MDFIDNet: Multi-domain Feature Integration Denoising Network

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Abstract

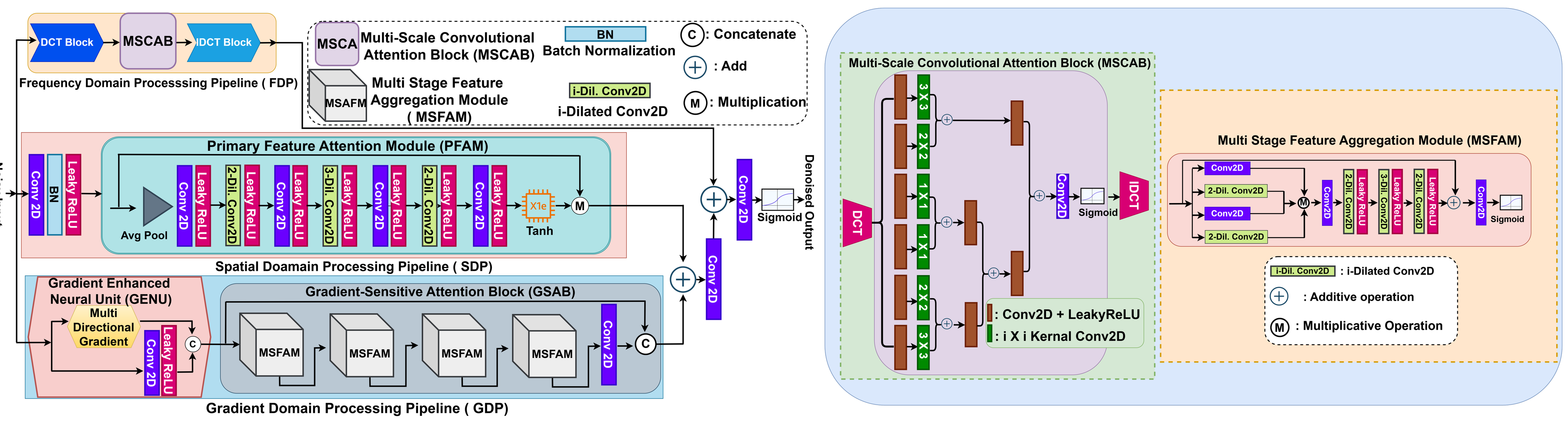
Image denoising is crucial in fields like medical imaging and photography. Existing CNN methods face challenges like training complexity, limited gradient use, and underutilized transform domain analysis. We propose MDFIDNet, a triple-phase fusion network with frequency, spatial, and gradient-domain pipelines. source code and further details are available in the https://github.com/debashis15/MDFIDNet

Keywords: Computer vision · Image denoising · Gradient information · Real images.

Introduction

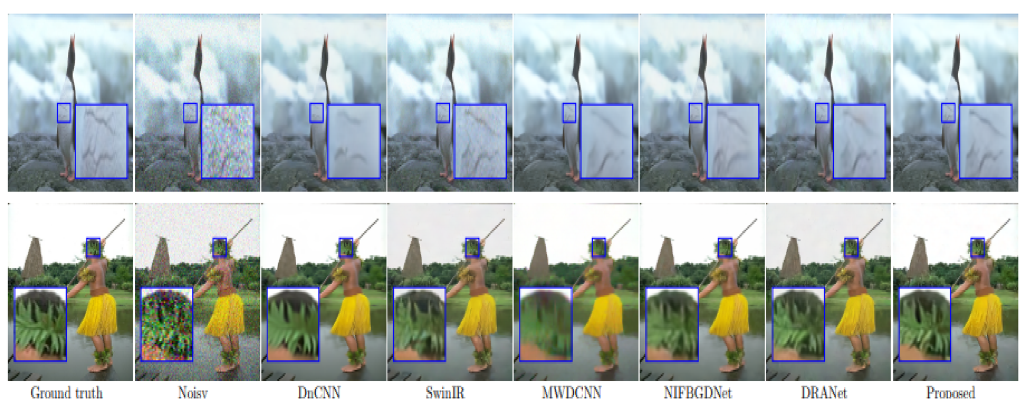
- **Image Denoising:** Enhances image quality by removing noise, essential for applications like medical imaging, remote sensing, and photography [1].
- **Filter-Based Methods:** Techniques like Gaussian and Median filters are simple but cause over-smoothing and detail loss [2].
- **CNN-Based Methods:** Learn noise patterns effectively but face challenges with network complexity and varying noise levels [3].
- **Research Gaps:** Persisting issues include over-smoothing, poor gradient integration, and inefficiencies in transform domain usage.
- **Motivation:** To develop a computationally efficient, end-to-end method that preserves details and integrates spatial and transform domain features [4].

