RenderNet: A deep convolutional network for differentiable rendering from 3D shapes

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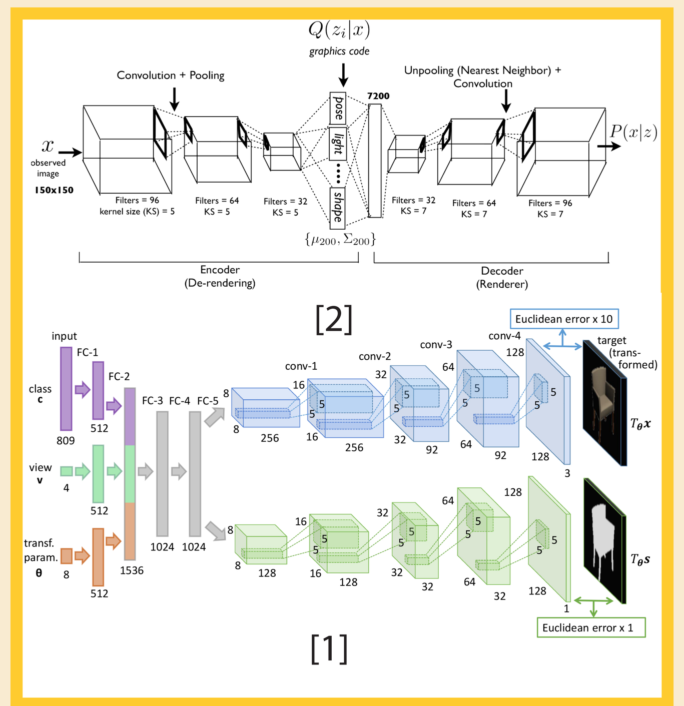
ADVANTAGES

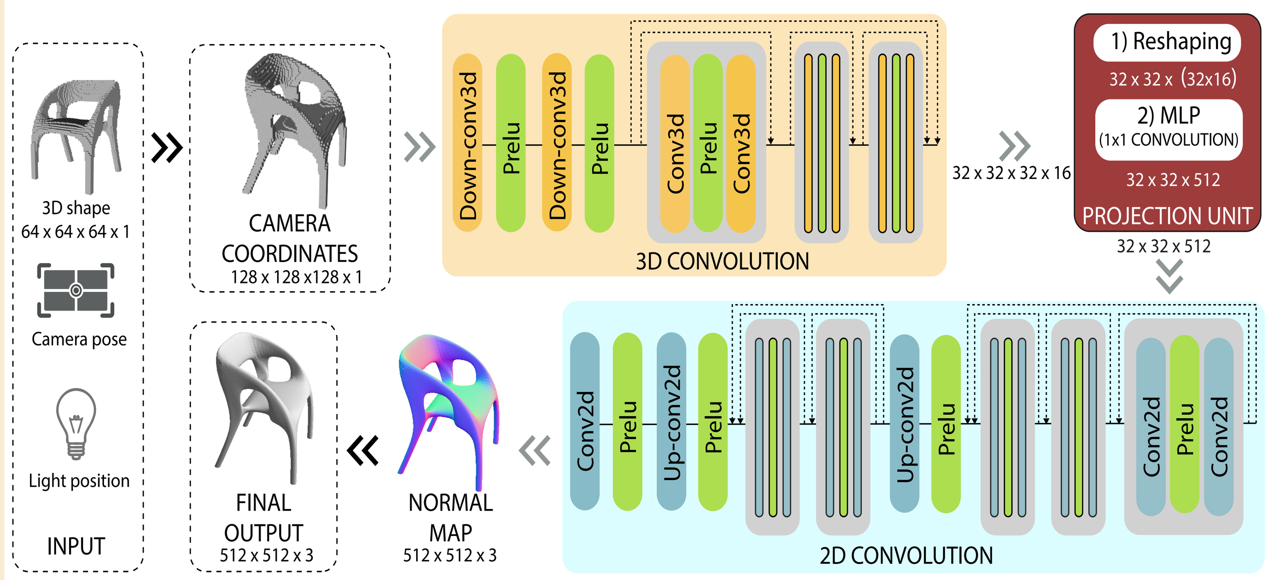
- A novel CNN architecture that enables both rendering and inverse rendering.
- Generalizes well to objects of unseen category and more complex scene geometry.
- Capable of producing textured images from textured voxel grids, where the input textures can be RGB colors or deep features computed from semantic inputs.
- Easy to integrate into other modules for applications, such as texturing or image-based reconstruction.

