“Training your image restoration network better with random weight network as optimization function” Supplementary Material

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This supplementary document is organized as follows:

Section 0.1 provides the quantitative results for pan-sharpening.

Section 0.2 provides the qualitative experimental results.

Section 0.3 provides more provides more quantitative experimental results over ablation studies.

0.1 Guided Image super-resolution.

The quantitative results for pan-sharpening are summarized in Tables 1 where the best results are highlighted in bold. From the results, by integrating with our proposed random weights network by alternative mathematical manifolds, all the reported baselines have achieved consistent performance gains across all the datasets in terms of all metrics, suggesting the effectiveness of our belief.

0.2 Visual comparison.

Due to the page limits, the main manuscript has not presented the sufficient visual results of the reported tasks over the reported baselines. In this section, we provide the representative samples to validate the effectiveness of our belief over image de-noising task of Figure 1, Figure 2, low-light image enhancement of Figure 3. As can be seen, integrating with our belief is capable of improving the visual quality.

0.3 Implementation details of ablation studies.

Initialization strategy. In our work, the default initialization strategy is Kaiming initialization. To explore the impact of initial mode, we replace the default Kaiming initialization by Xavier initialization, reported in Table 9 and Table 8 show that replacing the default almost has little impact on performance, thus verifying the robustness of our belief.

In our experiment, we select two representative random weights network manifolds by ***Central Difference Convolution Manifold*** and ***Invertible Neural Network Manifold*** for performance verification. In detail, we employ the Xavier initialization to weight the convolution kernels within the above manifolds.

Model architecture. All of the loss networks are implemented by convolution network as default. To explore the architecture impact, we replace the default CNN by Transformer. The results in Table 3 and Table 2 demonstrate that replacing it rarely affects the performance.

In our experiment, we select the following random weights network manifolds by ***Taylor’s Unfolding Manifold*** and ***Invertible Neural Network Manifold*** for performance verification. In detail, we replace the convolution part of main body part within Taylor’s Unfolding Manifold by the transformer and the translation functions F and G within Invertible Neural Network Manifold by transformer.

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Table 1: **Quantitative comparisons of guided image super-resolution.**

Model	Configurations	WorldView-II				GaoFen2			
		PSNR↑	SSIM↑	SAM↓	ERGAS↓	PSNR↑	SSIM↑	SAM↓	EGAS↓
	Original	41.6903	0.9704	0.0227	0.9514	47.3528	0.9893	0.0102	0.5479
INNformer	+Taylor	41.8168	0.9716	0.0224	0.9276	47.4058	0.9901	0.0101	0.5356
	+CDC	41.8072	0.9715	0.0224	0.9276	47.4121	0.9902	0.0100	0.5354
	+INN	41.8229	0.9717	0.0223	0.9276	47.4233	0.9904	0.0100	0.5353
	+Reverse	41.7293	0.9711	0.0226	0.9276	47.4010	0.9901	0.0101	0.5354
	Original	41.7244	0.9725	0.0220	0.9506	47.4712	0.9901	0.0102	0.5462
SFINet	+Taylor	41.9314	0.9723	0.0219	0.9278	47.6132	0.9911	0.0101	0.5277
	+CDC	41.8943	0.9719	0.0220	0.9283	47.5990	0.9910	0.0101	0.5281
	+INN	41.9521	0.9727	0.0217	0.9278	47.6316	0.9916	0.0101	0.5275
	+Reverse	41.9217	0.9722	0.0218	0.9281	47.6227	0.9914	0.0101	0.5275

The reason is that 1) Reverse Filtering Network Manifolds have to stand on the low-pass filters for convergence maintaining where Multi-scale Gaussian Convolution Module is devised in our paper. Therefore, the architecture cannot change; 2) Central Difference Convolution Manifold is inborn with convolution architectures and thus cannot change. To this end, we select the above two samples.

Model depth. For model depth, we change the model depth of loss network by adding the layers. To ensure a fair comparison, the other factor keeps the same. The results in Table 5 and Table 4 demonstrate the stable performance.

In our experiment, we select two representative random weights network manifolds by ***Central Difference Convolution Manifold*** and ***Invertible Neural Network Manifold*** for performance verification. In detail, we change the default three-layer Central Difference Convolution and Invertible Neural Network by seven layers.

Model numbers. In our experiment, we use the single loss network as default. As shown in Table 7 and Table 6, we employ multiple parallel loss networks to verify the impact of model numbers. The results indicates that increasing the number of models will improve the performance. It attributes to the advantages of model ensemble.

