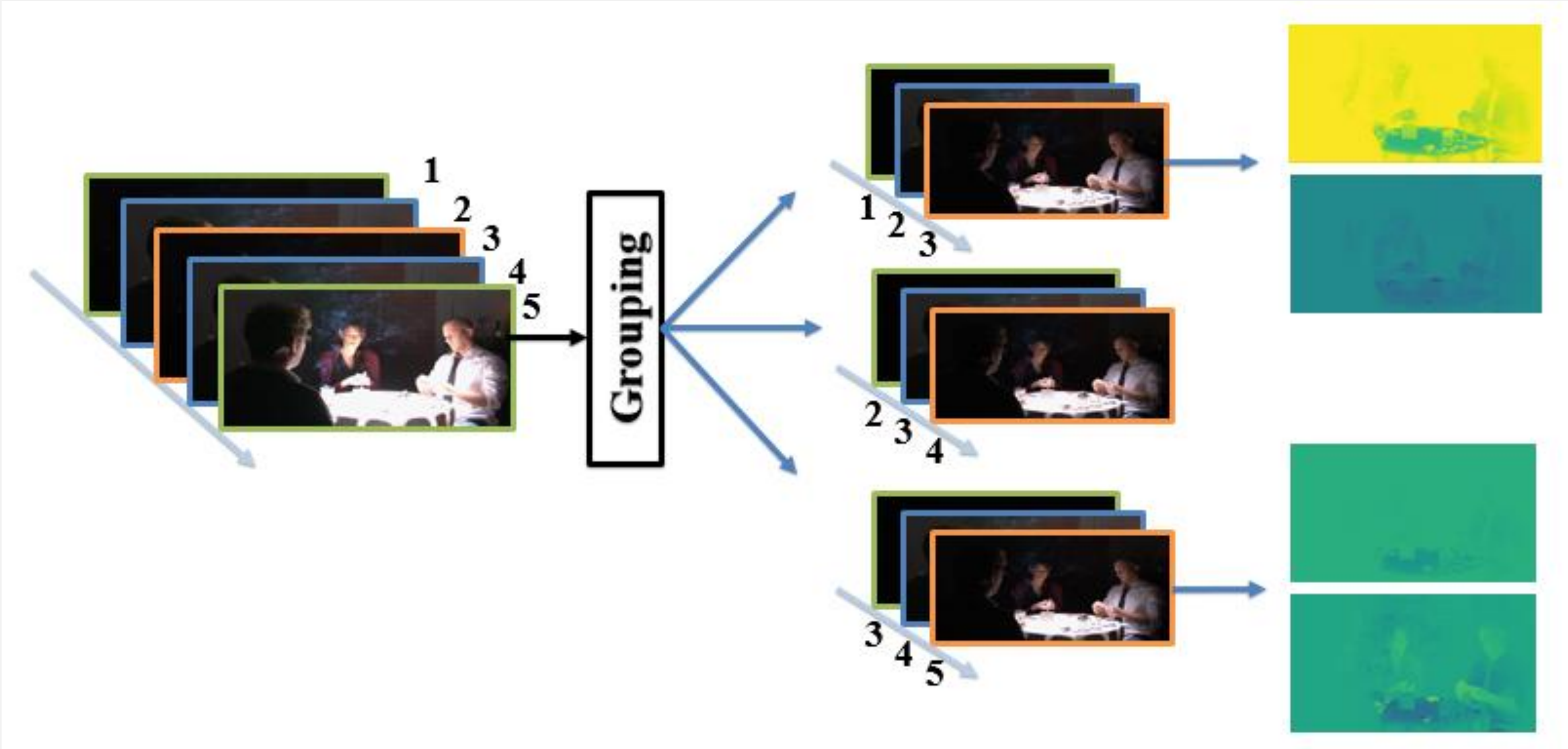
➢ Unlike previous methods, we treat LDR and gamma-corrected images uniformly and divide them into three groups to obtain more details about over and underexposed regions and spatial attention is used to extract feature.

➢ Then we introduce an efficient channel attention to fuse the concatenated features of LDR images and gamma-corrected images and overcome high complexity cost.



Gamma-enhanced Spatial Attention Network

➢ LDR images and gamma-corrected images are split to three groups to obtain more details about over and underexposed regions. To better integrate features from different groups, spatial attention module is introduced.

