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Deep Gaussian Denoiser Epistemic Uncertainty and Decoupled Dual-Attention Fusion

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Abstract

Deep denoising solutions suffer from **epistemic uncertainty** that can limit further advancements. This uncertainty is traditionally mitigated through different ensemble approaches. However, such ensembles are prohibitively costly with deep networks, which are already large in size. We propose a model-agnostic approach for reducing epistemic uncertainty while using only a **single pretrained network**. Our results significantly improve over the state-of-the-art baselines and across varying noise levels.

Key take-aways

- We study image manipulation techniques for a virtual ensemble on one pretrained denoiser.
- We propose a dual-attention fusion on our virtual ensemble, with decoupled attention paths.
- Our method is denoiser agnostic and can potentially be applied on other restoration tasks.

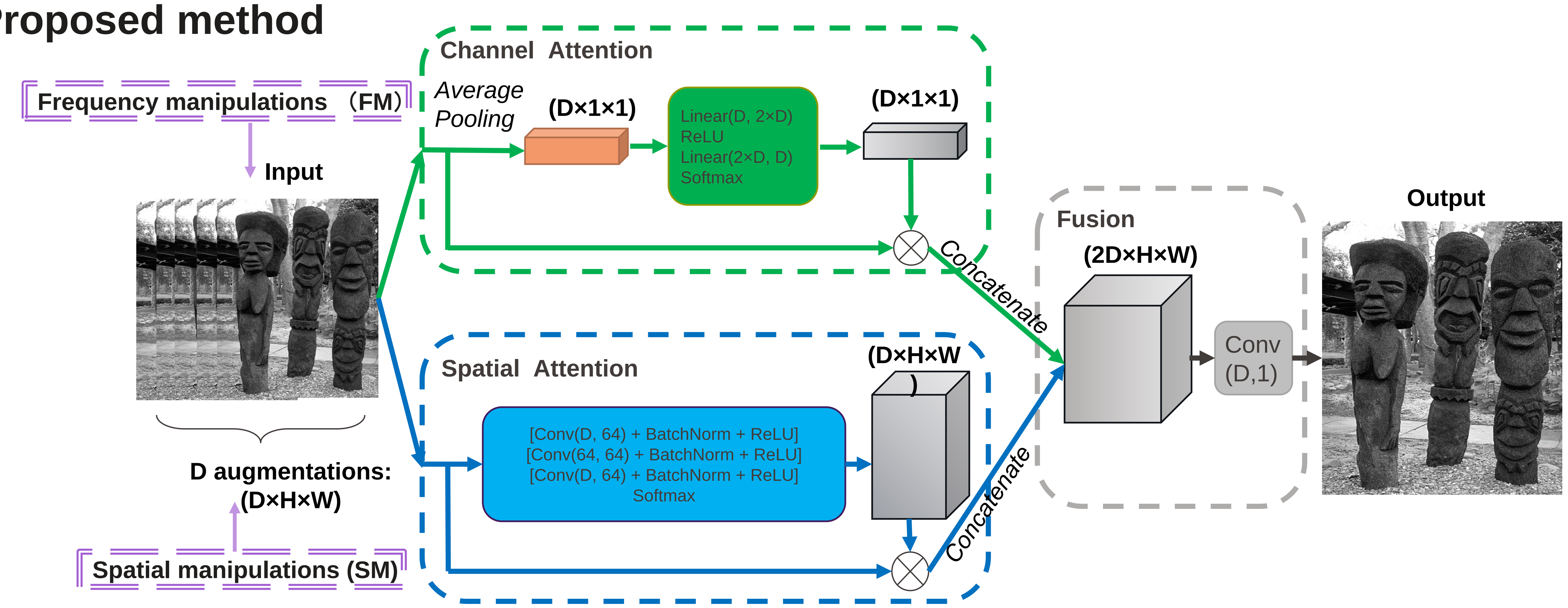
Proposed method

We tap into the epistemic denoiser uncertainty by:

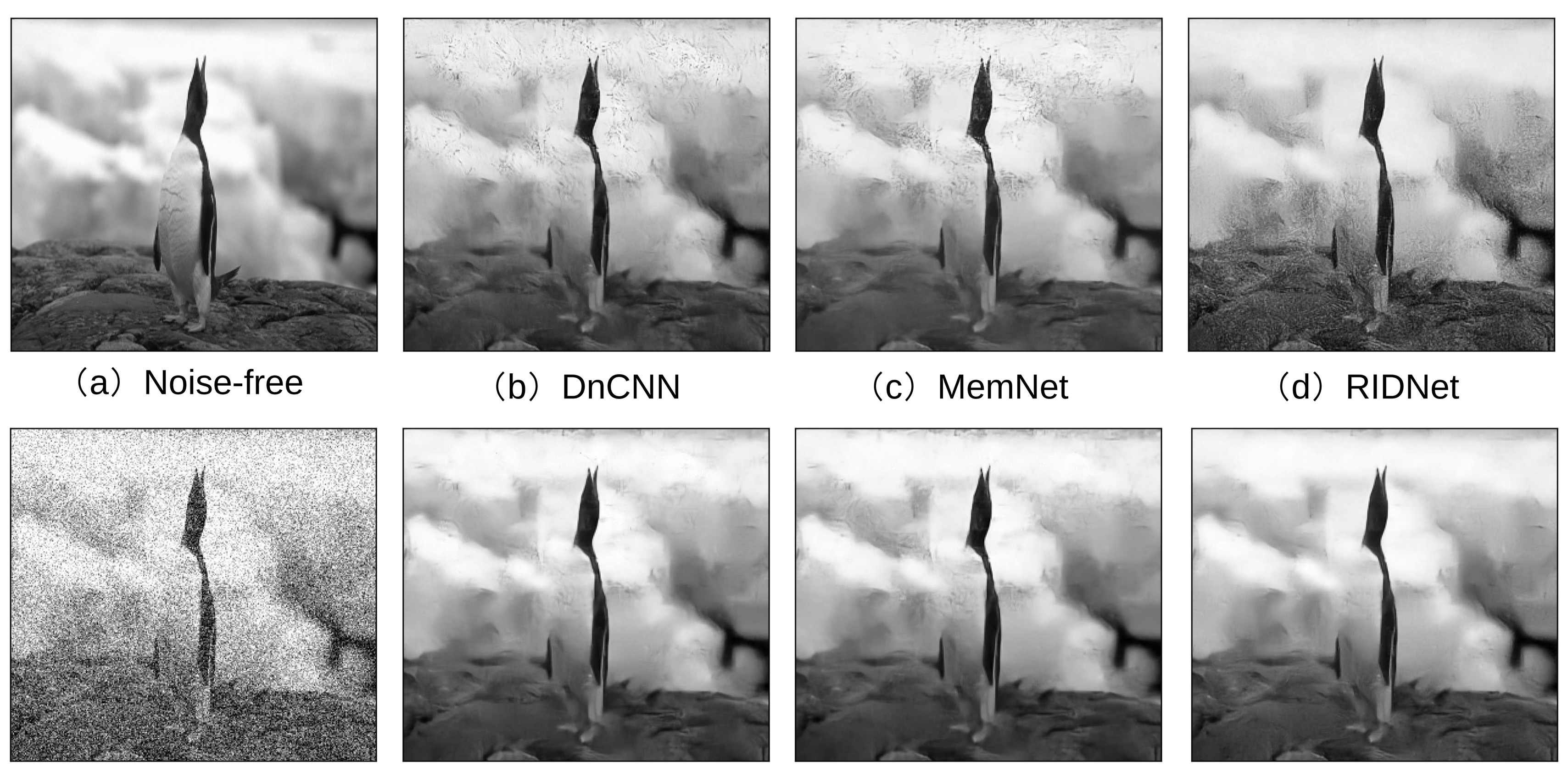
(1) Generating a virtual ensemble from a unique pretrained network using:
Spatial manipulations (SM): rotation and mirroring of images.
Frequency manipulations (FM): masking out different frequency bands [1].

(2) Performing a dual-attention fusion over our virtual ensemble with:
Spatial attention: providing a *pixel-wise* adaptation for each denoised manipulated image.
Channel attention: adapting to the quality of images for each manipulation *as a whole*.
Fusion phase: merging the outputs of the attention paths.

