HNN: Hierarchical Noise-Deinterlace Net Towards Image Denoising

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Abstract

In this paper, we propose Hierarchical Noise-Deinterlace Net (HNN), a hierarchical framework for image denoising aimed at recovering clean images from noisy observations. HNN processes both global and local information through a hierarchical encoder-decoder network with a Global-Local Spatio-Contextual (GLSC) block, learning fine-grained features and high-frequency details. This approach addresses limitations in existing methods such as vanishing gradients and lack of global context awareness. We demonstrate the efficacy of the HNN framework on benchmark datasets, showing a 5% (↑ in dB) increase in performance compared to state-of-the-art methods.

Contributions

- The main contributions of this work include:
  We propose a hierarchy-based framework (HNN) for image-denoising.
  - We propose a novel hierarchical feature encoder to obtain features from three distinct scales.
  - We propose a Global-Local Spatio-Contextual (GLSC) block for learning of fine-grained features and high-frequency details.
- We introduce LH N N as a weighted combination of L1loss, VGG-19 perceptual loss, and MS-SSIM to exploit local spatial and contextual information across scales while keeping the original resolution of the image intact.

• We demonstrate the results of image denoising on bench- mark, real and synthetic datasets, and compare the performance with SOTA methods using quantitative metrics.

HNN: Hierarchical Noise-Deinterlace Net

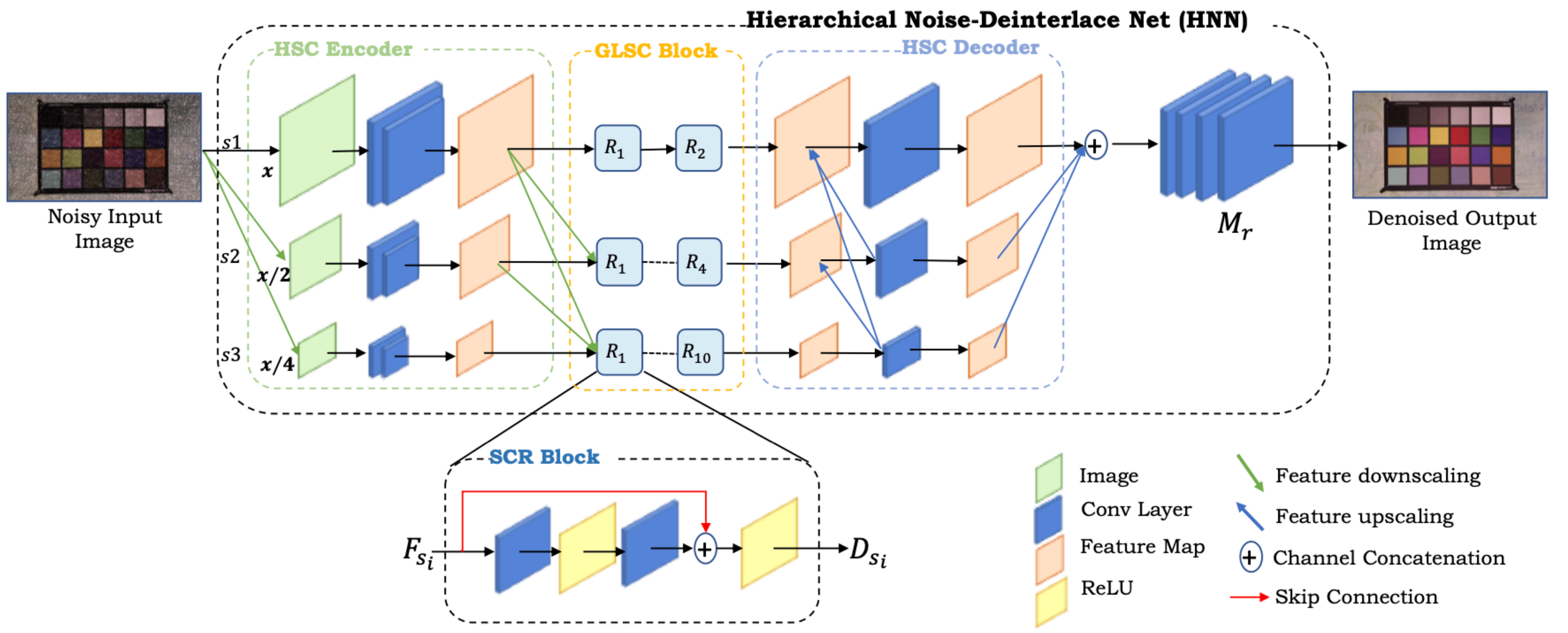

Table 2. Performance comparisons of HNN with SOTA methods on SIDD [1] and DND [23] datasets. † indicates the methods using additional data during training. **Note: the proposed HNN is trained on SIDD [1] dataset and tested on DND [23] dataset.** Cells highlighted in . represents highest values and, cells highlighted in . represents second highest values respectively.

