Texture Fields

Learning Texture Representations in Function Space

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DRIVING EMBEDDED EXCELLENCE

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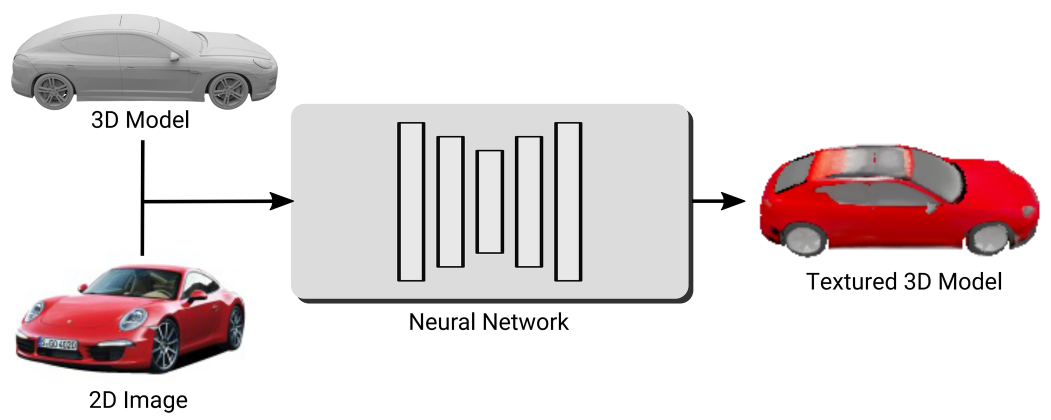
1. Motivation

Deep learning has achieved impressive results

- for image and texture generation in the **2D domain**
- for learning-based reconstruction of **3D geometry.**

However, texture generation in the 3D domain lacks far behind.