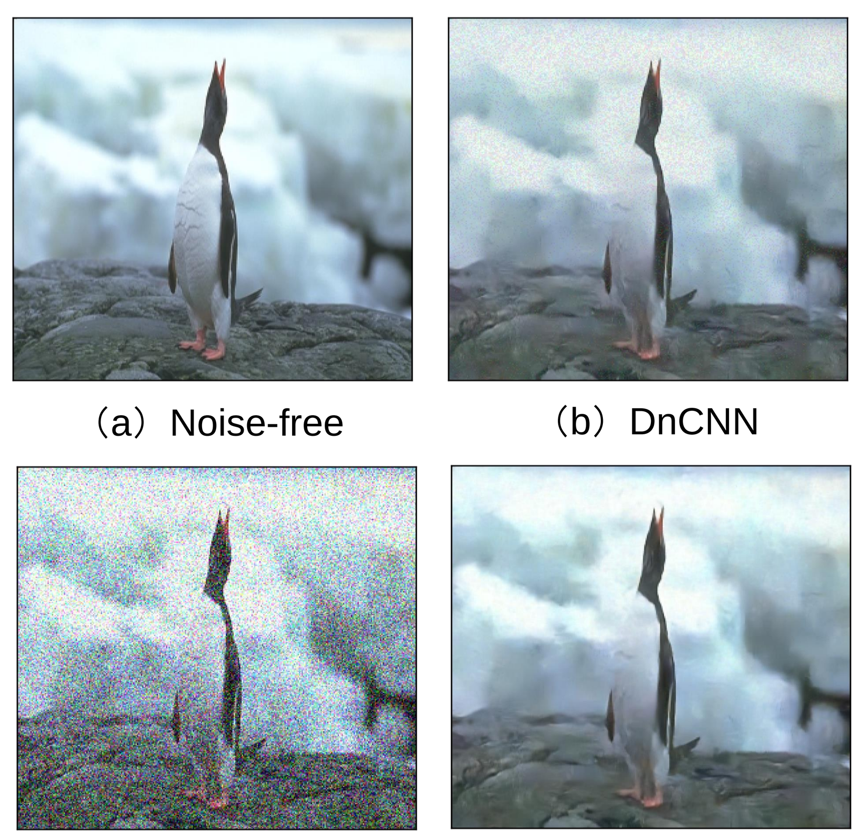
[1] El Helou et al. "Stochastic frequency masking to improve super-resolution and denoising networks." Proceedings of the European Conference on Computer Vision, 2020.



Sample results



(a) Noise-free (b) DnCNN (c) MemNet (d) RIDNet
(e) Noisy (sigma=50) (f) DnCNN + Fusion (g) MemNet + Fusion (h) RIDNet + Fusion



(a) Noise-free (b) DnCNN
(c) Noisy (sigma=50) (d) DnCNN + Fusion

Backbone denoiser	Noise level	Baseline results	Ensemble (SM - FM - Joint)	Spatial attention (SM - FM - Joint)	Channel attention (SM - FM - Joint)	Ours full (SM - FM - Joint)
	10	33.30	33.38 32.29 33.11	33.48 33.52 33.56	33.39 33.37 33.45	33.55 33.52 **33.58**
	20	29.72	29.78 29.25 29.67	29.84 29.92 29.90	29.78 29.73 29.79	29.99 29.98 **30.03**
DnCNN [6]	30	27.68	27.74 27.34 27.66	27.83 28.02 28.02	27.74 27.70 27.75	28.12 28.10 **28.16**
	40	26.19	26.24 25.87 26.18	26.41 26.72 26.70	26.24 26.25 26.29	26.88 26.89 **26.91**
	50	24.96	25.01 24.67 24.96	25.26 25.62 25.55	25.01 25.13 25.15	25.96 25.97 **25.99**
	10	33.40	33.52 32.36 33.25	33.52 33.55 33.60	33.52 33.43 33.54	33.64 33.52 **33.65**
	20	29.71	29.79 29.10 29.63	29.85 29.94 29.99	29.79 29.78 29.84	30.05 29.95 **30.06**
MemNet [7]	30	27.61	27.68 27.10 27.55	27.83 28.06 28.07	27.68 27.77 27.81	28.16 28.14 **28.18**
	40	26.11	26.17 25.64 26.06	26.36 26.70 26.78	26.17 26.37 26.39	26.92 26.93 **26.94**
	50	24.94	24.99 24.51 24.92	25.22 25.62 25.80	24.99 25.29 25.27	25.92 26.01 **26.02**
	10	33.58	33.67 32.41 33.35	33.66 33.65 33.70	33.67 33.59 33.67	**33.73** 33.63 **33.73**
	20	29.86	29.91 29.17 29.73	29.93 29.98 30.06	29.91 29.89 29.93	30.10 30.06 **30.11**
RIDNet [9]	30	27.71	27.76 27.13 27.61	27.87 28.11 28.11	27.76 27.83 27.87	28.22 28.19 **28.24**
	40	26.13	26.18 25.65 26.07	26.35 26.81 26.85	26.18 26.42 26.44	26.97 26.97 **27.01**
	50	24.90	24.95 24.50 24.88	25.17 25.60 25.55	24.95 25.32 25.32	26.01 26.06 **26.08**

Paper: https://arxiv.org/abs/2101.04631 **Code:** https://github.com/IVRL/DEU