Method	SIDD [1]		DND [23]	
	PSNR↑	SSIM↑	PSNR↑	SSIM↑
BM3D [8] (2007)	25.65	0.685	34.51	0.851
MLP [5] (2012)	24.71	0.641	34.23	0.833
DnCNN [39] (2017)	23.66	0.583	32.43	0.790
CBDNet† [13] (2019)	31.25	0.801	38.06	0.942
RIDNet† [4] (2019)	38.74	0.951	39.26	0.953
VDN [32] (2019)	39.28	0.956	39.38	0.952
AINDNet† [18] (2020)	38.74	0.952	39.37	0.951
SADNet† [6] (2020)	38.97	0.957	39.59	0.952
DANet+† [33] (2020)	39.15	0.957	39.58	0.955
CycleISP† [34] (2020)	39.52	0.957	39.56	0.956
DAGL [22] (2021)	38.94	0.953	39.77	0.956
DeamNet† [24] (2021)	38.79	0.957	39.63	0.953
MPRNet [36] (2021)	39.71	0.958	39.80	0.954
MIRNet-v2 [38] (2022)	39.84	0.959	39.86	0.955
HNN (ours)	**43.82**	**0.968**	**41.06**	**0.956**

Results in Darmsdadt Noise Dataset (DND)

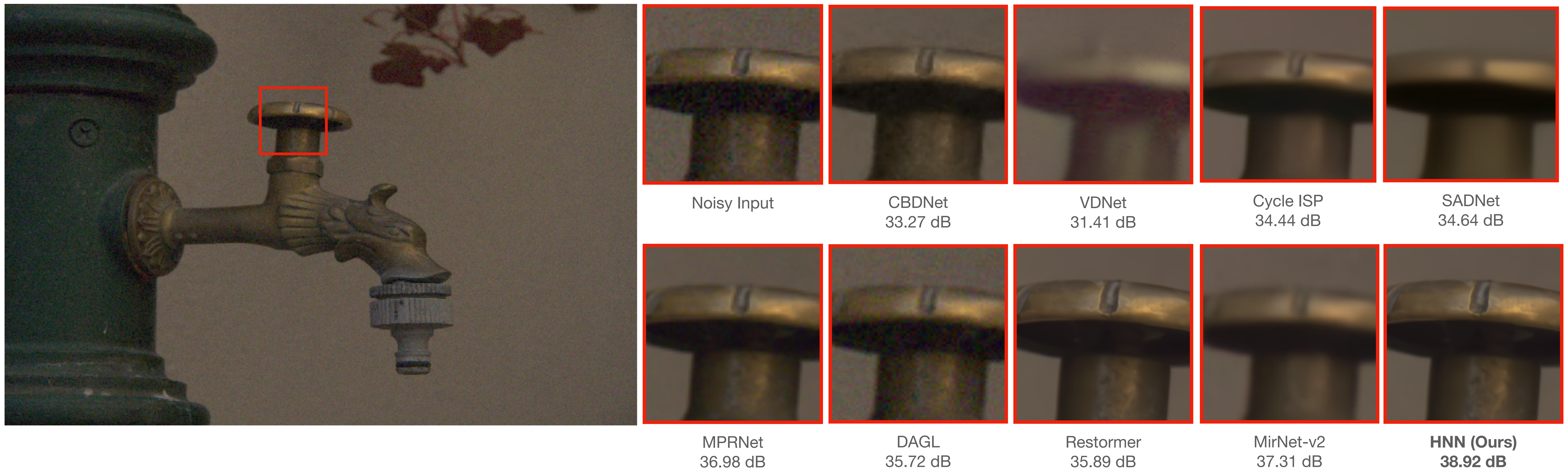

Table 1. Performance comparisons of HNN framework with SOTA methods on CBSD68 [21], Kodak24K [27], and McMaster [42] datasets with varying levels of σ. Cells highlighted in . represents highest values and, cells highlighted in . represents second highest values respectively.

Datasets	CBSD68 [21]				Kodak24K [27]				McMaster [42]			
Noise Levels	$\sigma = 5$	$\sigma = 15$	$\sigma = 25$	$\sigma = 50$	$\sigma = 5$	$\sigma = 15$	$\sigma = 25$	$\sigma = 50$	$\sigma = 5$	$\sigma = 15$	$\sigma = 25$	$\sigma = 50$
DnCNN [39] (2017)	23.89	21.86	19.94	18.11	22.31	21.84	19.56	17.40	24.09	22.84	20.11	18.60
CBDNet [13] (2019)	29.21	28.54	26.16	23.19	28.46	26.19	25.16	22.34	29.11	27.49	26.16	23.47
FFDNet [41] (2019)	33.81	32.59	29.66	27.42	32.69	31.09	28.63	25.94	33.94	32.17	30.45	28.44
SADNet [6] (2020)	35.31	34.04	34.10	31.74	36.10	35.44	32.71	31.44	36.40	34.31	32.75	29.97
CycleISP [34] (2020)	37.12	36.48	32.81	29.49	38.45	37.21	35.87	33.01	38.47	36.46	35.02	33.89
DAGL [22] (2021)	34.10	31.69	29.45	27.14	34.49	32.70	31.11	28.94	33.05	31.64	28.74	25.40
HNN (Ours)	**42.91**	**41.63**	**40.22**	**39.79**	**41.55**	**40.48**	**39.58**	**38.94**	**42.16**	**41.03**	**40.29**	**39.82**

Conclusions

In this work, we propose HNN, a hierarchical network for image denoising that improves fine-grained information learning by exchanging information across scales. We introduce LHNN, a weighted combinational loss incorporating L1 loss, VGG-19 perceptual loss, and MS-SSIM to enhance spatio-contextual learning. Our experiments on benchmark datasets demonstrate HNN's superior performance compared to state-of-the-art methods using various quantitative metrics.

References

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[36] Mehri, Armin, Parichehr B. Ardakani, and Angel D. Sappa. "MPRNet: Multi-path residual network for lightweight image super resolution." *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. 2021.

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