

# SimpleNeRF: Regularizing Sparse Input Neural Radiance Fields with Simpler Solutions

#### **Connecting STORIES**

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- NeRF [1] typically requires hundreds of images per scene.
- Produces severe distortions when trained with few images.
- Cause: Under-constrained volume rendering equations.



NeRF - Dense Input Views



NeRF - Sparse Input Views

[1] Mildenhall et al., "Representing Scenes as Neural Radiance Fields for View Synthesis", ECCV 2020.



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Our solution: learn without pre-training scene-specific depth supervision. — train augmented/helper models along with the NeRF model.



#### Floater artifacts



NeRF learns undesired depth discontinuities due to high positional encoding.

Duplication artifacts (shape-radiance ambiguity)



NeRF changes colour to over-fit observations by exploiting its ability to learn view-dependent colour.



Common cause: High capability of NeRF in regions where it is not necessary.



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### Mitigating Floaters with Simpler Solutions

NeRF



Depth edges are sharp, but contains floaters

Helper NeRF (lower positional encoding)



Floaters reduced, but depth edges are not sharp

SimpleNeRF



Floaters reduced while retaining sharp depth edges



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NeRF



Observe the change in position of the object on the table

Helper NeRF (View-independent color)



Does not support specularity

SimpleNeRF



Object does not change position while supporting specularity





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We employ DS-NeRF [CVPR '22] as our baseline

2



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Nearest input view



- Depth with higher similarity between reprojected patches  $\rightarrow$  more reliable.
- $\bigcup \bigotimes \diamond \square$
- Use the more reliable depth to supervise the other.





Nearest input view



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- $\longrightarrow \bigotimes \diamond_{\Box}$
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Reproject using main NeRF depth

Reproject using augmented NeRF depth



Nearest input view

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# **Qualitative Results**

Input views









NeRF - 3 input views



SimpleNeRF - 3 input views



NeRF - 54 input views





# **Qualitative Results**

Input views









NeRF - 3 input views



SimpleNeRF - 3 input views



NeRF - 54 input views







Significant improvement in estimating depth of the scene





## Quantitative Results - LPIPS

NeRF - LLFF [4]

Real Estate - 10K [5]



[5] Zhou et al., "Stereo Magnification: Learning View Synthesis using Multiplane Images", SIGGRAPH 2018.



- Design of lower capability helper models biased towards simpler solutions.
  - Reducing positional encoding to mitigate floaters.
  - View-independent colour to reduce shape-radiance ambiguity.
- Framework extensible to any volumetric model.



For paper, code and more, visit

https:// nagabhushansn95. github.io/ publications/2023/ SimpleNeRF.html





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