Binarized Diffusion Model for Image Super-Resolution

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Introduction

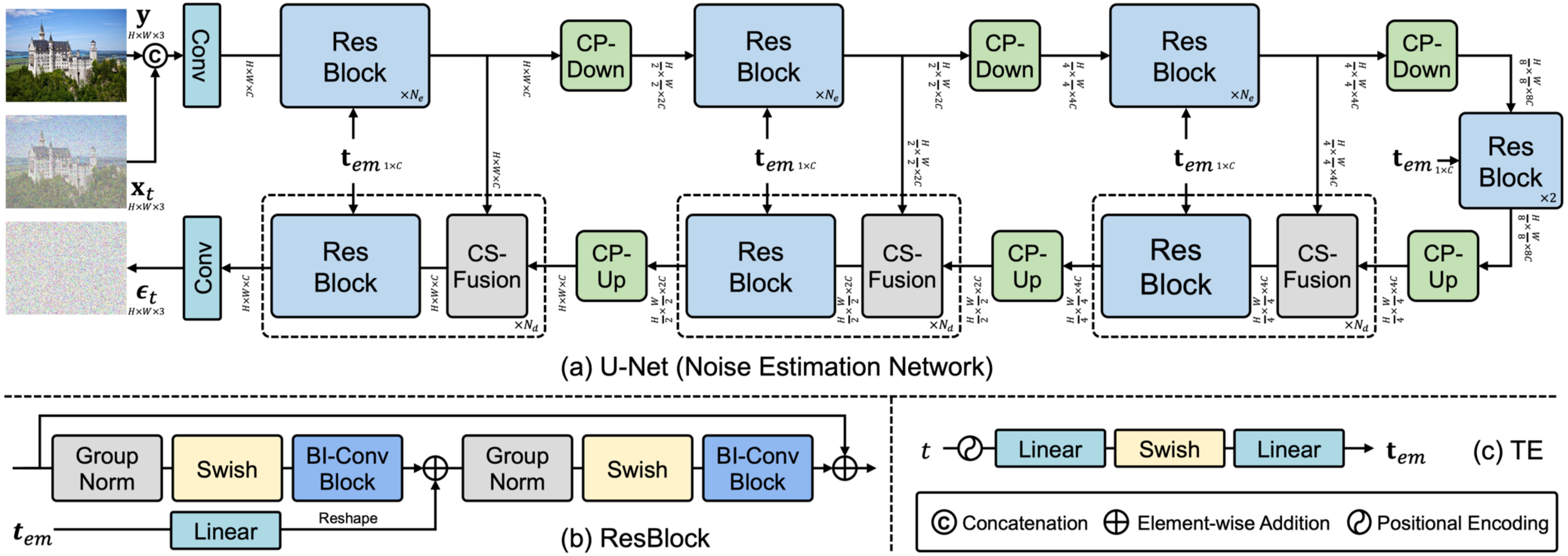
Motivation

- **Diffusion models (DMs)** excel in SR tasks but face high costs.
- **Binarization** (1-bit quantization) reduces memory and computation.
- However, the architecture and multi-step iterative design of DM limit its application.
- We propose **BI-DiffSR**, a novel binarized DM for image SR.

HR | **Bicubic** | **SR3(FP) [1]** | **BBCU(ICLR'22) [2]** | **BI-DiffSR(ours)**

[1] Chitwan Saharia, Jonathan Ho, William Chan, Tim Salimans, David J Fleet, and Mohammad Norouzi. Image super-resolution via iterative refinement. TPAMI, 2022.
[2] Bin Xia, Yulun Zhang, Yitong Wang, Yapeng Tian, Wenming Yang, Radu Timofte, and Luc Van Gool. Basic binary convolution unit for binarized image restoration network. In ICLR, 2022.