Proposed Methodology

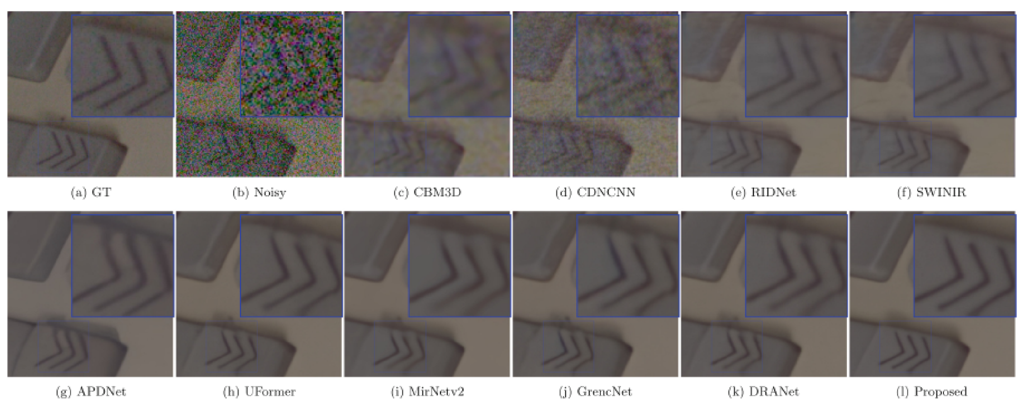


- The proposed methodology employs three distinct pipelines for parallel feature extraction in the **frequency, spatial, and gradient domains**.
- Introduces **multi-directional gradient utilization** to capture directional intensity changes, presenting a novel approach in denoising literature.
- The network is **trained on both synthetic and real image noise**, ensuring versatility.
- Designed as a **lightweight and fast denoising network** for practical applications.

Performance Analysis



Visual results of synthetic color image denoising from the CBSD68 dataset for $\sigma = 30$.



Visual results of real image denoising from the SIDD dataset.

Dataset	σ	BM3D	DNCNN	NIFBGDNet	FFDNet	APDNet	SWINIR	DRANet	MWDCNN	Proposed
		Metric [PSNR/SSIM]								
CBSD68	30	27.21/0.748	28.78/0.853	30.08/0.855	29.78/0.842	30.04/0.853	29.76/0.815	30.08/0.856	29.95/0.851	**30.18/0.860**
	40	26.58/0.738	27.92/0.808	28.71/0.814	28.50/0.803	29.11/0.783	28.50/0.791	28.79/0.820	28.72/0.814	**29.16/0.822**
	50	25.85/0.729	26.49/0.766	27.71/0.779	27.66/0.771	27.88/0.763	27.49/0.769	27.92/**0.782**	27.84/0.773	**27.93**/0.780
	60	24.83/0.695	25.23/0.729	26.90/0.749	26.93/0.747	26.98/0.753	25.37/0.753	27.31/0.772	27.22/0.757	**27.34/0.773**
CUrban100	30	23.03/0.615	26.45/0.623	28.14/0.849	28.19/0.856	28.42/0.861	29.53/0.834	29.67/0.866	29.02/0.843	**29.84/0.873**
	40	22.66/0.576	25.01/0.589	27.40/0.782	27.33/0.778	27.51/0.786	28.76/0.801	29.02/0.840	28.69/0.831	**29.22/0.841**
	50	22.03/0.512	24.56/0.521	26.21/0.723	26.56/0.745	26.96/0.756	28.02/0.745	28.52/0.814	28.03/0.801	**28.71/0.820**
	60	21.54/0.489	23.69/0.502	25.88/0.682	26.02/0.667	26.22/0.691	27.62/0.702	**27.86/0.793**	27.75/0.787	27.84/0.790
Manga109	30	28.80/0.858	26.78/0.725	31.09/0.897	31.02/0.871	31.03/0.884	29.82/0.868	31.29/0.894	31.22/0.885	**31.30/0.895**
	40	23.54/0.607	23.98/0.638	29.58/0.873	30.21/0.879	30.05/0.871	27.72/0.815	**30.18**/0.874	30.06/0.871	**30.18/0.878**
	50	19.20/0.428	21.82/0.569	28.34/0.849	28.36/0.839	28.45/0.841	26.34/0.793	29.04/0.848	28.95/0.844	**29.07/0.855**
	60	16.63/0.296	20.03/0.493	27.10/0.811	27.03/0.804	27.11/0.801	25.21/0.729	27.82/0.816	27.78/0.807	**27.88/0.818**