CURRENT APPROACHES

- Focus on losses and training regimes
- Make few assumptions about the 3D world and the image formation process
- Rotation in latent space using a CNN is hard! [1, 2]
- Do not generalise well to different object categories
- Current differentiable renderers are limited to a single fixed shader. [3, 4]



METHOD



- Rigid-body transformation (world coordinate system to camera coordinate system) followed by trilinear resampling.
- 3D convolutions morph the scene and enable perspective camera views.
- 2D convolutions compute shading color for each pixel
- Projection unit:

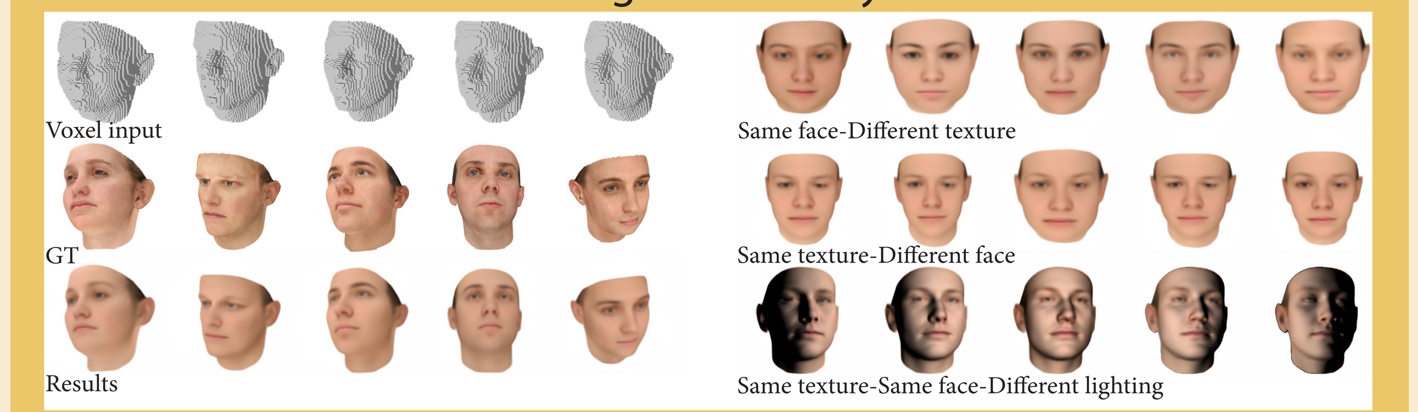
$$I_{i,j,k} = f\left(\sum_{dc} w_{k,dc} \cdot V'_{i,j,dc} + b_k\right)$$

- Pixel-wise loss function:

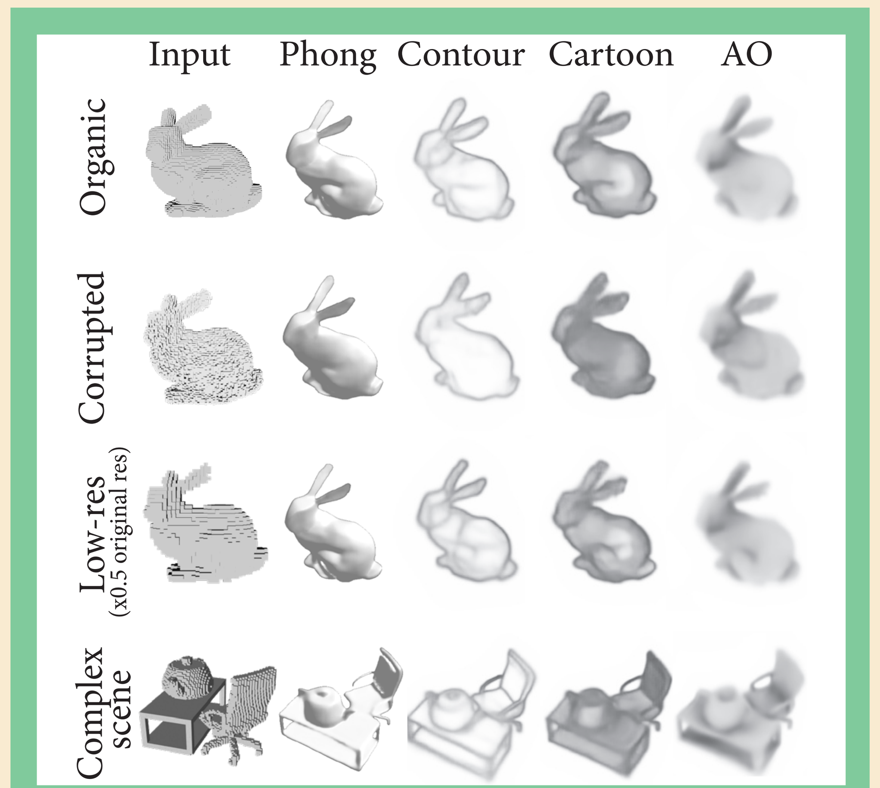
$$L_{recon} = \frac{1}{n}\sum_{i}^{n} ||y_i - y'_i||^2$$

