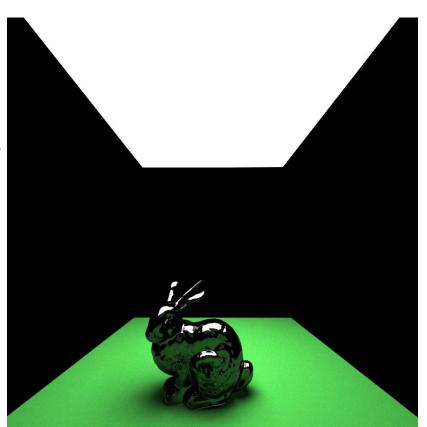
Another Image (AI) Denoiser

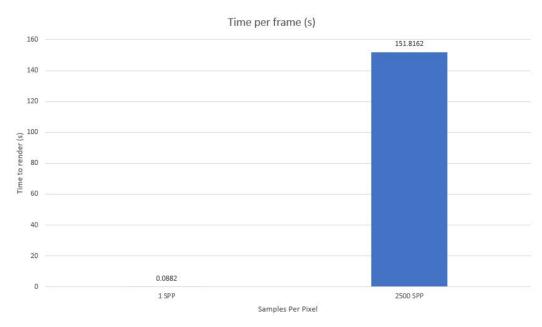
CIS 565 - Vaibhav Arcot (yvarcot@seas.upenn.edu) and Dewang Sultania (dewang@seas.upenn.edu)

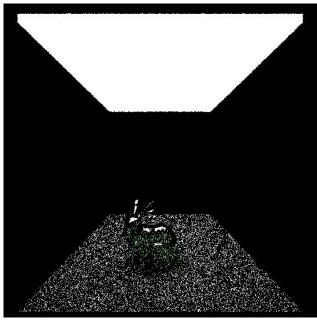
Motivation

- Path Tracing uses random sampling to render a scene
- The metric is Samples Per Pixel (SPP)

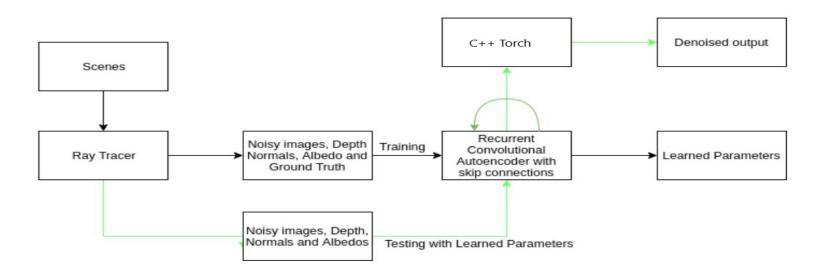


Motivation





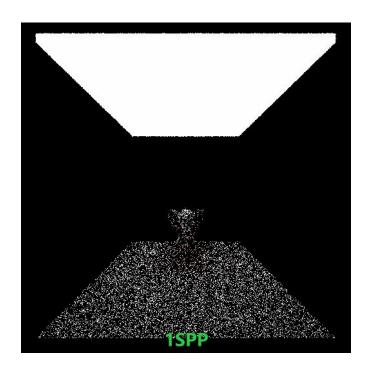
Approach



Data



Data



Denoising Network

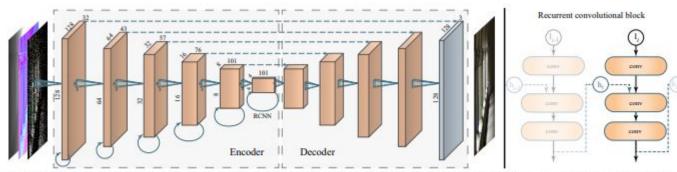


Fig. 2. Architecture of our recurrent autoencoder. The input is 7 scalar values per pixel (noisy RGB, normal vector, depth, roughness). Each encoder stage has a convolution and 2×2 max pooling. A decoder stage applies a 2×2 nearest neighbor upsampling, concatenates the per-pixel feature maps from a skip connection (the spatial resolutions agree), and applies two sets of convolution and pooling. All convolutions have a 3×3 -pixel spatial support. On the right we visualize the internal structure of the recurrent RCNN connections. I is the new input and h refers to the hidden, recurrent state that persists between animation frames.

