Random Sub-Samples Generation for Self-Supervised Real Image Denoising

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Codes Wechat (Pan) Wechat (Liu)

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Motivations and Contribution

Motivations:

Noise2Void Analysis: $L_{BSN} = E_y\{\|B(y) - y\|_2^2\}$

However, real images do not satisfy the pixel-wise independent noise assumptions of BSN and often have a limited number of captured images.

AP-BSN Analysis: $L_{AP-BSN} = E_y\{\|B(PD(y)) - PD(y)\|_1\}$

However, real datasets tend to have a much smaller sample number than synthetic datasets, BSN requires noisy-noisy pairs for training. The overfitting of BSN will make the denoising result fit the noisy image and affect the denoising performance.

Sampling Difference as Perturbation: $L_{SDBSN} = E_y\{\|B(PD_1(y)) - PD_2(y)\|_1\}$

PD can produce a series of similar sub-images (PD1(y), PD2(y), ... Since the PD sampling process does no overlap, the pixels in the sub-images that are at the same position are not located at the same position in the original image. There are certain differences between these sub-images, which we refer to as sampling difference.

Cyclic Sampling Difference BSN Loss: $L_{CSDBSN} = \sum_{i=1}^{s^2} \|B(RSG_i(y)) - RSG_{i+1}(y)\|_1$

(1) It imposes constraints on the full pixel of the original noisy image; (2) It ensures that all the sub-samples generated by RSG are well exploited; (3) It makes the training of BSN more robust.

Proposed SDAP Framework:

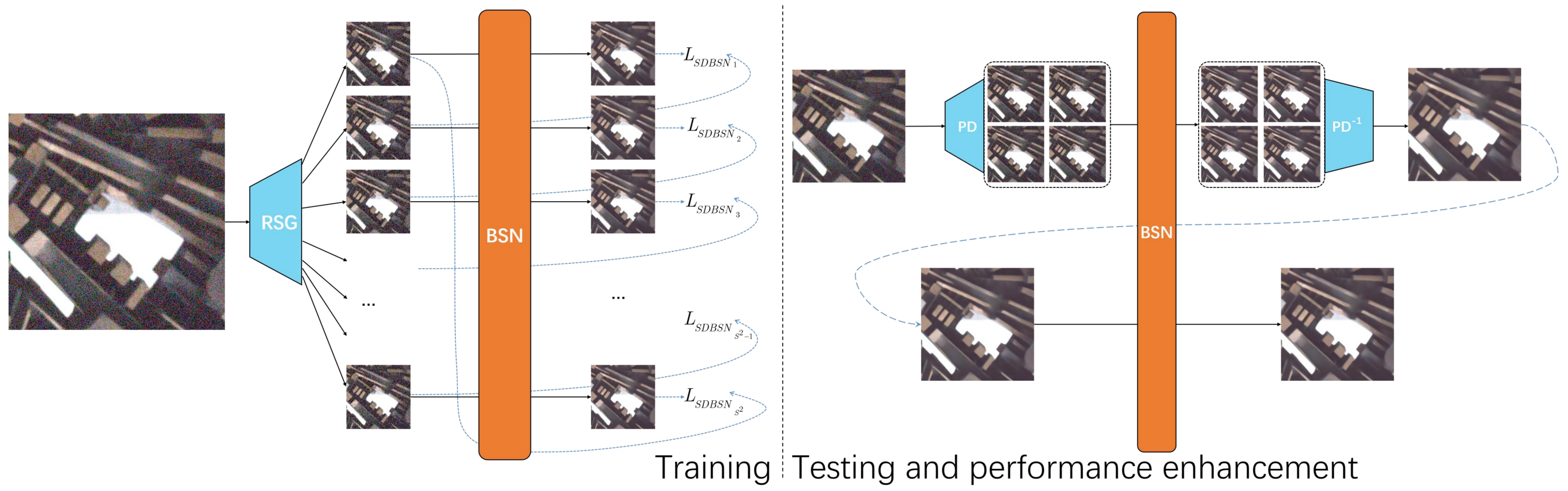
For the training stage, we first sample the noisy images into s^2 sub-samples by RSG. Then, we denoise sub-samples by BSN. The loss is calculated by cross-pairing the subsamples after denoising with those before denoising. Finally, the above steps are iterated, and the loss function is updated to optimize the BSN until it converges.

