Binarized Spectral Compressive Imaging

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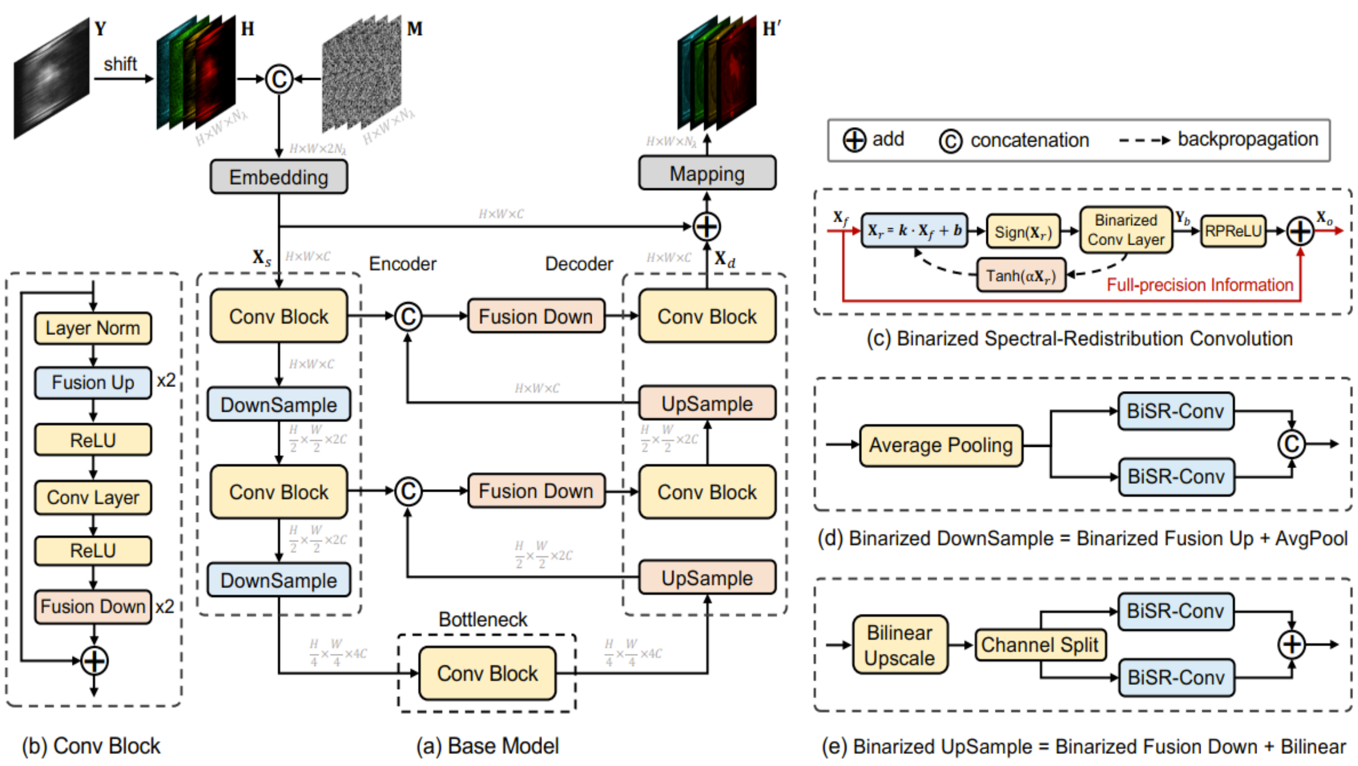
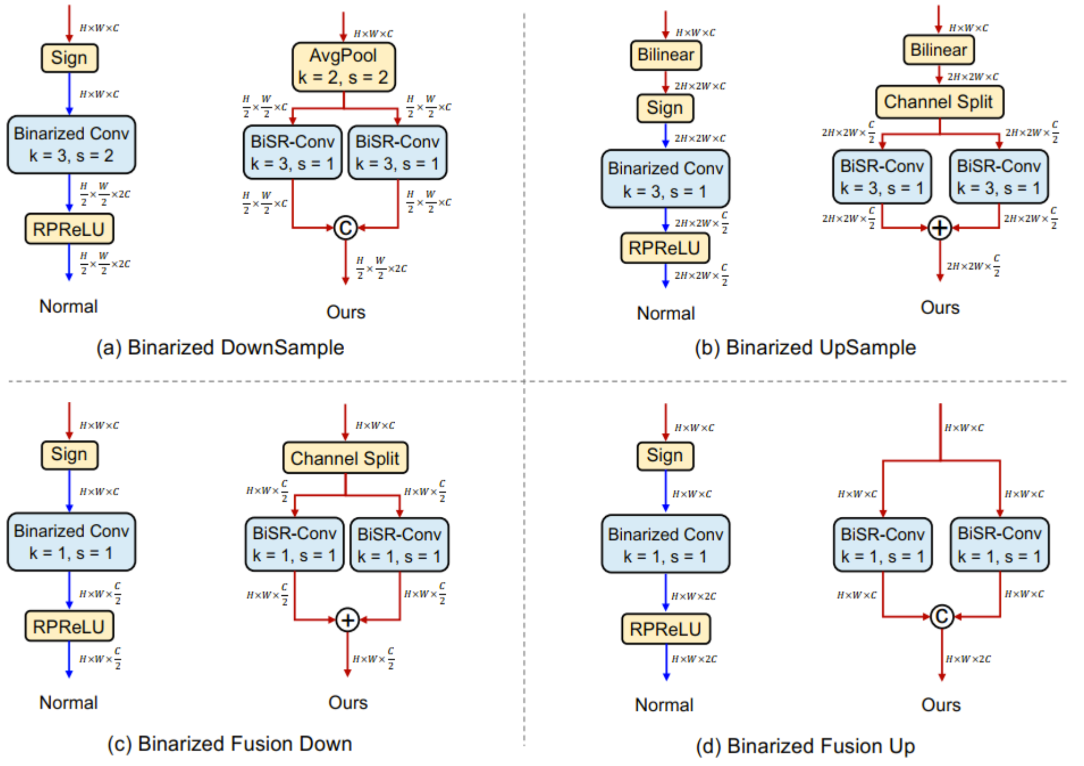
Overview