Major problem: Representation of texture in 3D



2. Existing Texture Representations

Colored Voxels

- \+ Grid structure
- − Memory requirement
- − Low-frequency texture

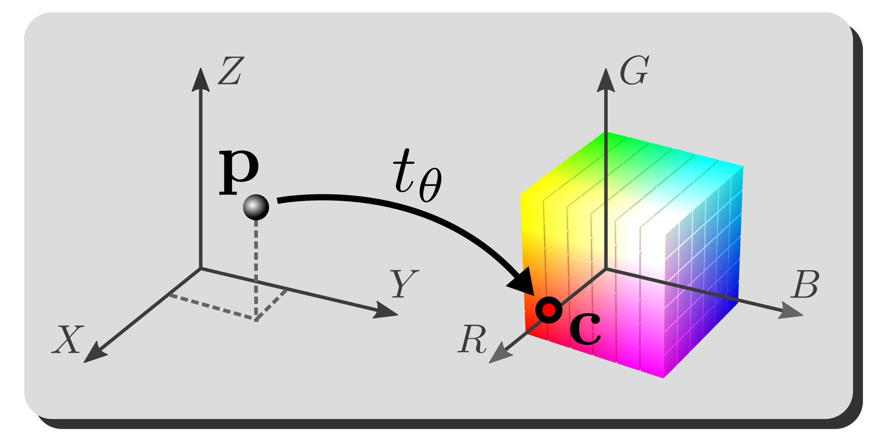
Texture Atlas

- \+ High-frequency texture
- − Template required
- − Discontinuities

3. Our Representation

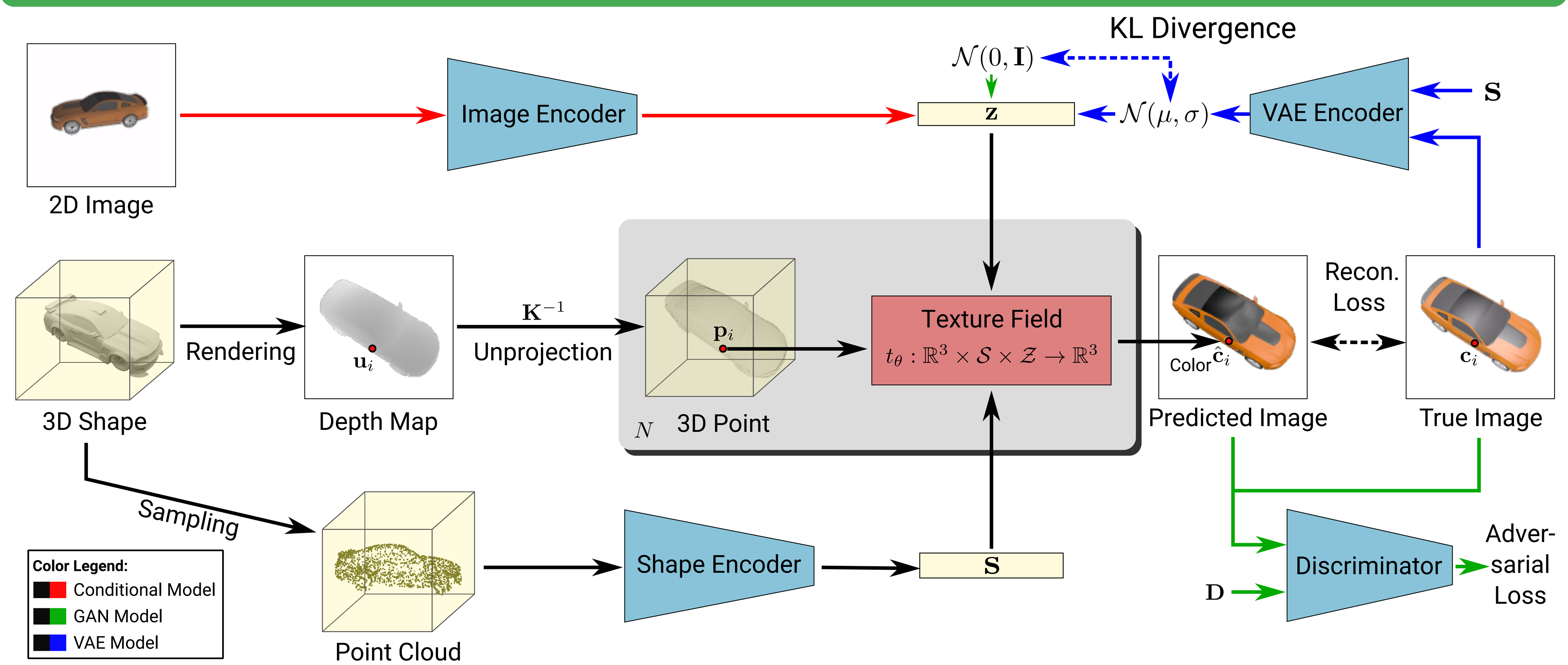
Idea: Represent texture as continuous 3D field $t_\theta : \mathbb{R}^3 \rightarrow \mathbb{R}^3$

- \+ No discretization
- \+ No template required
- \+ Independent of shape representation