RENDERING RESULTS

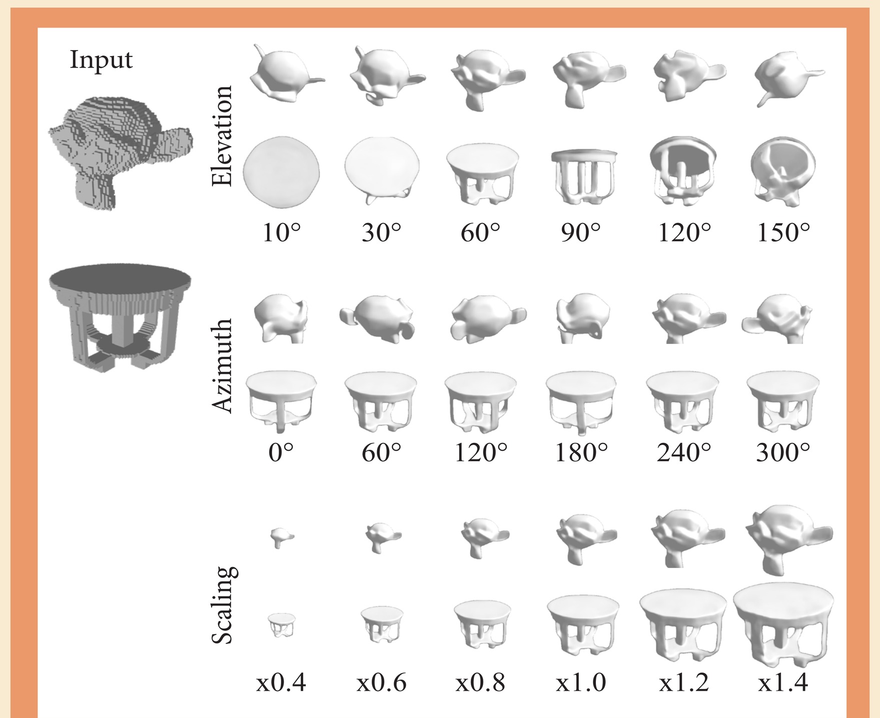
Rendering different styles



Rendering textures



Generalisation



Rigid transformation test

INVERSE RENDERING RESULTS

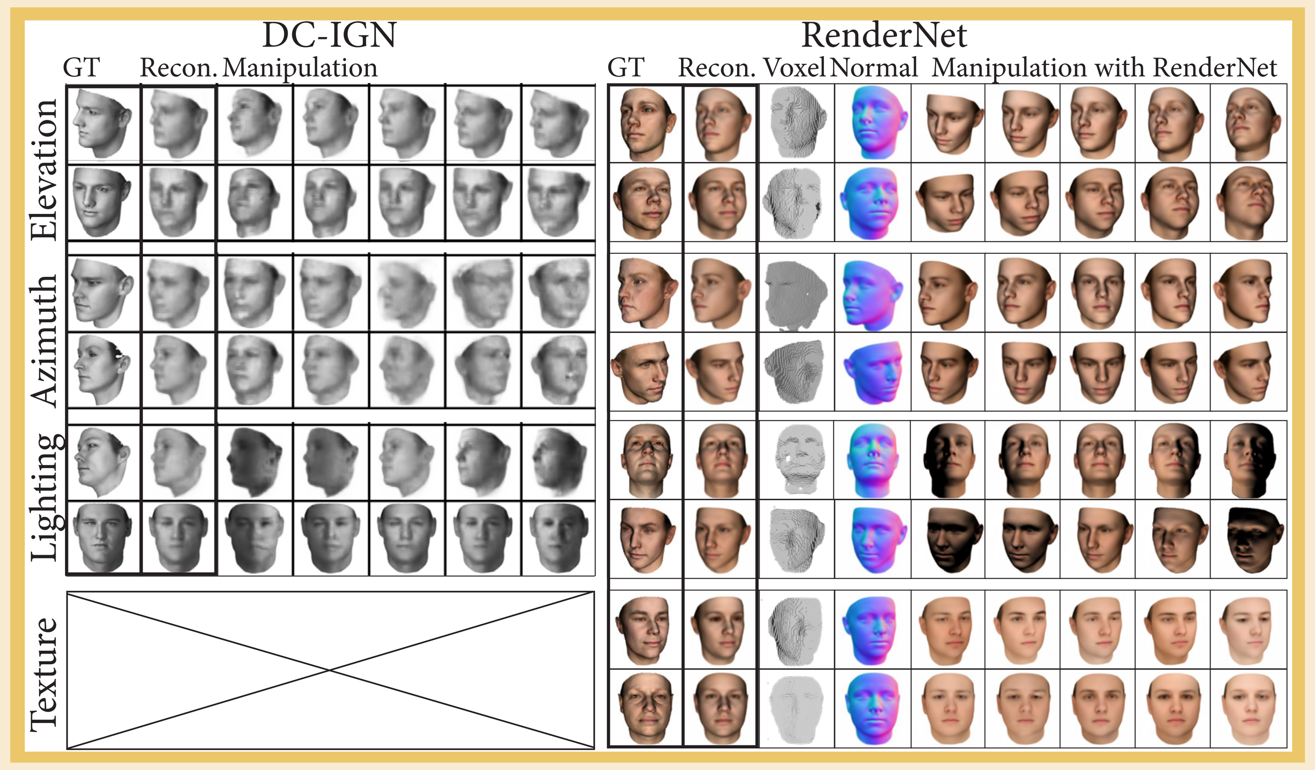
MAP estimation:

