Efficient Super Resolution by Recursive Aggregation

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Problems
Nowadays super-resolutions are becoming dramatically deep and large. While their performance on benchmark datasets are beginning to saturate.

PSNR results of SotA methods on benchmark datasets

(a) Overall structure of second-order RAN

(b) Structure of one-order RAN

(c) Structure of two-order RAN

Efficiency Comparison
To intuitively compare the overall efficiency, we plot the PSNR results on Set5 [1] of different models with respect to their Flops and number of parameters. We compare with the state-of-the-art models such as RCAN [2], RDN [5]. As one can see, RANs take up the left-up corner of the two diagrams. It indicates that RAN can achieve relatively better performance while with relative smaller model size and computational cost.

References

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Basic Convolutional Block
We simplify the residual block to only one convolutional layer. Thus it allows more skip connections with the same number of layers. The multiple skip connections introduced by BCB will lead to better gradient flow in RAN.

Recursive Aggregation
We construct the model starting from a basic convolutional block (BCB), i.e. the blue boxes in the figure. Every time a small number of BCBs are stacked, we concatenate the outputs as green boxes. The followed aggregation layers (yellow boxes) will further fuse their information. And when the aggregated layers are stacked up, we also concatenate them by a second-order aggregation. In the same way, we can construct models with different orders by recursive aggregation. The gradienst (pink solid arrows) are generated from the top the network, and the intensive shortcuts in the network can help gradients better conducted to all inner layers and make the networks more sufficiently optimized.