

DEEP VIEW SYNTHESIS FROM SPARSE PHOTOMETRIC IMAGES

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Render real scenes







[Furukawa and Ponce 2008]



[Newcombe et al. 2011]





[Xu et. al 2016]









Light transport acquisition

Light Transport Function



Image-based relighting

Our relighting under environment map illumination



[Xu et al. 2018]

Light transport acquisition for changing view



Sparse input views



Novel view appearance

Novel view synthesis



[Chen and Williams 1993]



[Flynn et al. 2016]



[Kalantari et al. 2016]

- Unstructured views
- Small baseline
- Natural illumination



[Levoy and Hanrahan 1996]



[Penner and Zhang 2017]

[Zhou et al. 2018]

Sparse sampling for light transport acquisition

- Large baseline
- Controlled lighting



Preview

- Large baseline
- Controlled lighting



Preview



Preview



- Sparse
- Good coverage



- 12 vertices
- 20 faces
- Symmetric



















Synthetic scenes

Geometry:

Procedurally Generated Objects





Material images courtesy: Allegorithmic and Adobe Stock

Reflectance:

Adobe Stock Material

Synthetic scenes

Geometry:

Procedurally Generated Objects



Reflectance:

Adobe Stock Material



CNN





CNN

Input views

8





CNN



Input views

Novel view



Input views

Novel view





Novel view





Novel view





Novel view










Plane sweep volume



Input views

Plane sweep volume



Input views

Plane sweep volume











Input views















Infer geometry (depth)
 Infer attention maps











Shading branch



Depth probability maps

Shading branch



Shading branch



Shading Predictor (3D CNN)



Corr-Branch + Shade-Branch







Real Data Results

Data #1: input images and corresponding views









6





Data #1: compare with [Penner and Zhang 2017] using the same inputs









Penner and Zhang 2017 Our results

Ground truth

(Some views are occluded)

Data #1: compare with [Sun et al. 2018] using the same inputs







Sun et al. 2018

Our results

Ground truth

(Some views are occluded)

Data #2: input images and corresponding views







Data #2: our results and ground truth



Inputs and viewing directions







Ground truth (Some views are occluded)

Data #3: input images and corresponding views





Data #3: our results and ground truth



Inputs and viewing directions

Our results



Data #4: input images and corresponding views



Data #4: our results and ground truth



(Some views are occluded)

Novel view relighting





Novel view relighting





Data #4: our novel view relighting results





Our synthesized images

Relighting

Environment map 1

Multi-view stereo



Input images

Reconstruction

Data #2: Multi-view stereo from synthesized images



Reconstruction from 56 captured images

Reconstruction from 56 synthesized images using our method Reconstruction from 56 synthesized images using our method (rendered with color)

Limitations

- Highly specular objects
 - 64 x 64 image crops for training
 - Limited receptive field



Our result

Ground truth

Limitations

- Highly specular objects
 - 64 x 64 image crops for training
 - Limited receptive field
- Highly non-convex shape
 Visible from 1 or 2 views



Our result

Ground truth

Conclusion





Our Result





Ground Truth
Conclusion





Our Result

Ground Truth



Novel view relighting



Multi-view stereo

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