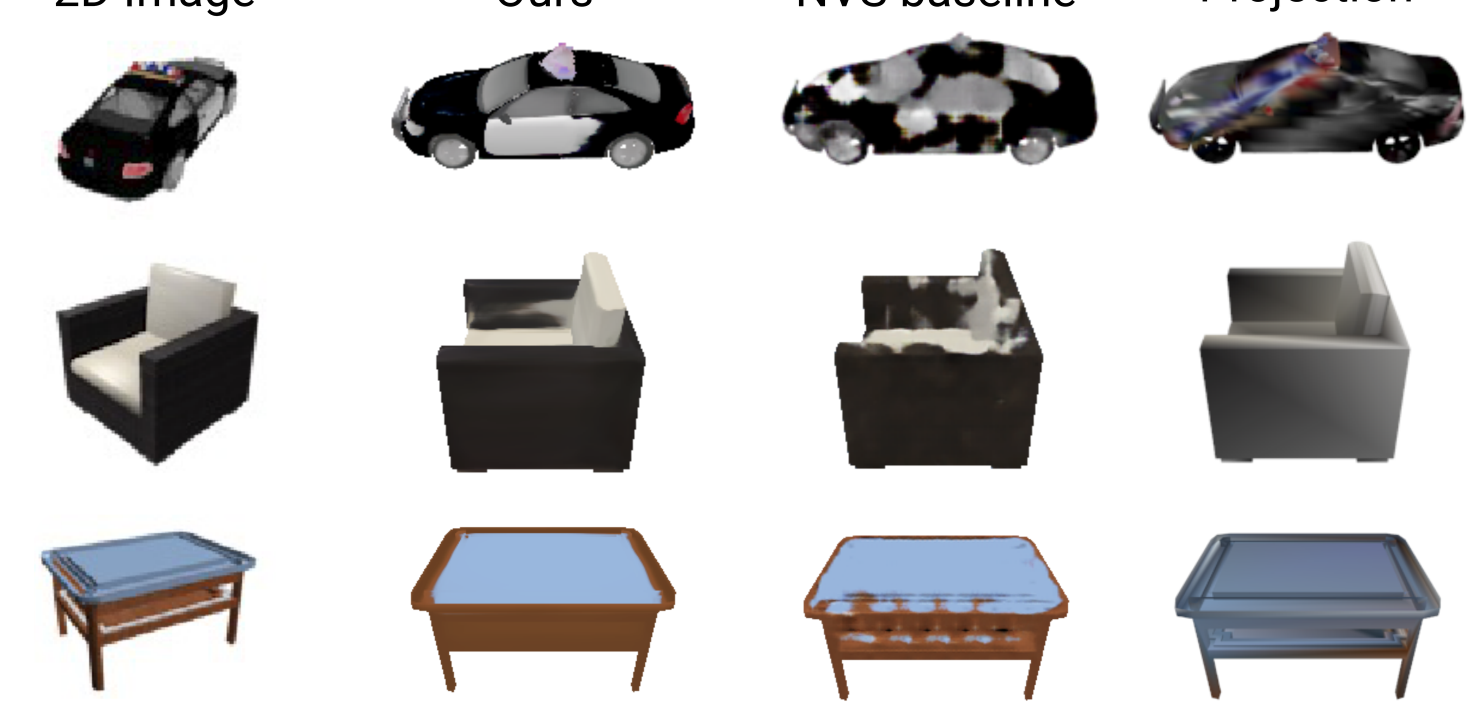
For learning texture reconstruction, we condition the Texture Field on an image and an untextured 3D model.