In our experiment, we select two representative random weights network manifolds by ***Central Difference Convolution Manifold*** and ***Invertible Neural Network Manifold*** for performance verification. In detail, we change the default single loss network with three ones by 3-3-3 variants and 3-5-7 variants.

Table 2: **Ablation studies of model architecture for image enhancement.**

Model	Configurations	LoL		
		PSNR	SSIM	NIQE
	Original	20.2461	0.7920	4.1586
SID	+Taylor+epochR	20.6018	0.7975	3.8079
	+Taylor+epochR+Transformer	20.5864	0.7971	3.8348
	+INN+epochR	20.3958	0.7924	3.9210
	+INN+epochR+Transformer	20.3178	0.7944	3.8889
	Original	19.8509	0.7769	4.7738
DRBN	+Taylor+epochR	20.2405	0.7791	4.6721
	+Taylor+epochR+Transformer	20.1826	0.7784	4.6968
	+INN+epochR	20.1913	0.7769	4.8067
	+INN+epochR+Transformer	20.1196	0.7772	4.7163

Table 3: **Ablation studies of model architecture for image de-noising.**

Model	Configurations	SIDD	
		PSNR↑	SSIM↑
	Original	37.1992	0.8954
DnCNN	+Taylor+epochR	37.3719	0.8954
	+Taylor+epochR+Transformer	37.3560	0.8958
	+INN+epochR	37.3318	0.8964
	+INN+epochR+Transformer	37.3297	0.8961
	Original	39.2372	0.9159
MPRnet	+Taylor+epochR	39.3283	0.9161
	+Taylor+epochR+Transformer	39.2783	0.9160
	+INN+epochR	39.3317	0.9162
	+INN+epochR+Transformer	39.2756	0.9159

Table 4: **Ablation studies of model depth for image enhancement.**

Model	Configurations	LoL		
		PSNR	SSIM	NIQE
	Original	20.2461	0.7920	4.1586
SID	+CDC+epochR	20.4750	0.7999	3.6636
	+CDC(3)+epochR+Depth	20.3464	0.7915	3.8620
	+CDC(7)+epochR+Depth	20.4258	0.7857	4.4067
	+INN+epochR	20.3858	0.7924	3.9210
	+INN(3)+epochR+Depth	20.4946	0.7862	4.1512
	+INN(7)+epochR+Depth	20.2816	0.7959	3.7419
	Original	19.8509	0.7769	4.7738
DRBN	+CDC+epochR	20.0756	0.7837	4.7850
	+CDC(3)+epochR+Depth	19.9188	0.7808	4.7074
	+CDC(7)+epochR+Depth	19.9769	0.7795	4.8156
	+INN+epochR	20.1913	0.7769	4.8067
	+INN(3)+epochR+Depth	20.0330	0.7758	4.5883
	+INN(7)+epochR+Depth	20.1153	0.7787	4.7089

Table 5: **Ablation studies of model depth for image de-noising.**

Model	Configurations	SIDD	
		PSNR↑	SSIM↑
	Original	37.1992	0.8954
DnCNN	+CDC+epochR	37.2784	0.8955
	+CDC(3)+epochR+Depth	37.2218	0.8921
	+CDC(7)+epochR+Depth	37.2923	0.8930
	+INN+epochR	37.3218	0.8964
	+INN(3)+epochR+Depth	37.3213	0.8967
	+INN(7)+epochR+Depth	37.3142	0.8967
	Original	39.2372	0.9159
MPRnet	+CDC+epochR	39.2821	0.9161
	+CDC(3)+epochR+Depth	39.2814	0.9160
	+CDC(7)+epochR+Depth	39.2740	0.9161
	+INN+epochR	39.2729	0.9162
	+INN(3)+epochR+Depth	39.2758	0.9160
	+INN(7)+epochR+Depth	39.2737	0.9160

