Supplementary Materials of PARNet

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1 Experiments and Results

Due to space limitations and in line with the research practices of others in related work [4,2,1,5], our experimental results only show the average across all datasets. To further illustrate the effectiveness and superior performance of our proposed algorithm, we present its specific performance on the aforementioned datasets in the supplementary material. This is to prevent any misunderstanding regarding the adequacy of our experiments on mainstream public datasets.

After cross-dataset data preprocessing, the performance differences among the various models on different datasets are not substantial. The tables show that PARNet outperforms other 3D reconstruction methods across all evaluation metrics and datasets.

Table 1: Quantitative Results of Different Methods on Aortic 3D Reconstruction on the LIDC-IDRI Dataset

Method	PSNR ↑	SSIM ↑	CS ↑	MAE ↓	MSE ↓
PSR [3]	39.303	0.760	0.576	36.919	13900.159
X2CT [4]	43.582	0.863	0.731	24.213	9833.726
XTransCT [5]	40.277	0.822	0.598	28.418	12677.607
3DSRNet [1]	44.487	0.875	0.730	22.347	7935.129
Ours(PARNet)	**46.926**	**0.898**	**0.763**	**17.859**	**3088.529**

The hyperparameter values set in L347 have the best performance on PARNet as shown in Tab 5.

Our method also outperforms the best-performing 3DSRNet in the benchmarks on the spinal reconstruction task, and we will include the following data in 6 in the final version.

PARNet, while more complex compared to other models in 7, delivers superior performance. As aortic reconstruction is more challenging than tasks such as spinal reconstruction, our method sacrifices acceptable efficiency for advanced performance. This improves the speed and accuracy of guidewire positioning, reduces procedure time, and minimizes radiation and contrast agent exposure for both patients and surgeons.

Table 2: Quantitative Results of Different Methods on Aortic 3D Reconstruction on the VerSe '20 Dataset

Method	PSNR ↑	SSIM ↑	CS ↑	MAE ↓	MSE ↓
PSR [3]	36.793	0.725	0.531	34.398	14719.872
X2CT [4]	41.979	0.838	0.682	27.622	11833.189
XTransCT [5]	37.021	0.791	0.560	30.981	14122.879
3DSRNet [1]	42.673	0.858	0.701	25.258	8568.139
Ours(PARNet)	**44.778**	**0.872**	**0.735**	**21.326**	**3507.269**

Table 3: Quantitative Results of Different Methods on Aortic 3D Reconstruction on the VerSe '19 Dataset

Method	PSNR ↑	SSIM ↑	CS ↑	MAE ↓	MSE ↓
PSR [3]	36.681	0.718	0.538	34.473	14517.596
X2CT [4]	42.103	0.842	0.679	27.730	11027.354
XTransCT [5]	37.138	0.789	0.562	31.767	14927.013
3DSRNet [1]	42.781	0.857	0.699	25.237	8607.326
Ours(PARNet)	**44.068**	**0.876**	**0.741**	**20.858**	**3516.315**

Table 4: Quantitative Results of Different Methods on Aortic 3D Reconstruction on the LungCT-Diagnosis Dataset

Method	PSNR ↑	SSIM ↑	CS ↑	MAE ↓	MSE ↓
PSR [3]	37.755	0.769	0.575	35.491	14095.822
X2CT [4]	41.756	0.853	0.722	25.867	9479.155
XTransCT [5]	39.376	0.806	0.591	30.178	13185.353
3DSRNet [1]	43.111	0.858	0.718	24.694	8314.422
Ours(PARNet)	**44.840**	**0.878**	**0.725**	**17.469**	**2964.731**

Table 5: Comparison of the Loss hyperparameters.

λ_{GAN}	λ_{WGS}	λ_{3D}	PSNR ↑	SSIM ↑
0.2	0.4	0.4	44.735	0.870
0.4	0.4	0.2	44.369	0.876
0.3	0.4	0.3	**45.153**	**0.881**

Table 6: Comparison of Performance on spine reconstruction.

Method	PSNR ↑	SSIM ↑
3DSRNet	45.455	0.879
Ours(PARNet)	**46.372**	**0.898**

Table 7: Comparison of Model complexity.

Method	X2CT	3DSRNet	Ours(PARNet)
FLOPs	599.762G	813.677G	1303.255G

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