NTIRE 2025 Efficient SR Challenge Factsheet
-SCMSR-

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1. Team details

- Team name: SCMSR
- Team leader name: Mingyang Li
- Leader Affiliation: Sichuan University, Email: 2024222055110@stu.scu.edu.cn
- Rest of the team members: Guanglu Dong, Xiangtai Li, Lu Qi, Xin Lin and Chao Ren
- Affiliations: Sichuan University
- User names and entries on the NTIRE 2025 Codalab competitions (development/validation and testing phases): Mingyang_Li
- Best scoring entries of the team during the development/validation phase: We don't submit the lastest result for the validation phase. But for testing phase, we got a PSNR of 27.01dB.
- Link to the codes/executables of the solution(s): https://github.com/sdjvhfb/NTIRE2025_SCMSR

2. Method details

2.1. Method Description

We propose the Simplified Content Mixer (SCM) module, as illustrated in Figure 1. SCM is based on CAMixerSR [4]. First, it dynamically allocates computational resources based on content complexity: convolution is applied to simple regions, while a symmetric activation function combined with residual connections, which is inspired by SPAN [3] , is used to compute attention maps in complex regions, instead of the deformable window attention employed in CAMixerSR. This design reduces computational overhead. Then, a Lightweight Gated Convolutional Unit (LGU) is introduced to further integrate information. The overall architecture remains similar to CAMixerSR, consisting of 20 blocks with 42 channels. As a result, the proposed SCMSR is both lightweight and efficient.

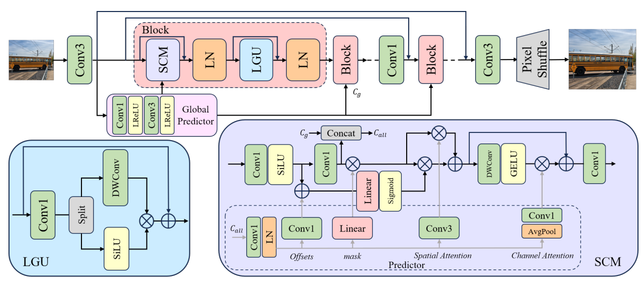

Figure 1. *Team SCMSR*:The architecture of SCMSR

2.2. Training Description

The model is trained on DIV2K [2] and and LSDIR [1]. First, the model is trained for a total of 500k iterations by minimizing L1 loss with Adam optimizer. The training HR patch size is set to 256×256 with data augmentation and the batch size is set to 32. The initial learning rate is set to 5e-4 and halved at 250k, 400k, 450k, 475k iterations. Then, the training HR patch size is set to 384×384 and the batch size is set to 16. The model is further trained for 300k iterations by minimizing L1 loss with Adam optimizer. The initial learning rate is set to 2e-5 and halved every 100k iterations.

References

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