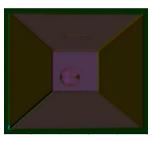
Loss Functions

Spatial L1 Loss



Ground Truth

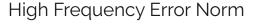
Reduces difference b/w the entire img

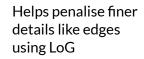


Denoiser Output



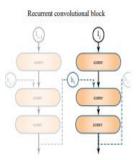
Ground Truth







Temporal Loss

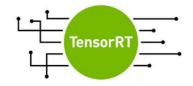


Speeding Up Inference







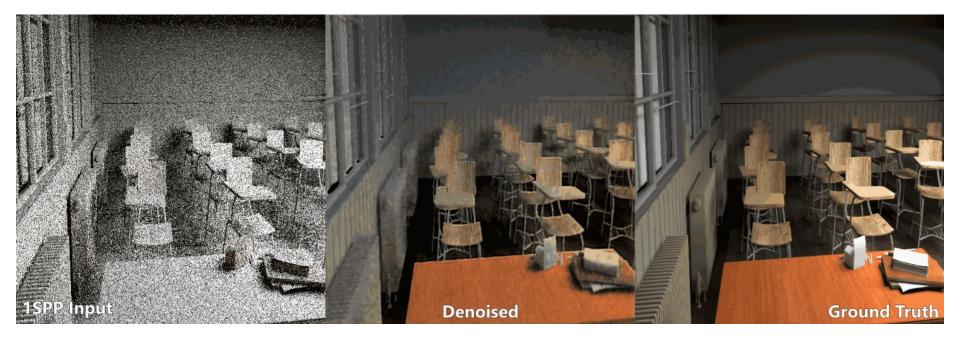




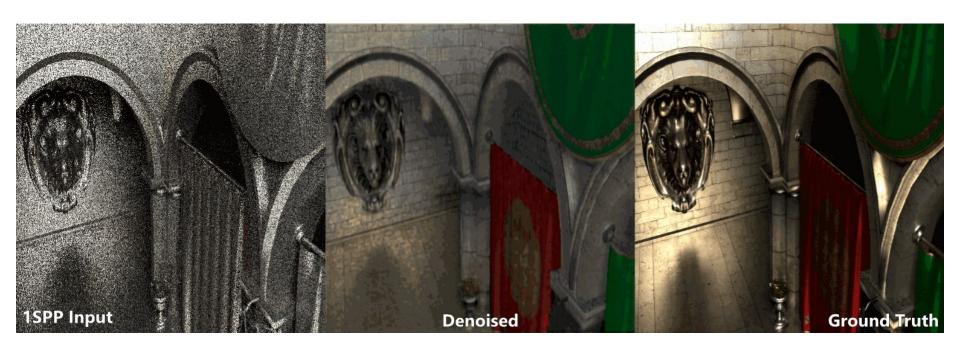
Trained On



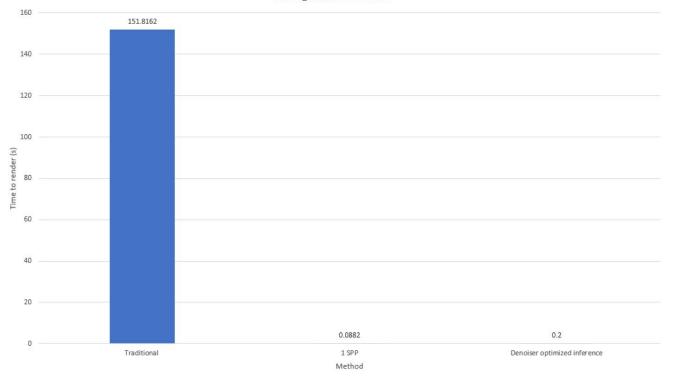
Never seen before



Never seen movement







Demo

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- We would also like to thank our shadow team (DroneMoM) for all their inputs

Thank You



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