SVS: Adversarial refinement for sparse novel view synthesis

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Introduction

Current methods:
- Very expensive
- Fully differentiable
- Few input views
- Many input views
- Unseen scenes
- Sparse View Synthesis
- Artefacts
- Large baseline changes
- No fine-tuning
- General

Ours:
- Sparse View Synthesis
  - Few input views
  - Large baseline changes
  - Unseen scenes
  - No fine-tuning
  - General
  - Fully differentiable

Geometry Volume Generator

- Image feature plane sweep volume
- Variance-based cost volume
- Extracts correlations between images
- Reasons about scene geometry
- Helps generalise to unseen scenes

Patch-based Neural Radiance Field

- MLP decodes embedding into density and radiance
- Sample from encoding volume and image colour
- Spatial structure for adversarial training
- Increases number of training examples
- More efficient adversarial training
- Variable receptive field

References


Conclusion

- Generalisable
- Sparse input views
- Larger baseline changes
- Perceptual quality improvements up to 60%
- Training instability
- Some lack of fidelity

Download the code! [github.com/violetamenendez/svs-sparse-novel-view]