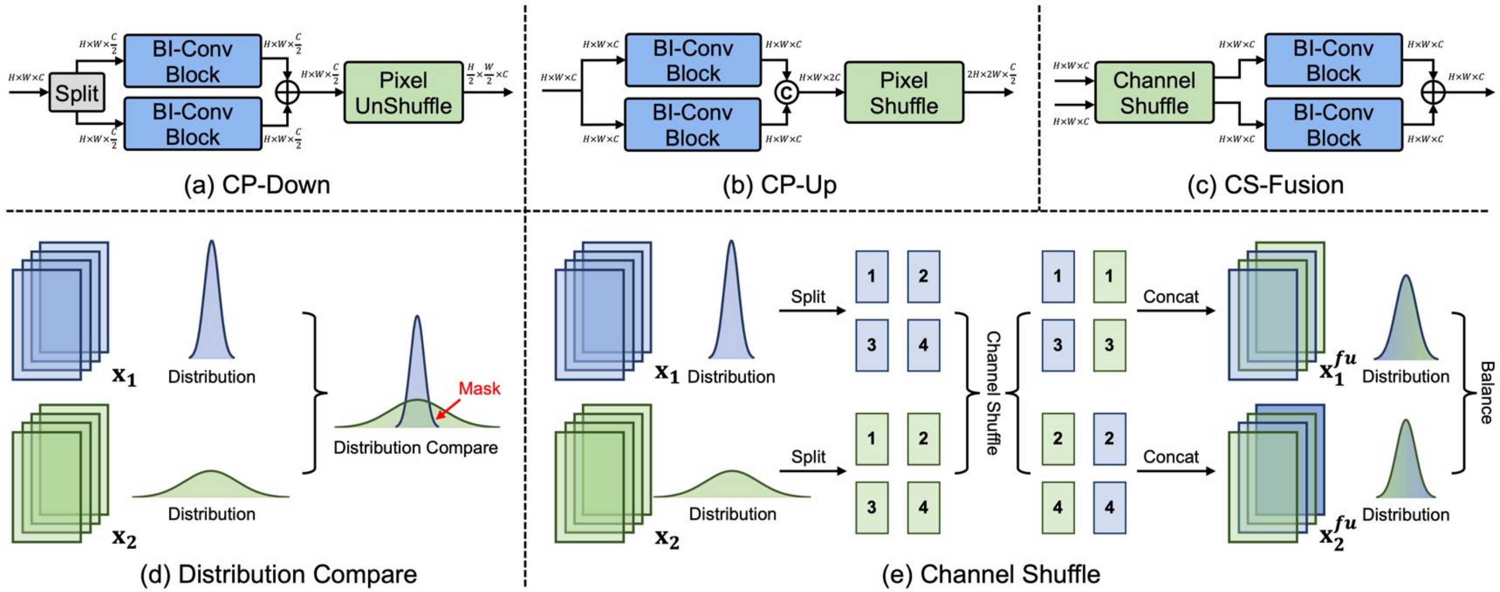
Method



Overall

- The overall structure of the noise estimation network in BI-DiffSR.
- **Analysis:** UNet struggles with binarization due to dimension mismatch and fusion.