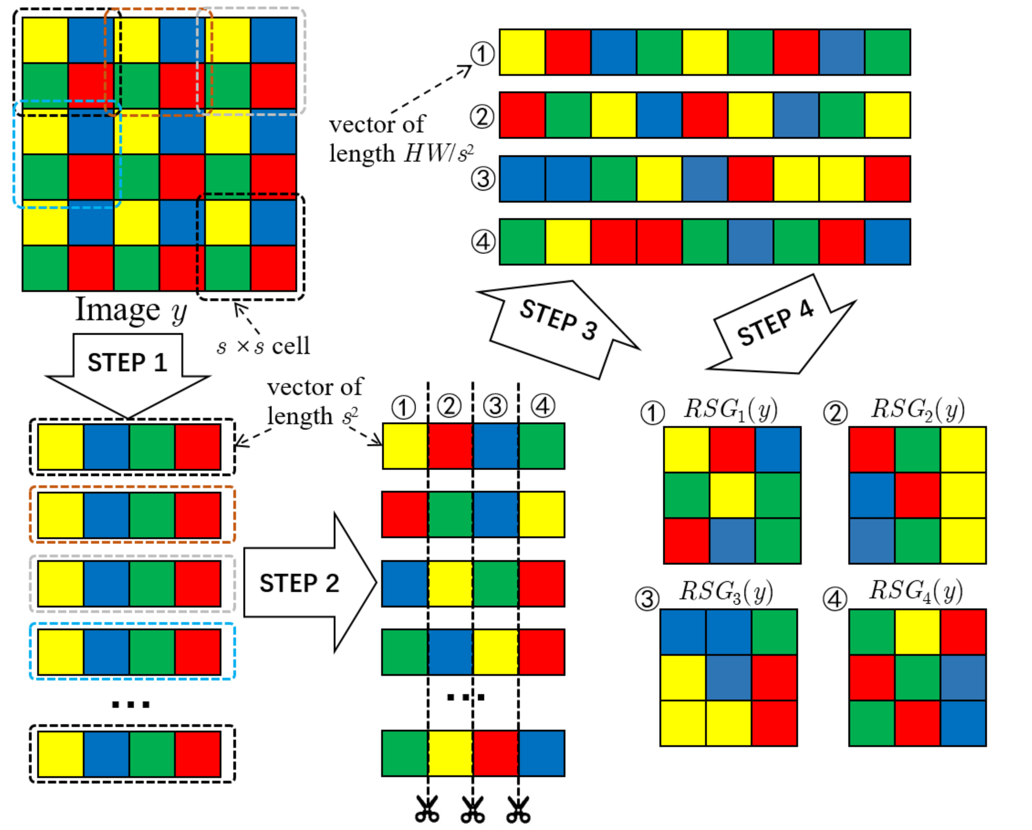
Contributions:

- We propose to add perturbations to the training data to improve the BSN performance and suggest that the sub-samples difference generated by sampling can be considered as perturbations for higher performance.
- We propose a new self-supervised framework for real image denoising with random sub-samples generation and cyclic sampling difference loss.
- Our method performs very favorably against state-of-the-art (SOTA) self-supervised denoising methods on real-world datasets.