4. Our Model



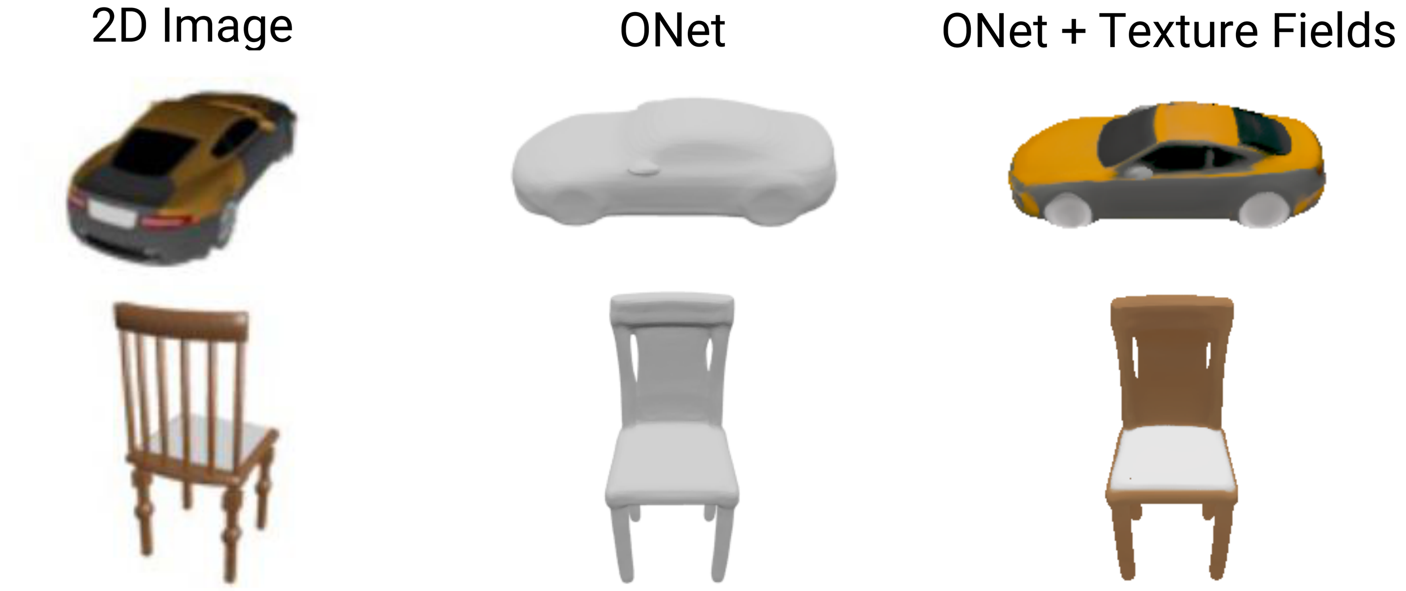
5. Experiments - Texture Reconstruction

Texture from a Single Rendered Image



Texture from a Single Real Image

Full Pipeline



Quantitative Evaluation

	FID	SSIM	Feature-ℓ_1
Projection	23.379	0.919	0.162
NVS	28.370	**0.939**	0.164
Texture Field	**14.801**	0.937	**0.149**

Texture from a Single Rendered Image

	FID	SSIM	Feature-ℓ_1
Projection	65.745	0.850	0.229
Im2Avatar	141.209	0.734	0.281
NVS	73.223	**0.870**	0.228
Texture Field	**59.424**	**0.870**	**0.217**

Full Pipeline with ONet

Blog

with slides, videos and more

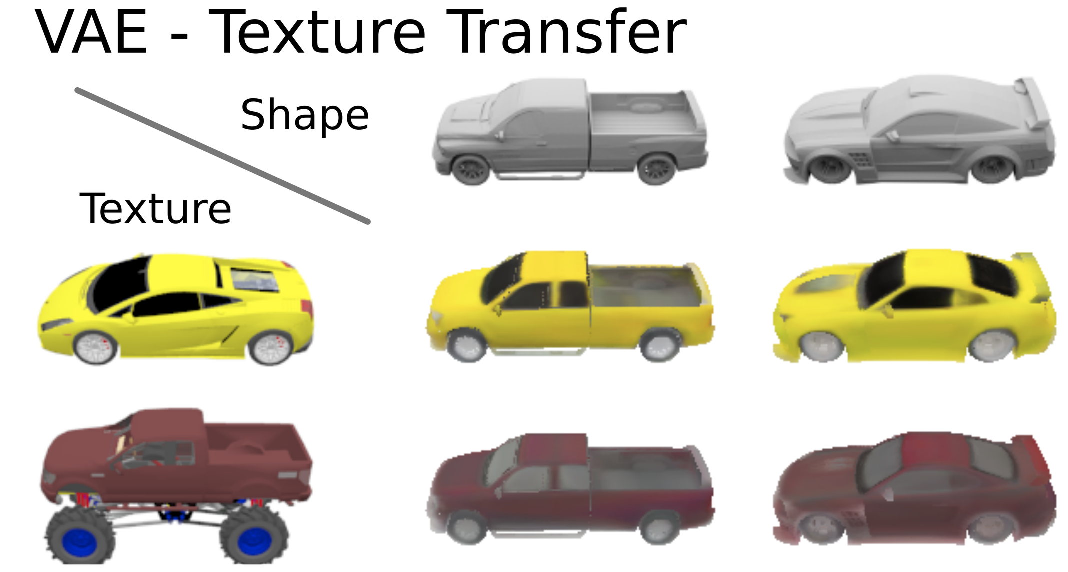
tiny.cc/texfield

6. Experiments - Generative Model

VAE - Samples

GAN - Samples

VAE - Texture Transfer



VAE - Latent Space Interpolations

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