Method



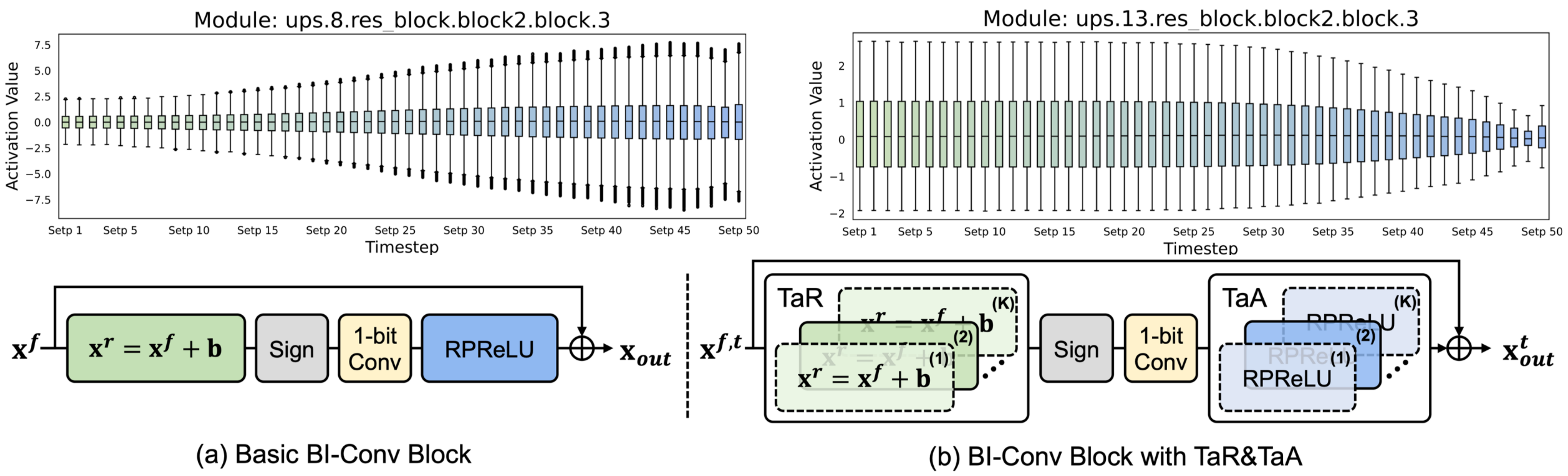
Challenge

- **Dimension Mismatch:** Resolution changes disrupt full-precision propagation.
- **Fusion Difficulty:** Activation range differences hinder feature fusion.

Structure

- **CP-Down/Up:** Enables consistent reshaping, preserving full precision.
- **CS-Fusion:** Uses channel shuffle for balanced distribution, enhancing fusion.

Method



(a) Basic BI-Conv Block

(b) BI-Conv Block with TaR&TaA

Activation

- **Analysis:** Activation distributions differ in multi-step iterations.
- **TaR/TaA:** Adjusts activations across timesteps, enhancing the binarized module.

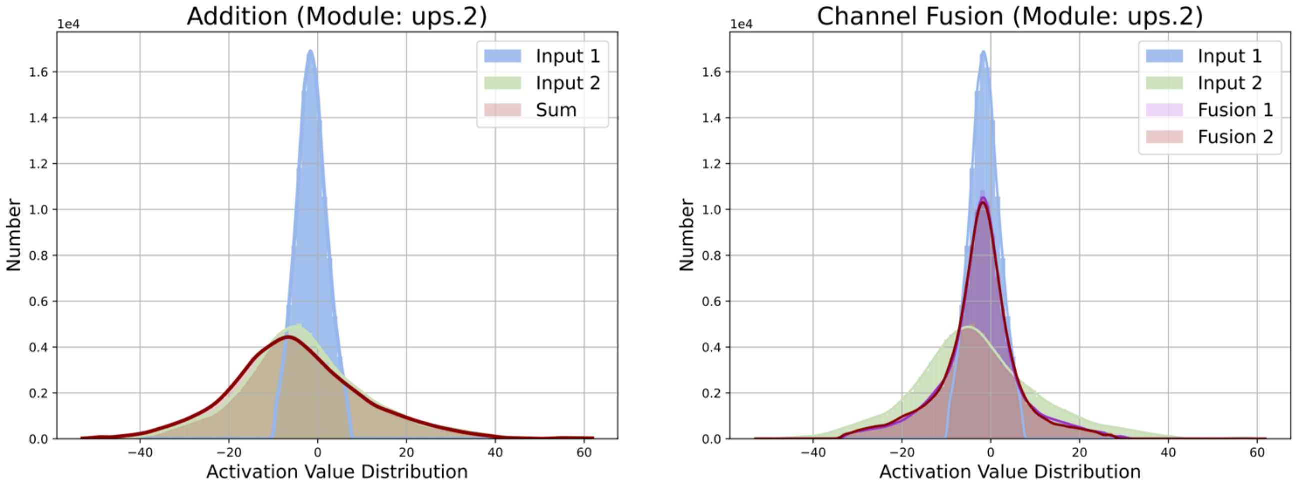
Experiments

Method	Baseline	+Identity	+CP-Down&Up	+CS-Fusion	+TaR&TaA
Params (M)	4.29	4.29	4.29	4.30	4.58
OPs (G)	36.67	36.67	36.67	36.67	36.67
PSNR (dB)	27.66	29.29	31.08	31.99	32.66
LPIPS	0.0780	0.0658	0.0327	0.0261	0.0200

(a) Break-down ablation.

Method	Params (M)	OPs (G)	PSNR (dB)	LPIPS
Add	4.10	33.40	18.89	0.1695
Concat	4.29	36.67	31.08	0.0327
Split	4.30	36.67	29.67	0.0384
CS-Fusion	4.30	36.67	31.99	0.0261

(b) Ablation on feature fusion.