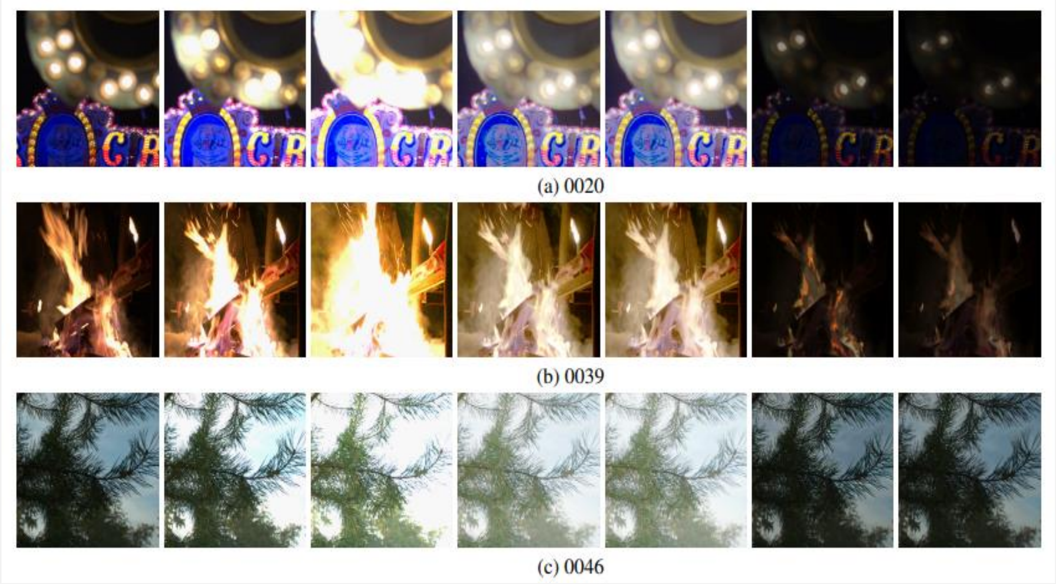


Efficient channel attention

➢ The fusion network mainly consists of channel attention module and dilated residual dense block. In order to reduce the number of operations, separable convolution is used to decrease some channels and achieve fewer parameters.

EXPERIMENT RESULTS

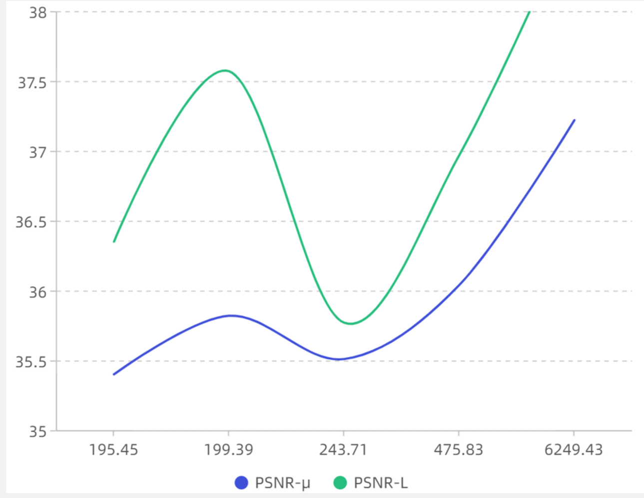
➢ Subjective results of a comparison between our method and ADNet.



The figures show results of our method and ADNet are shown in this figure. The (a)–(c) mean the label of the validation images.

➢ Quantitative comparison of our method

Model	GMAcs	Param.(M)	PSNR-μ
ADNet	6249.43	280	37.22
-PCD	475.83	0.21	36.04
-DRDB	243.71	0.16	35.51
+SepConv	195.45	0.07	35.40
+CA(Ours)	199.39	0.08	35.82



Due to competition constraints, the number of operations of our model is below 200GMAccs. We found that in our model the smaller the computation, the smaller the number of parameters in the model. But the number of parameters is not always the same trend as the number of operations. Although the score is not best, our model has fewest parameters.

FUTURE DIRECTION

➢ First, the separable convolution in fusion network squeezes the channel dimension to 32, leading to information loss. Therefore, we can use channel split to reduce the channel dimension in the bottleneck and add parameters, avoiding too much information loss.

➢ Second, our efficient channel attention module also use separable convolution. We find another method that can develop our channel attention module without channel dimensionality reduction. These will be our work in the future.

REFERENCE

➢ Guanying Chen et al. Hdr video reconstruction: A coarse-to-fine network and a real-world benchmark dataset. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 2502–2511, 2021. 2

➢ Zhen Liu et al. Adnet: Attention-guided deformable convolutional network for high dynamic range imaging. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 463–470, 2021. 2, 5, 8

➢ Takashi Isobe et al. Video super-resolution with temporal group attention. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8008–8017, 2020. 2