Table 6: **Ablation studies of model numbers for image enhancement.**

Model	Configurations	LoL		
		PSNR	SSIM	NIQE
	Original	20.2461	0.7920	4.1586
SID	+CDC+epochR	20.4750	0.7999	3.6636
	+CDC+epochR+Number(357)	20.4879	0.7991	3.6793
	+CDC+epochR+Number(555)	20.5424	0.7889	3.7738
	+INN+epochR	20.3858	0.7924	3.9210
	+INN+epochR+Number(357)	20.3516	0.7843	4.2365
	+INN+epochR+Number(555)	20.3316	0.7911	4.1289
	Original	19.8509	0.7769	4.7738
DRBN	+CDC+epochR	20.0756	0.7837	4.7850
	+CDC+epochR+Number(357)	20.0200	0.7789	4.6900
	+CDC+epochR+Number(555)	20.0403	0.7750	4.7060
	+INN+epochR	20.1913	0.7769	4.8067
	+INN+epochR+Number(357)	20.0510	0.7779	4.6957
	+INN+epochR+Number(555)	20.2572	0.7767	4.6169

Table 7: **Ablation studies of model numbers for image de-noising.**

Model	Configurations	SIDD	
		PSNR↑	SSIM↑
	Original	37.1992	0.8954
DnCNN	+CDC+epochR	37.2784	0.8925
	+CDC+epochR+Number(357)	37.4377	0.8969
	+CDC+epochR+Number(555)	37.3208	0.8948
	+INN+epochR	37.3218	0.8964
	+INN+epochR+Number(357)	37.3374	0.8937
	+INN+epochR+Number(555)	37.3581	0.8944
	Original	39.2372	0.9159
MPRnet	+CDC+epochR	39.2821	0.9162
	+CDC+epochR+Number(357)	39.2704	0.9161
	+CDC+epochR+Number(555)	39.2764	0.9160
	+INN+epochR	39.2729	0.9162
	+INN+epochR+Number(357)	39.2767	0.9160
	+INN+epochR+Number(555)	39.2818	0.9160

Table 8: **Ablation studies of initialization strategy for image enhancement.**

Model	Configurations	LoL		
		PSNR	SSIM	NIQE
	Original	20.2461	0.7920	4.1586
SID	+CDC+epochR	20.4750	0.7999	3.6636
	+CDC+epochR+xavier	20.3271	0.7847	4.1454
	+INN+epochR	20.3858	0.7924	3.9210
	+INN+epochR+xavier	20.3257	0.7927	4.1187
	Original	19.8509	0.7769	4.7738
DRBN	+CDC+epochR	20.0756	0.7837	4.7850
	+CDC+epochR+xavier	20.0136	0.7760	4.7566
	+INN+epochR	20.1913	0.7769	4.8067
	+INN+epochR+xavier	20.0948	0.7773	4.6879

Table 9: **Ablation studies of initialization strategy for image de-noising.**

Model	Configurations	SIDD	
		PSNR↑	SSIM↑
	Original	37.1992	0.8954
DnCNN	+CDC+epochR	37.2784	0.8925
	+CDC+epochR+xavier	37.2567	0.8963
	+INN+epochR	37.3218	0.8964
	+INN+epochR+xavier	37.2890	0.8957
	Original	39.2372	0.9159
MPRnet	+CDC+epochR	39.2821	0.9161
	+CDC+epochR+xavier	39.2768	0.9160
	+INN+epochR	39.2729	0.9162
	+INN+epochR+xavier	39.2779	0.9160