Ablation

- **Break Down:** Each module improves performance.
- **CS-Fusion:** Effectively fuses different features.
- **Visualization:** Distribution.

Experiments

Method	TaR	TaA	Params (M)	Ops (G)	PSNR (dB)	LPIPS
w/o			4.30	36.67	31.99	0.0261
In	✓		4.37	36.67	29.27	0.0337
Out		✓	4.51	36.67	29.13	0.0308
All	✓	✓	4.58	36.67	32.66	0.0200

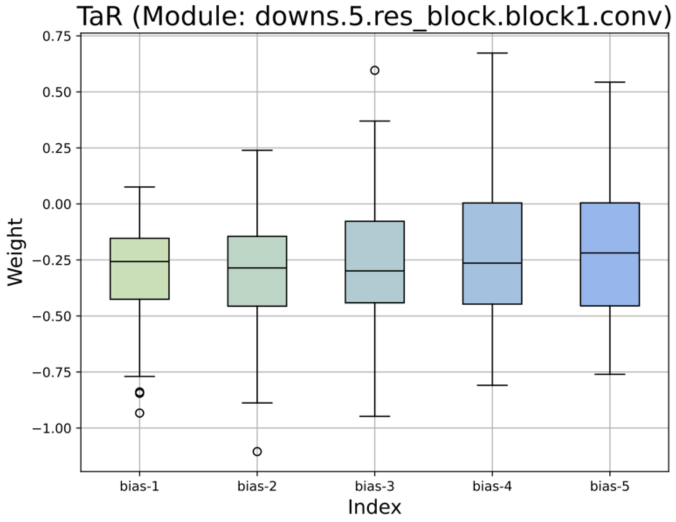
(c) Ablation on time aware module (TaR and TaA).

#Pair	1	2	5
Params (M)	4.30	4.37	4.58
OPs (G)	36.67	36.67	36.67
PSNR (dB)	31.99	32.42	32.66
LPIPS	0.0261	0.0229	0.0200

(d) Numbers (#) of bias and RPReLU pair.

Ablation

- **Timestep-aware (TaA/TaR):** Effective improvements are achieved only when both TaR and TaA are used, with 5 biases and RPReLU providing notable gains.
- **Visualization:** Five learnable biases in TaR.



