Asymmetric Information Distillation Network for Lightweight Super Resolution

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Introduction:

The purpose of this paper is to design a lightweight network to achieve image super resolution performance equivalent to SRResNet. We design an asymmetric information distillation block (AIDB) with distillation information multiplexing and asymmetric information extraction capabilities to better achieve this goal. Distillation information multiplexing refers to the repeated processing of distilled information to supplement the ability of key information extraction. Asymmetric information enhancement block (AIEB) refers to identify different features in the image by the horizontal and vertical feature extraction. AIEB greatly reduces the number of parameters, and distillation information multiplexing works as a supplement to the lost high dimensional information. Our proposed AIDN ranked runner up in the model complexity track of NTIRE2022 efficient super resolution challenge. Compared with the first place in this track, we achieves higher PSNR performance on testset with a slight disadvantage in the number of parameters. The code is available at *https://github.com/zzksdu/AIDN*.

Material and method:

The overall network structure consists of four parts: the head block, information extraction module, feature fusion module and upsampling module.

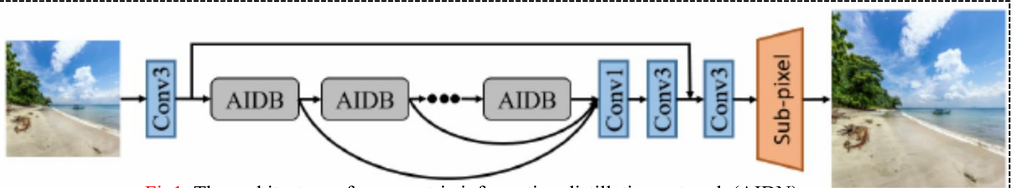


Fig1. The architecture of asymmetric information distillation network (AIDN)

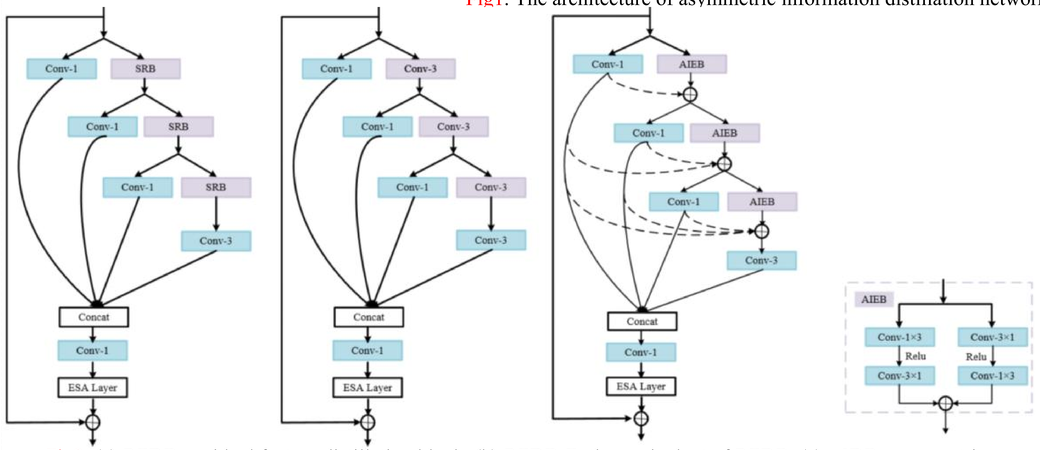


Fig2. (a) RFDB: residual feature distillation block. (b) RFDB-E: the equivalent of RFDB. (c) AIDB: asymmetric information distillation block. (d) Asymmetric information enhancement block (AIEB)

The information extraction module is formed by four AIDB stacks. With the enhancement of AIDB's ability to distill information, the output feature of each block are more accurate and more expressive. Moreover, we verified that with the increase of the number of AIDB, the performance of super resolution will significantly improved, with small increase in the number of parameters.

Conclusion:

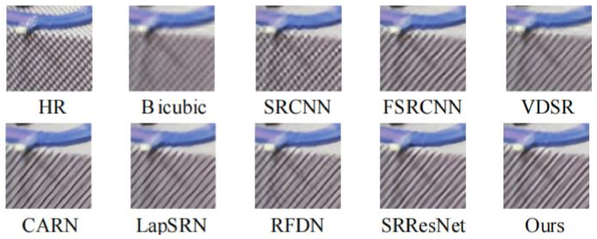
In this paper, we propose a relatively lightweight image super resolution network (AIDN), and get the runner up in the efficient super resolution challenge model complexity track of NTIRE2022. In particular, we propose a new feature distillation block (AIDB), which greatly reduces the amount of parameters while ensuring the accuracy of distilled information. In addition, the asymmetric feature enhancement block (AIEB) focuses on the features in the image from different directions and performs more effective enhancement. Moreover the nonlinear layer of AIEB further improves the nonlinear feature extraction ability. The multiplexing of distilled information makes up for the lost information caused by the reduction of channel dimension. A large number of experiments show that our model AIDN can achieve comparable performance to state-of-the-art lightweight networks.

Implementation details:

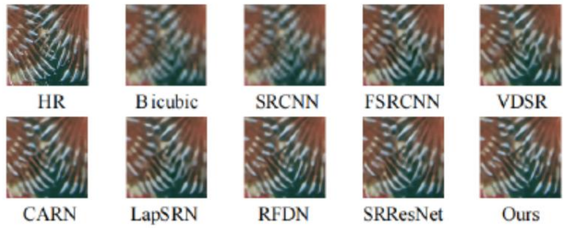
In the training phase, we use three commonly used datasets (DIV2K, Flickr2K, OST) to train our AIDN. LR images (×2, ×3, and ×4) are obtained by downsampling HR image using bicubic in MATLAB.

Results:

barbara from Set14



12084 from B100



Scale	Method	Params	Set5 / PSNR	Set14 / PSNR	B100 / PSNR	Urban100 / PSNR	Manga109 / PSNR
×2	CARN [1]	1592K	37.76	33.52	32.09	31.92	38.36
×2	SRResNet [15]	1370K	38.05	33.64	32.22	32.23	38.05
×2	RFDN [20]	534K	38.05	33.68	32.16	32.12	38.88
×2	AIDN(ours)	323K	38.07	33.72	32.18	32.24	38.89
×3	CARN [1]	1592K	34.29	30.29	29.06	28.06	33.50
×3	SRResNet [15]	1554K	34.41	30.36	29.11	28.20	33.54
×3	RFDN [20]	541K	34.41	30.34	29.09	28.21	33.67
×3	AIDN(ours)	330K	34.43	30.35	29.11	28.25	33.69
×4	CARN [1]	1592K	32.13	28.60	27.58	26.07	30.47
×4	SRResNet [15]	1518K	32.17	28.61	27.59	26.12	30.48
×4	RFDN [20]	550K	32.24	28.61	27.57	26.11	30.58
×4	AIDN(ours)	339K	32.26	28.60	27.58	26.16	30.59

We show the visual comparison results of different methods. For 'barbara' images, our method can produce more accurate lines than other methods. For '12084' images, our method can achieve the same visual effect with fewer parameters than other methods.
It can be clearly found that AIDN proposed by us is superior to CARN, SRResNet and RFDN in different upsapling multiples of five benchmark datasets. Importantly, our parameter quantities are 1 / 5 of CARN, 1 / 4 of SRResNet and 1 / 2 of RFDN.