NTIRE 2023 Efficient SR Challenge Factsheet
-Residual Interactive Partial Feature Distillation Network-

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1. Team details

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- Affiliation of the team and/or team members with NTIRE 2023 sponsors (check the workshop website)
  N/A
- User names and entries on the NTIRE 2023 Codalab competitions (development/validation and testing phases)
  User name: Lumos
  Development phase entries: 5
  Testing phase entries: 2
- Best scoring entries of the team during development/validation phase
  Best entries: 5
- Link to the codes/executables of the solution(s)
  https://github.com/Lumos-Leo/ESR23-RIPFDN.git

2. Method details

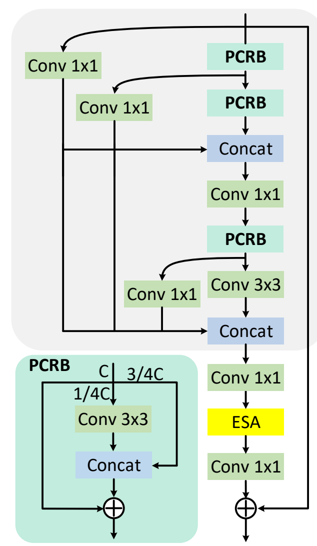

Figure 1. The overall architecture of RIPFDB.

We have revamped the Residual Feature Distillation Block (RFDB) blocks of RFDN [4] based on partial convolution [1], resulting in the key design called Residual Interactive Partial Feature Distillation Block (RIPFDB), which is illustrated in Figure 1. To further reduce complexity compared to the Shallow Residual Block (SRB) in RFDB, we proposed the Partial Convolution Residual Block (PCRB), which performs convolutional operations on only a few channels while directly concatenating the remaining channels with the feature after convolutional operation, thus significantly reducing time cost compared with depth-wise convolution. Additionally, to enhance information interaction between different distillation features, we introduced an interactive mechanism that concatenates distillation features from different stages and performs a 1×1 convolutional layer to fuse the features. To further improve performance, we applied ESA [5] to enhance spatial attention.

Motivated by BSRN [3], which uses CCA [2] to improve model ability from a channel-wise perspective, we multiplied a learnable parameter along the channel direction to fully explore model capacity.

In this work, we adopt DIV2K and Flickr2K as training dataset which includes 3450 images. We employed the Adam optimizer with an initial learning rate of 5×10^{-4} to minimize the L1 loss function on patches of size 64×64 pixels. Data augmentation is performed, such as random horizontal flipping and $90°$ rotation. The network parameters were first optimized for 1.2×10^{6} iterations using a batch size of 64. Subsequently, the batch size was increased to 256 for an additional 5×10^{5} iterations of training. The ultimate architecture consists of 4 RIPFDB blocks, where the partial coefficient is set to 0.25 and the number of channels is set to 52.

References

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