- Method
- Result
- Ablation

Method



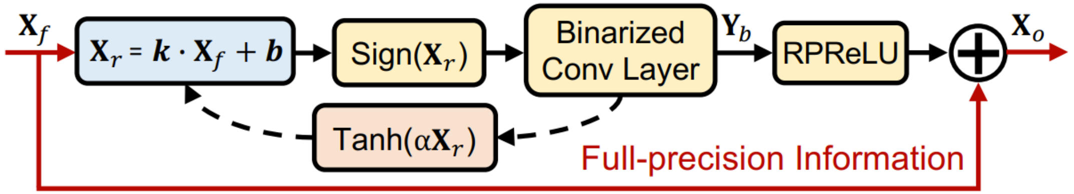


Previous Spectral Compressive Imaging Methods

- Require powerful hardwares with abundant computing and memory resources, such as high-end GPU
- However, edge cannot meet the requirements because of their limited memory, computational power, and battery

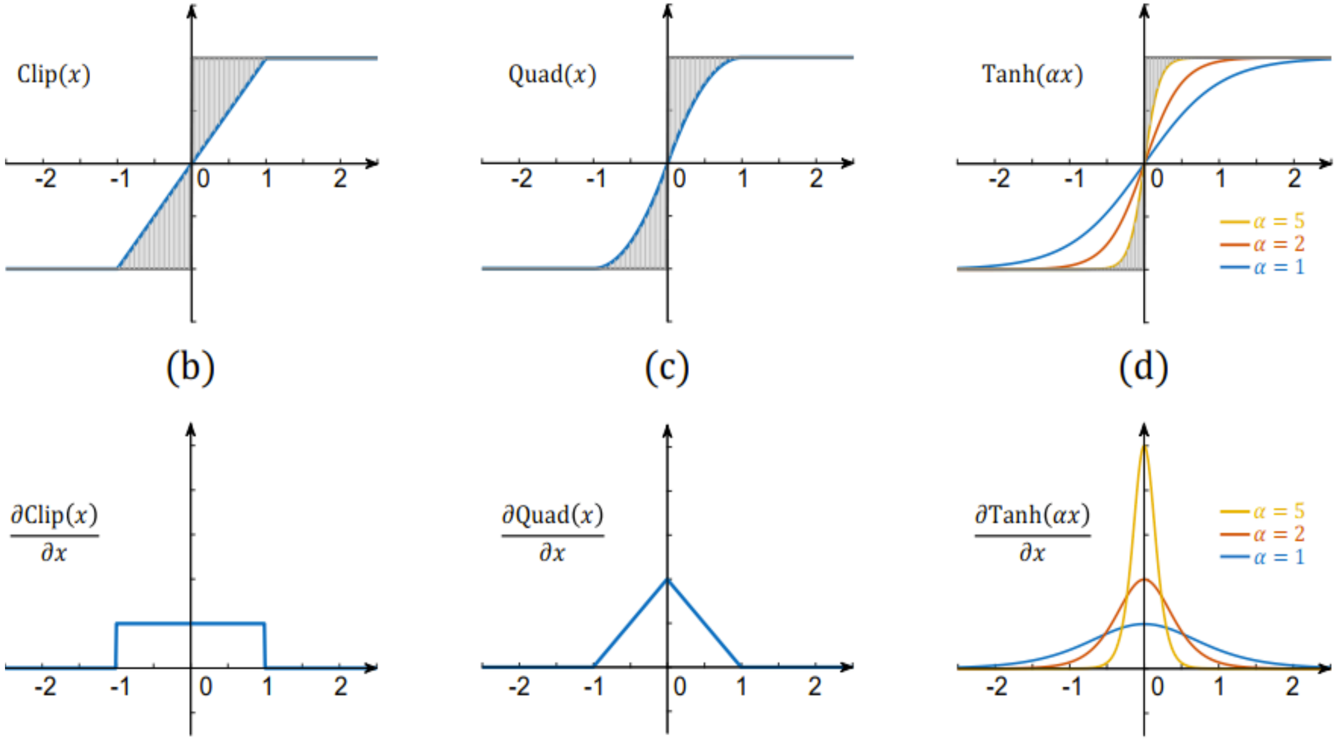
Our Binarized Spectral-Redistribution Network

- Easy to deploy
- Allow the full-precision information to flow through the whole network



$$\lim_{\alpha\to+\infty} \mathrm{Tanh}(\alpha x) = \begin{cases} \lim\limits_{\alpha\to+\infty} \dfrac{e^{\alpha x} - 0}{e^{\alpha x} + 0} & = +1, \quad x > 0 \\ \lim\limits_{\alpha\to+\infty} \dfrac{e^{0} - e^{0}}{e^{0} + e^{0}} & = \quad 0, \quad x = 0 \\ \lim\limits_{\alpha\to+\infty} \dfrac{0 - e^{-\alpha x}}{0 + e^{-\alpha x}} & = -1, \quad x < 0 \end{cases}$$

$$x_b = \mathrm{Tanh}(\alpha x_r) = \frac{e^{\alpha x_r} - e^{-\alpha x_r}}{e^{\alpha x_r} + e^{-\alpha x_r}}$$



We design a Binarized Spectral-Redistribution Convolution unit that can better approach the Sign function and has smaller approximation error