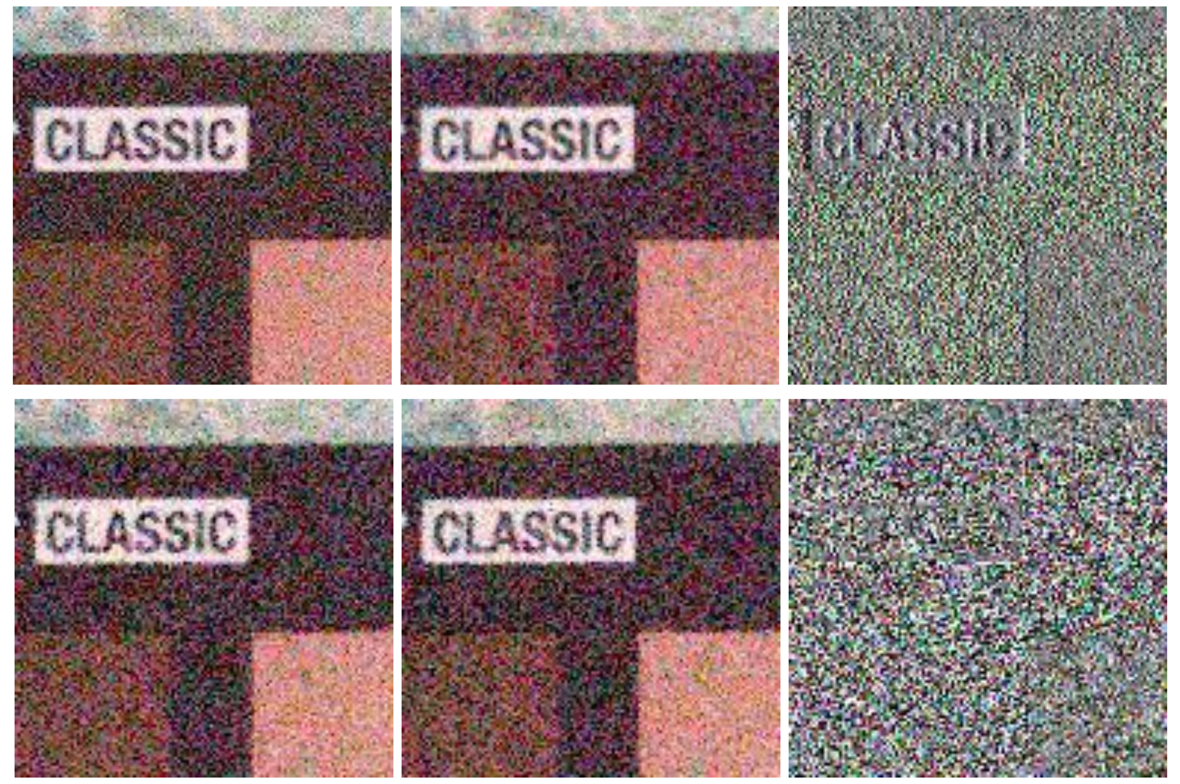
Method

Network Architecture:





Random Sub-Samples Generation (RSG)



Results of sampling by RSG and PD

Conclusion

- We first analyze the reasons for the limited performance of BSN when used for real image denoising. Based on this, we propose to add perturbations to the training data and consider sampling difference as perturbation.
- We propose SDAP framework with random sub-samples generation and cyclic sampling difference loss. Our SDAP does not require clean images for training and outperforms existing pseudo-supervised/self-supervised methods.

Results

- **Quantitative comparisons on the SIDD/DND dataset:**

Type of supervision	Training data	Method	SIDD validation	SIDD benchmark	DND benchmark
Non-learning based	-	BM3D [12]	31.75/0.7061	25.65/0.685	34.51/0.8507
		WNNM [13]	26.31/0.5240	25.78/0.809	34.67/0.8646
Supervised	Paired noisy-clean	DnCNN [44]	26.20/0.4414	23.66/0.583	32.43/0.7900
		TNRD [10]	26.99/0.7440	24.73/0.643	33.65/0.8306
		CBDNet [14]	30.83/0.7541	33.28/0.868	38.06/0.9421
		RIDNet [2]	38.76/0.9132	37.87/0.943	39.25/0.9528
		VDN [40]	39.29/0.9109	39.26/0.955	39.38/0.9518
		Zhou *et al.* [47]	-	34.00/0.898	38.40/0.945
		DeamNet [28]	39.40/0.9169	39.35/0.955	39.63/0.9531
Pseudo-supervised	Unpaired noisy-clean	GCBD [8]	-	-	35.58/ 0.9217
		D-BSN [36]	-	-	37.93/0.9373
		C2N [18]	35.36/0.8901	35.35/0.937	37.28/0.9237
	Paired noisy-noisy	R2R [26]	35.04/0.8440	34.78/0.898	37.61/0.9368
Self-supervised	Single noisy	N2V [20]	29.35/0.6510	27.68/0.668	-
		N2S [3]	30.72/0.7870	29.56/0.808	-
		NAC [38]	-	-	36.20/0.9252
		Neighbor2Neighbor [17]	28.00/0.5890	27.96/0.670	31.40/0.7880
		CVF-SID [25]	34.17/0.8719	34.71/0.917	36.50/0.9233
		AP-BSN [22]	34.46/0.8501	34.90/0.900	37.46/0.9244
		SDAP (Ours)	**36.58/0.8630**	**36.54/0.919**	**37.71/0.9278**
		SDAP (S) (Ours)	**36.71/0.8640**	**36.68/0.919**	**38.18/0.9322**
		SDAP (E) (Ours)	**37.30/0.8937**	**37.24/0.936**	**37.86/0.9366**
		SDAP (S)(E) (Ours)	**37.55/0.8943**	**37.53/0.936**	**38.56/0.9402**

- **Qualitative comparisons on the SIDD/DND dataset:**