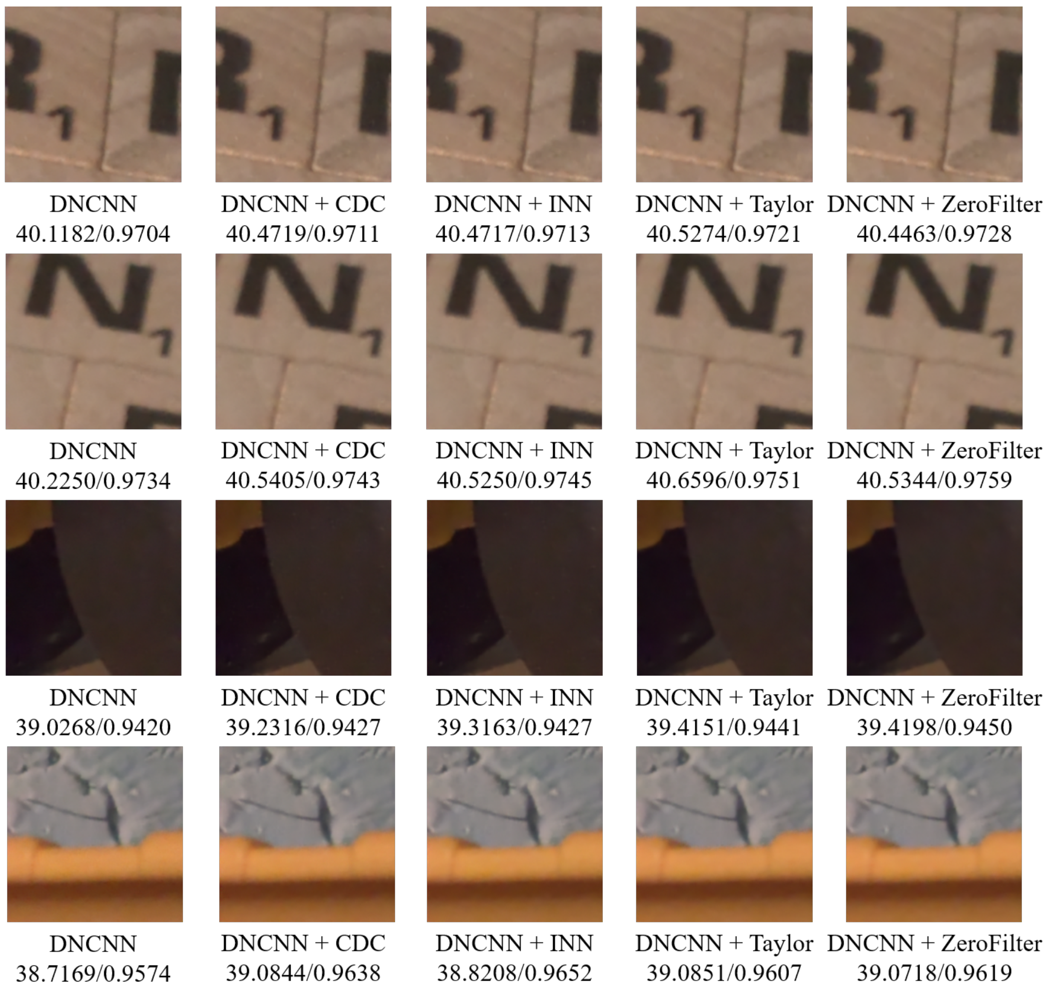

Figure 1: The visual comparison for the image de-noising. We also list the PSNR/SSIM scores under each case.

Figure 2: The visual comparison for the image de-noising. We also list the PSNR/SSIM scores under each case.

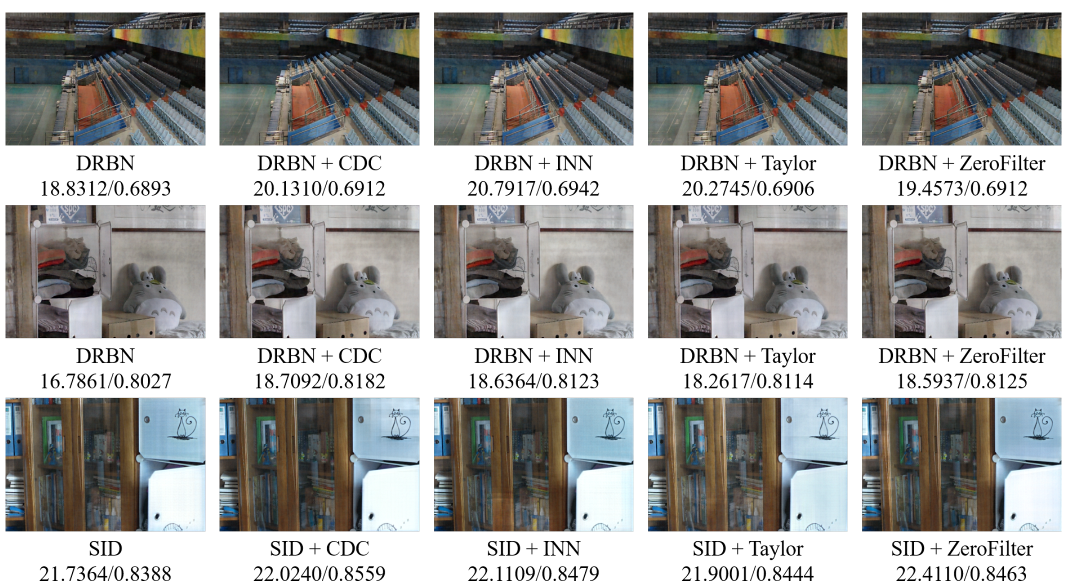

Figure 3: The visual comparison for the image enhancement. We also list the PSNR/SSIM scores under each case.