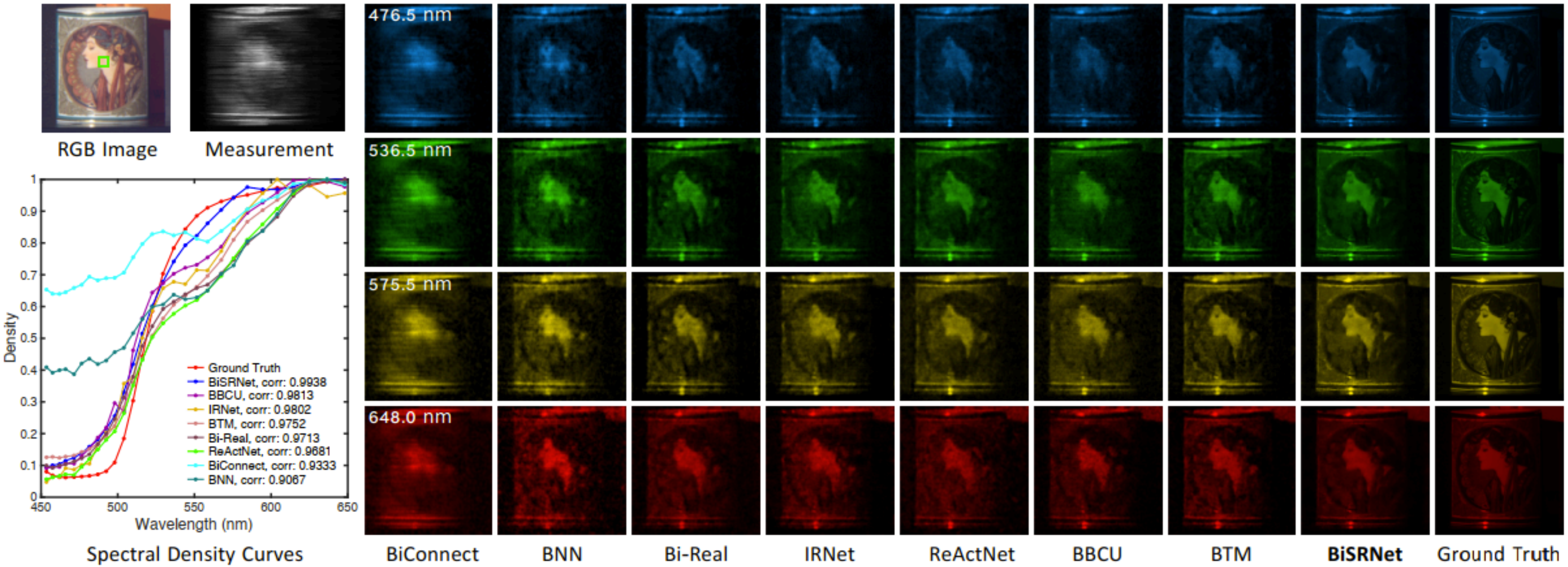
$$\begin{aligned} \int_{-\infty}^{+\infty} |\mathrm{Sign}(x) - \mathrm{Tanh}(\alpha x)| \, \mathrm{d}x &= 2\int_{0}^{+\infty} (1 - \mathrm{Tanh}(\alpha x)) \, \mathrm{d}x \\ &= 2(x - x + \frac{1}{\alpha}\log(\mathrm{Tanh}(\alpha x) + 1))\Big|_{x=0}^{x=+\infty} \\ &= \frac{2}{\alpha}(\log(2) - \log(1)) = \frac{2\log(2)}{\alpha}. \end{aligned}$$