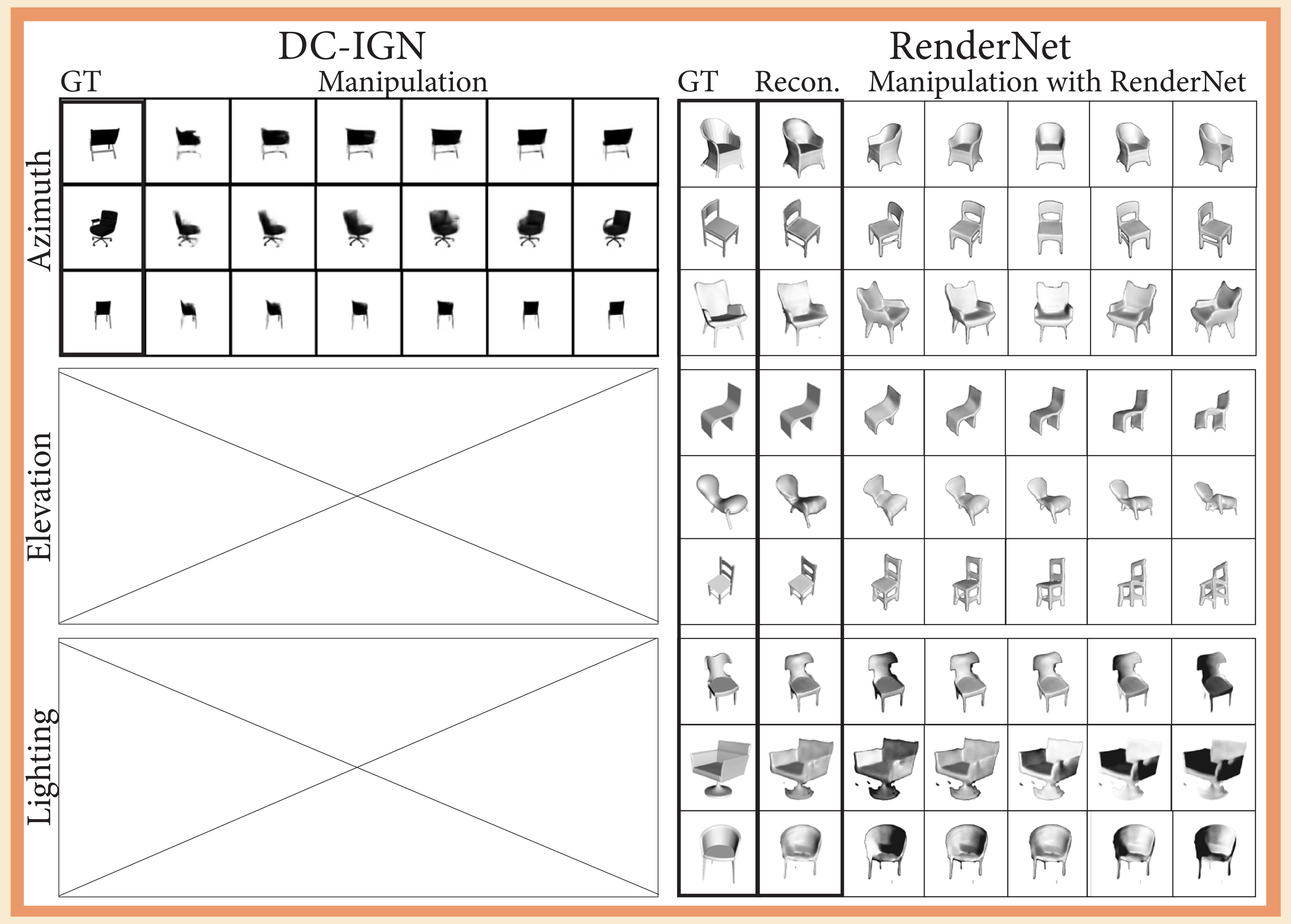
$$\underset{z',\theta,\phi',\eta}{\text{minimize}} \quad ||I - f(g(z'), \theta, h(\phi'), \eta)||^2$$

where I is the observed image and f is our pre-trained RenderNet. z' is the shape vector to reconstruct, g is the decoder of a pretrained 3D auto-encoder, θ and η are the pose and lighting parameters, and Φ is the texture vector.

$$\underset{z,\theta}{\text{minimize}} \quad \alpha||I - f(g(z'), \theta)||^2 + \beta(z-\mu)^T\Sigma^{-1}(z-\mu)$$

where μ and Σ are the mean and covariance of z' estimated from the training set respectively.





COMPARISON

PSNR score	
Name	PSNR
RenderNet Phong	25.39
EC Phong	24.21
EC-Deep Phong	20.88
RenderNet Contour	19.70
RenderNet Toon	17.77
RenderNet AO	22.37
RenderNet Face	27.43

DISCUSSSION

- Using adversarial loss instead of MSE or BCE
- Using more efficient voxel representation (octree)
- Considering other 3D data types (mesh, point clouds, etc.)
- Learning multiple shaders with one network

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Code available on GITHUB