

Exploiting spatial attention mechanism

for improved depth completion and feature fusion



in novel view synthesis

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Goal: Given a set of images and corresponding depth maps from sparse camera setup → render novel view images with deep image-based rendering technique

Limitations of prior methods: artifacts (blurry textures) caused by

• Incorrect geometry estimates.

Plane-sweep volume

• Attention mechanism focus solely on the view and channel axes.





Key Insights:

- Extract **spatial features from color images** by leveraging a monocular depth estimation pipeline.
- Combine spatial features from color images to enhance depth completion.
- Combine an **attention mechanism on spatial**, **channel**, **and view axes** to enhance the rendering results (SpatialAttentionGRU).

Framework







 $\boldsymbol{D}_1, \dots, \boldsymbol{D}_K$: input depth maps

 I_1, \dots, I_K : input color maps

 $\boldsymbol{P}_1, \dots, \boldsymbol{P}_K$: projection matrices

 $\boldsymbol{D}_{1}^{\mathrm{P}},...,\boldsymbol{D}_{\mathrm{K}}^{\mathrm{P}}$: "reprojected" depth maps $\boldsymbol{I}_{1}^{\mathrm{P}},...,\boldsymbol{I}_{\mathrm{K}}^{\mathrm{P}}$: reprojected color maps





Table 4.2: Ablation study on DTU MVS dataset: We presented the results of the novel view synthesis by replacing the proposed depth completion module and the feature fusion module with different methods. The best results are in bold.



Extraction	\mathbf{Depth}	Completion	PSNR	SSIM	LPIPS
VGG	-	FVS [125]	15.92	0.73	0.27
VGG	Our	$FVS \ [125]$	22.12	0.82	0.17
Swin	-	Our	19.03	0.78	0.22
\mathbf{Swin}	FWD [12]	Our	21.36	0.76	0.21
\mathbf{Swin}	DDP [128]	Our	21.19	0.81	0.20
Swin	CA [1]	Our	21.71	0.82	0.19
Swin	Our	FVS [125]	23.02	0.84	0.17
Swin	Our	FWD [12]	23.00	0.80	0.19
\mathbf{Swin}	Our	Our	23.44	0.84	0.16