Dataset	Metric	DnCNN	FFDNet	CBDNet	RIDNet	GrencNet	MPRNet	APD-Nets	MIRNetv2	MCWNNM	DRANet	Uformer	Proposed
SIDD	PSNR	29.50	34.22	33.26	38.70	39.42	39.71	39.75	39.82	39.54	39.53	39.89	39.98
	SSIM	0.610	0.855	0.869	0.914	0.957	0.958	0.959	0.959	0.952	0.959	0.960	0.962
PolyU	PSNR	36.24	36.84	37.81	38.57	39.69	39.84	39.92	39.85	39.68	39.71	39.85	40.14
	SSIM	0.944	0.892	0.956	0.960	0.965	0.966	0.968	0.967	0.965	0.966	0.968	0.970
Nam	PSNR	37.45	37.67	39.09	39.20	39.79	39.97	40.24	40.12	39.72	39.93	40.22	40.28
	SSIM	0.954	0.936	0.969	0.973	0.979	0.981	0.989	0.989	0.986	0.977	0.990	0.992

Computational Analysis

Method	BM3D	MPRNet	FFDNet	Uformer	APDNet	DRANet	GrencNet	MirNet-v2	MWDCNN	MDFIDNet
Device	CPU	GPU	GPU	GPU	GPU	GPU	GPU	GPU	GPU	GPU
Params (M)	-	15.8	**0.87**	51.22	18.61	5.62	5.1	5.9	4.6	4.1
Depth	-	66	64	111	–	48	68	42	36	**28**
MACs	-	587	**71.13**	141.88	212.13	116.36	106.46	106.21	112.21	102.46
FLOPs	-	294	**18.02**	217.56	282.26	187.24	164.76	142.18	174.21	158.33
times (s)	4.23	0.83	**0.28**	0.72	0.80	0.33	0.59	0.48	0.55	0.31
PSNR	36.35	39.84	36.83	39.85	39.92	39.71	39.69	39.85	39.68	**40.14**
SSIM	0.861	0.966	0.892	0.968	0.968	0.966	0.965	0.967	0.965	**0.970**

Ablation Studies

Method	w/o frequency Transform	w/o MSCAB	w/o SDP	w/o GENU	w/o GSAB	MDFIDNet
PSNR	30.11	30.08	29.91	29.98	30.01	**30.18**
SSIM	0.854	0.849	0.828	0.818	0.843	**0.860**

Conclusion

- Introduced a **novel attention-based denoising network** tailored for real-world applications.
- Demonstrated robust performance on **both synthetic and real-world datasets**.
- Outperformed **state-of-the-art methods**, setting new benchmarks in image denoising.
- Computational analysis highlights the method's **lightweight and efficient** nature for denoising tasks.
- Ablation studies validate the **effectiveness of each submodule**, reinforcing MDFIDNet as a top choice in denoising.

Future Research

- Extend MDFIDNet to advanced tasks such as image deblurring, dehazing, and super-resolution.
- Address the dependency on noisy-clean image pairs, which limits practicality in real-world scenarios.
- Develop self-supervised or unsupervised learning methods to improve adaptability.
- Enhance applicability for diverse fields like medical imaging, surveillance, and space exploration.

References

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