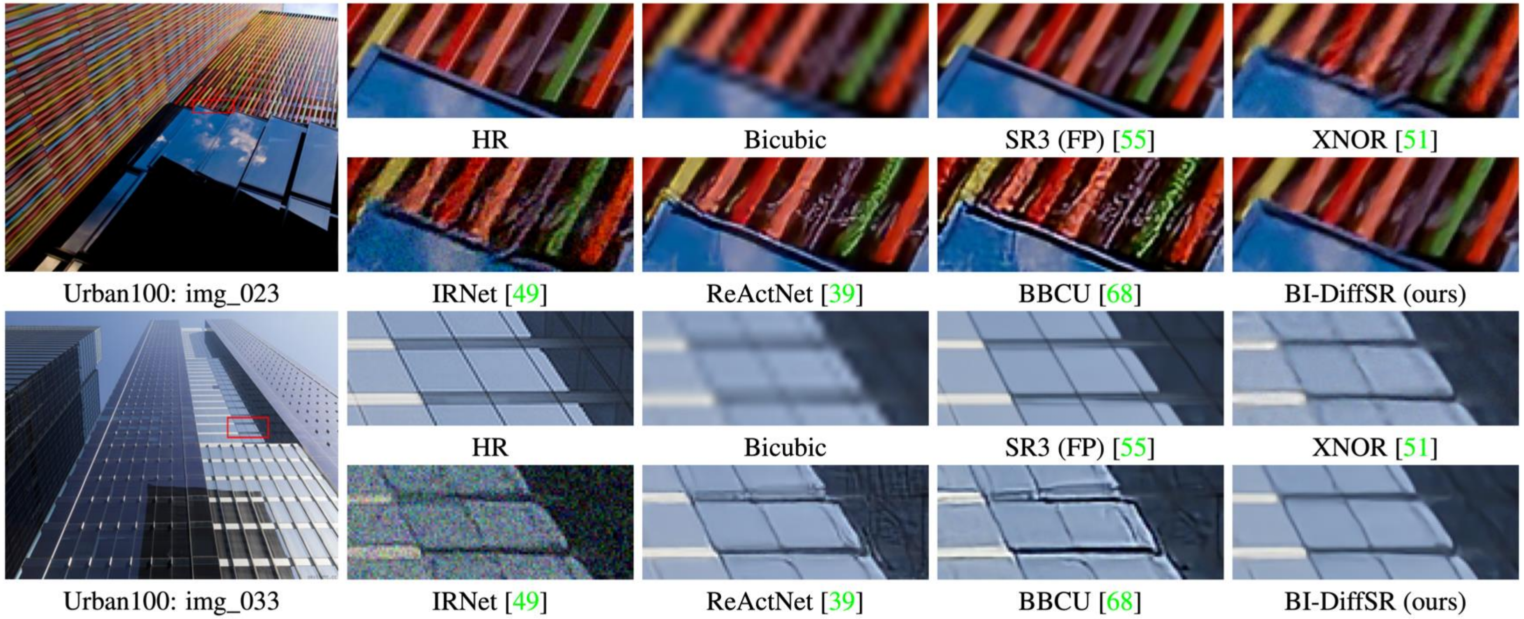
Experiments

Method	Scale	Params (M)	Ops (G)	Set5 PSNR	Set5 SSIM	Set5 LPIPS	B100 PSNR	B100 SSIM	B100 LPIPS	Urban100 PSNR	Urban100 SSIM	Urban100 LPIPS	Manga109 PSNR	Manga109 SSIM	Manga109 LPIPS
Bicubic	×2	N/A	N/A	33.67	0.9303	0.1274	29.55	0.8431	0.2508	26.87	0.8403	0.2064	30.82	0.9349	0.1025
SR3 [55]	×2	55.41	176.41	36.69	0.9513	0.0310	30.41	0.8683	0.0700	30.29	0.9060	0.0430	35.11	0.9682	0.0161
BNN [19]	×2	4.78	37.93	13.97	0.5210	0.4529	13.73	0.4553	0.5784	12.75	0.4236	0.5575	9.29	0.3035	0.7489
DoReFa [74]	×2	4.78	37.93	16.43	0.6553	0.2662	16.11	0.5912	0.3972	15.09	0.5495	0.4055	12.35	0.4609	0.5047
XNOR [51]	×2	4.78	37.93	32.34	0.8661	0.0782	27.94	0.7548	0.1665	27.47	0.8225	0.1153	31.99	0.9428	0.0326
IRNet [49]	×2	4.78	37.93	32.55	0.9340	0.0446	27.76	0.8199	0.1115	26.34	0.8452	0.0913	23.89	0.7621	0.1820
ReActNet [39]	×2	4.85	37.93	34.30	0.9271	0.0351	28.36	0.8158	0.0943	27.43	0.8563	0.0731	32.16	0.9441	0.0379
BBCU [68]	×2	4.82	37.75	34.31	0.9281	0.0393	28.39	0.8202	0.0905	28.05	0.8669	0.0620	32.88	0.9508	0.0272
BI-DiffSR (ours)	×2	4.58	36.67	35.68	0.9414	0.0277	29.73	0.8478	0.0682	28.97	0.8815	0.0522	33.99	0.9601	0.0172

Quantitative

- **Best Performance:** Achieves the best results among recent binarization methods.
- **Perceptual Metrics:** Comparable to the full-precision SR3 model in LPIPS.

Experiments



Visual

- Our method restores clearer images with more texture details.
- The gap between BI-DiffSR and full-precision models is small.

Method	Params (M)	OPs (G)	Simulated Time (s)
SR3 [55]	55.41	176.41	55.37
BI-DiffSR	4.58	36.67	13.00

Cost

- Runs much faster than full-precision methods.

Conclusion

Contribution

We propose **BI-DiffSR**, a novel binarized DM for image SR.

- **Architecture:** Design modules for binarization: **CP-Down**, **CP-Up**, **CS-Fusion**.
- **Activation:** Introduce **TaR** and **TaA** to enhance binarized modules.
- **Performance:** Outperforms SOTA binarization methods.

Poster

- Time: Fri 13 Dec
  11 a.m. - 2 p.m. PST

Project

Thanks!