SynSin: End-to-end View Synthesis from a Single Image

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GOAL

A model (**SynSin**) that performs view synthesis from a **single** image.

Figure 1: The task: given an image and new viewpoint, the task is to synthesize an image at that new viewpoint.

Requires:
- 3D scene understanding to model the 3D geometry
- Context understanding to fill in missing regions

Our key contributions to solve these challenges:
- A **differentiable point cloud renderer** to model the 3D geometry
- Using GAN techniques to fill in missing regions
- Training the whole model end to end in a self-supervised manner

SELF SUPERVISED TRAINING

Training Inputs:
Assume we have an image I, and a target image I_t of the same scene and the corresponding change in pose T.

Setup

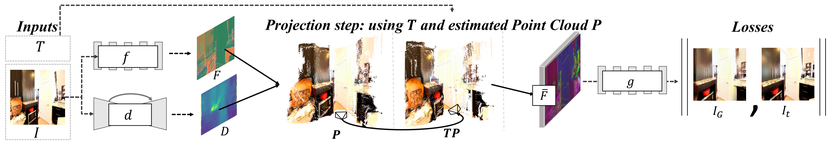


Figure 2: Overview of the training pipeline.

- Given I, SynSin predicts a set of features F at the same resolution as the image and a depth map D
- The depth map Is used to project the features into 3D, creating a point cloud P
- The point cloud is transformed according to the new view using T
- Our **differentiable point cloud renderer** is used to render the point cloud into the new view, creating features $\bar{F}$
- The **refinement network** g is used to fill in missing regions and synthesis an image of the scene at the new viewpoint
- A combination of GANs, L1, and perceptual losses are used to train the model

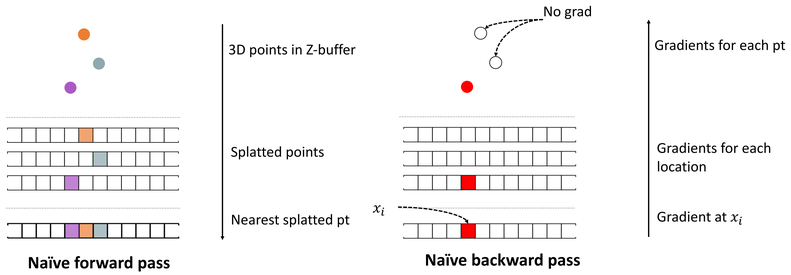
Testing Time:
Given **only** an image of an unseen scene and desired camera viewpoint, the model synthesizes new views of the scene.

NEURAL POINT CLOUD RENDERER

Desired properties:
- End-to-end differentiable
- Differentiate with respect to both the features and 3D positions to train f and d

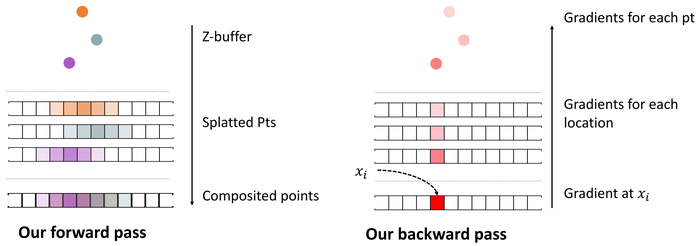
The renderer gives us features $\bar{f}_i$ at 2D locations p_i. As p_i is a function of the depth, this means we need derivatives with respect to both the projected features and the projected location. This is sufficient to train f and d.

NAIVE RENDERER



- Shown in 2D → 1D projections
- **Problems:** Local neighborhoods; Hard Z-buffer

OUR RENDERER



- **Larger neighborhoods:** 3D points are projected to a region with varying weights
  - Weights are proportional to 2D distance, allowing backpropagation to the 2D location p_i
- **Soft z-buffer:** Projected points are composited using alpha compositing
  - All points contribute to the final value
- **Performance:** 36 ms (forward pass), 5 ms (backward pass) for six 512^2 point clouds to 256x256 images. [1] takes ~1000ms (forward pass) and 2000ms (backward pass) for the same set of point clouds.

RESULTS

Baselines:
- Uses same info at train/test: **Vox,** based on [2]; **Im2Im** [3]
- Uses additional info at test: **StereoMag** (2 views) [4]**; 3D Photos** (depth), similar to [5]

Datasets:
- Train on Matterport [6], test on Matterpot and Replica [7]
- Train/test on RealEstate10K [4]

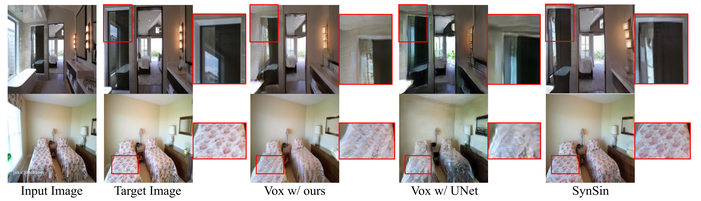


Figure 3: Results on Matterport. SynSin's results are higher quality than those of the baselines.

Figure 4: SynSin's 3D predictions.

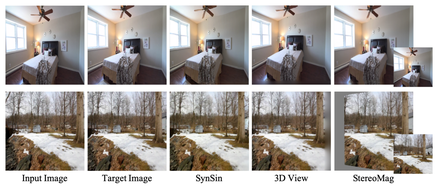


Figure 5: Results on RealEstate10K. SynSin outpaints better and can hallucinate missing regions.

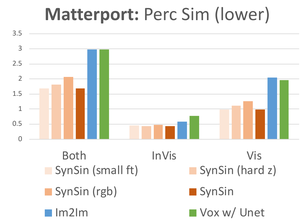


Table 1: Ablations and comparison to baselines on Matterport.

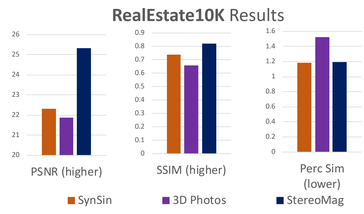


Table 2: Comparison with state of the art methods on RealEstate10K. The other methods use auxiliary information (e.g. depth or multiple views).

REFERENCES

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[6] Chang et al. "Matterport3d: Learning from RGB-D data in indoor environments." 3DV 2017.
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