DRCR Net: Dense Residual Channel Re-calibration Network with Non-local Purification for Spectral Super Resolution

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Motivation

- Despite the accurate performance has been implemented in SSR when input the 'clean' RGB images as shown in Fig. 1 (a), some methods are not robust enough to the degraded RGB images as depicted in Fig. 1 (b).
- Existing models blindly pursue the algorithm complexity and fail to exploit the information interaction between intermediate features, limit the expressiveness of CNN.

(a) (b)

Fig 1: **Visual comparison of 'clean' and degraded RGB images.**

Contributions

1. We proposed the DRCR Net with non-local purification for spectral super resolution, which takes an RGB image with severe artifacts as input.
2. As the main component of DRCR Net, DRCR block which is cascaded with an encoder-decoder paradigm through several cross-layer dense residual connections is employed to capture the deep spatial-spectral interactions.
3. To eliminate the degeneration of various artifacts, such as noise, compression and poor illumination polluting the input RGB images at different scales, we design a simple but effective NPM with a hierarchical structure.
4. Dual CRMs embedded in each DRCR block are developed to adaptively re-calibrate channel-wise feature responses through explicitly modeling interdependencies between channels for pursuing desirable spectral recovery.

Network Architecture

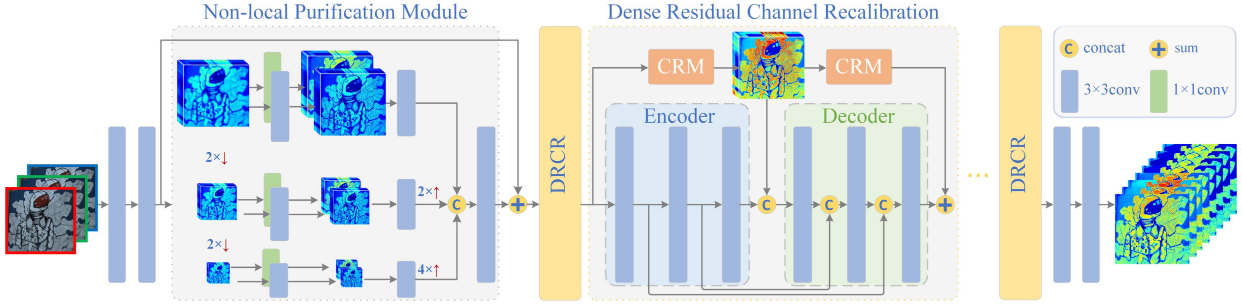
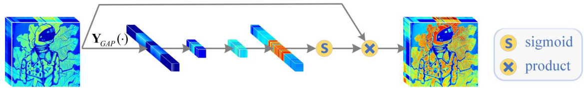


Fig 2: **Architecture of dense residual channel re-calibration network for Spectral Super Resolution from RGB Images.** ↓ and ↑ indicate downsampling and upsampling, respectively.



$$\mathbf{F}^m = H^m_{DRCR}(\mathbf{F}^{m-1}) = H^m_{DRCR}(H^{m-1}_{DRCR}(\cdots H^1_{DRCR}(\mathbf{F}^0)\cdots))$$

$$\mathbf{F}_{CFI} = \delta(\mathbf{W}_V(\mathbf{W}_U(\mathbf{W}_D(Y_{GAP}(\mathbf{F}_{n-1})))))$$

Fig 3: **Architecture of channel re-calibration module.**

Visual Results

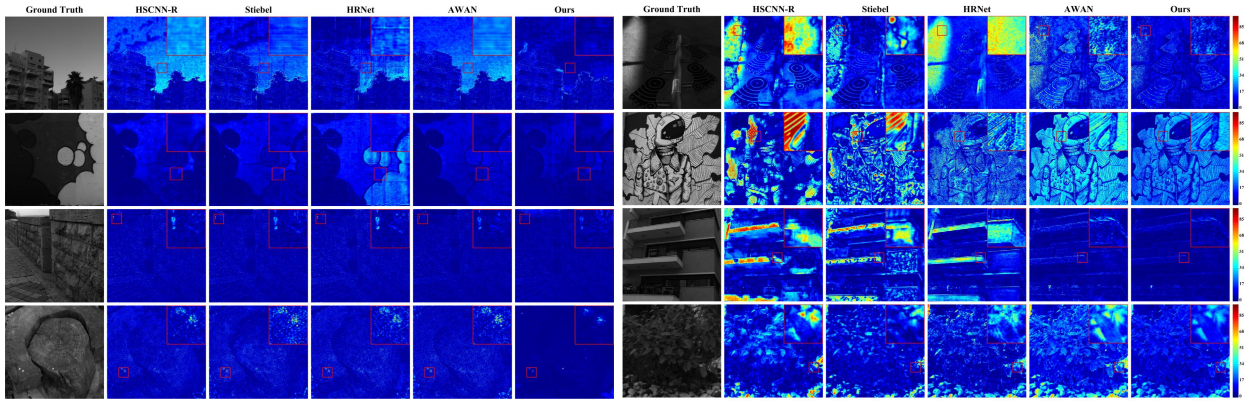


Fig 4: **Visual quality comparison of the 18-th band on four images of NTIRE2020 (left) and NTIRE2022 (right).** The ground truth, MRAE heat maps for HSCNN-R/Stibel/HRNet/AWAN/Ours methods. Note that the MRAE heat maps have been scaled for optimal display.

Quantitative Results

Metric1(evaluate fidelity): $MRAE = \frac{1}{N}\sum_{i=1}^{N}\frac{|G(x)^i - y^i|}{y^i}$

Metric2(evaluate fidelity): $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(G(x)^i - y^i)^2}$

Table 1: The final testing results of NTIRE 2022 Spectral Reconstruction from RGB Images Challenge. Our entry obtain 3rd ranking on the official test set, the results are **highlighted**.

Team	MRAE(↓)	RMSE(↓)
THU-SIGS-MEAI	0.1131211099	0.02308144229
mialgo_ls	0.1247392967	0.02569337961
deeppf	**0.1766834871**	**0.03217000226**
Ptdoge	0.2106939205	0.03654118167
anjing_guo	0.2802988331	0.04161410992

Conclusion

In this paper, we present a novel dense residual channel re-calibration network (DRCR Net) with non-local purification for SSR. Specifically, a NPM is proposed to perform artifact removal and self purification through a hierarchical pyramid structure. Besides, a trainable DRCR block is designed for the deep feature extraction and to improve the generalization ability of the network. To further improve the recovery accuracy of DRCR Net, we develop a CRM which can adaptively recalibrate channel-wise feature response. Experimental results on three datasets demonstrate the superiority and effectiveness of our DRCR Net.

Code Link

https://github.com/jojolee6513/DRCR-net