Result

Algorithms	Bit	Category	Params (K)	OPs (G)	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Avg
TwIST [59]	64	Model	-	-	25.16 0.700	23.02 0.604	21.40 0.711	30.19 0.851	21.41 0.635	20.95 0.644	22.20 0.643	21.82 0.650	22.42 0.690	22.67 0.569	23.12 0.669
GAP-TV [56]	64	Model	-	-	26.82 0.754	22.89 0.610	26.31 0.802	30.65 0.852	23.64 0.703	21.85 0.663	23.76 0.688	21.98 0.655	22.63 0.682	23.10 0.584	24.36 0.669
DeSCI [53]	64	Model	-	-	27.13 0.748	23.04 0.620	26.62 0.818	34.96 0.897	23.94 0.706	22.38 0.683	24.45 0.743	22.03 0.673	24.56 0.732	23.59 0.587	25.27 0.721
λ-Net [20]	32	CNN	62640	117.98	30.10 0.849	28.49 0.805	27.73 0.870	37.01 0.934	26.19 0.817	28.64 0.853	26.47 0.806	26.09 0.831	27.50 0.826	27.13 0.816	28.53 0.841
TSA-Net [18]	32	CNN	44250	110.06	32.03 0.892	31.00 0.858	32.25 0.915	39.19 0.953	29.39 0.884	31.44 0.908	30.32 0.878	29.35 0.888	30.01 0.890	29.59 0.874	31.46 0.894
BiConnect [36]	1	BNN	35	1.18	25.85 0.676	22.07 0.530	18.92 0.558	25.18 0.636	21.21 0.568	21.82 0.547	21.84 0.570	22.25 0.580	19.57 0.556	23.18 0.524	22.19 0.575
BNN [35]	1	BNN	35	1.18	26.69 0.661	23.98 0.551	20.58 0.566	28.53 0.679	22.96 0.584	24.12 0.599	23.20 0.568	23.29 0.590	21.65 0.588	23.86 0.547	23.88 0.593
Bi-Real [34]	1	BNN	35	1.18	28.06 0.701	26.05 0.644	24.92 0.654	31.04 0.733	25.32 0.664	26.54 0.671	25.09 0.631	25.47 0.678	24.69 0.644	25.41 0.622	26.26 0.664
IRNet [33]	1	BNN	35	1.18	27.91 0.700	25.84 0.620	25.27 0.661	31.77 0.723	25.12 0.663	26.31 0.685	25.29 0.665	25.14 0.662	25.07 0.668	25.20 0.603	26.30 0.665
ReActNet [32]	1	BNN	36	1.18	27.91 0.707	26.17 0.633	25.40 0.682	31.58 0.725	25.43 0.675	26.43 0.670	25.85 0.703	25.50 0.650	25.47 0.677	25.11 0.583	26.48 0.671
BBCU [31]	1	BNN	36	1.18	27.91 0.706	26.21 0.628	25.44 0.654	31.33 0.741	25.30 0.677	26.68 0.704	25.42 0.668	25.59 0.671	25.69 0.670	25.59 0.615	26.51 0.673
BTM [30]	1	BNN	36	1.18	28.75 0.739	26.91 0.674	26.14 0.708	32.74 0.794	25.87 0.692	27.37 0.739	26.26 0.707	26.20 0.718	26.10 0.717	25.73 0.671	27.21 0.716
BiSRNet (Ours)	1	BNN	36	1.18	**30.95 0.847**	**29.21 0.791**	**29.11 0.828**	**35.91 0.903**	**28.19 0.827**	**30.22 0.863**	**27.85 0.800**	**28.82 0.843**	**29.46 0.832**	**27.88 0.800**	**29.76 0.837**

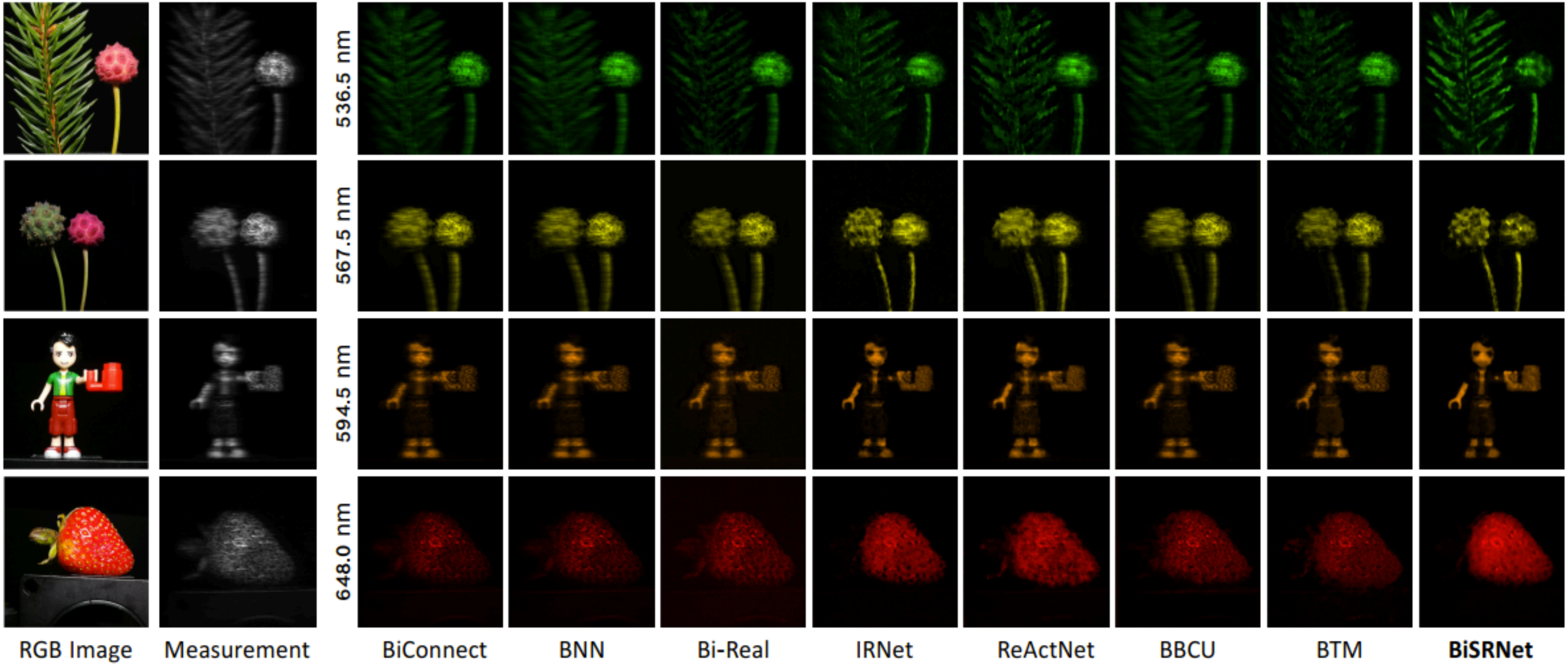
Quantitative Results

- Our BiSRNet surpasses previous BNN-based methods by large margins, over 2.55 dB
- Our BiSRNet achieves comparable results with CNN-based methods



Quantitative Results — Simulation

- More visually pleasant
- The spectral curve achieves the highest correlation score with the ground truth



Quantitative Results — Real

- More detail reconstruction, Less artifact introduction, More effective noise suppression

Ablation

Method	Baseline-1	+BiSR-Conv	+BiDS	+BiUS	+BiFD	+BiFU
PSNR	23.90	27.80	27.97	28.07	28.31	**29.76**
SSIM	0.594	0.737	0.729	0.758	0.776	**0.837**
OPs (M)	1176	1176	1176	1176	1176	1176
Params (K)	34.82	35.48	35.49	35.51	35.72	35.81

(a) Break-down ablation study towards higher performance

Baseline-2	SR	Tanh(αx)	PSNR	SSIM
✓			27.68	0.723
✓	✓		28.97	0.783
✓		✓	28.74	0.782
✓	✓	✓	**29.76**	**0.837**

(b) Ablation study of BiSR-Conv

Method	PSNR	SSIM
Clip(x)	28.97	0.783
Quad(x)	29.02	0.794
Tanh(αx)	**29.76**	**0.837**

(c) Study of approximation

Binarized Part	OPs^f (M)	OPs^b (M)	Params^f	Params^b	PSNR^b	SSIM^b
Encoder $\mathcal{E}$	3390	53	177878	5559	32.28	0.905
Bottleneck $\mathcal{B}$	1096	17	278889	8715	33.80	0.932
Decoder $\mathcal{D}$	5005	78	186562	5830	33.03	0.919

(d) Ablation study of binarizing different parts of the base model

(a) When we apply BiSR-Conv and the four blocks, the model achieves 3.90 and 1.96 dB improvements

(b) The SR and Tanh(αx) contribute 1.29 and 1.06 dB gains

(c) Compared with Clip(x) and Quad(x), our Tanh(αx)

(d) Binarizing the bottleneck B reduces the Params the most with the smallest performance drop. Binarizing the decoder D achieves the largest OPs reduction while the performance degrades by a moderate margin

Thanks for your time

Welcome to scan the QR code and follow our work

Code for BiSCI : https://github.com/caiyuanhao1998/BiSCI

Code for MST : https://github.com/caiyuanhao1998/MST

Code for MST++ : https://github.com/caiyuanhao1998/MST-plus-plus