Intrinsic Neural Fields: Learning Functions on Manifolds

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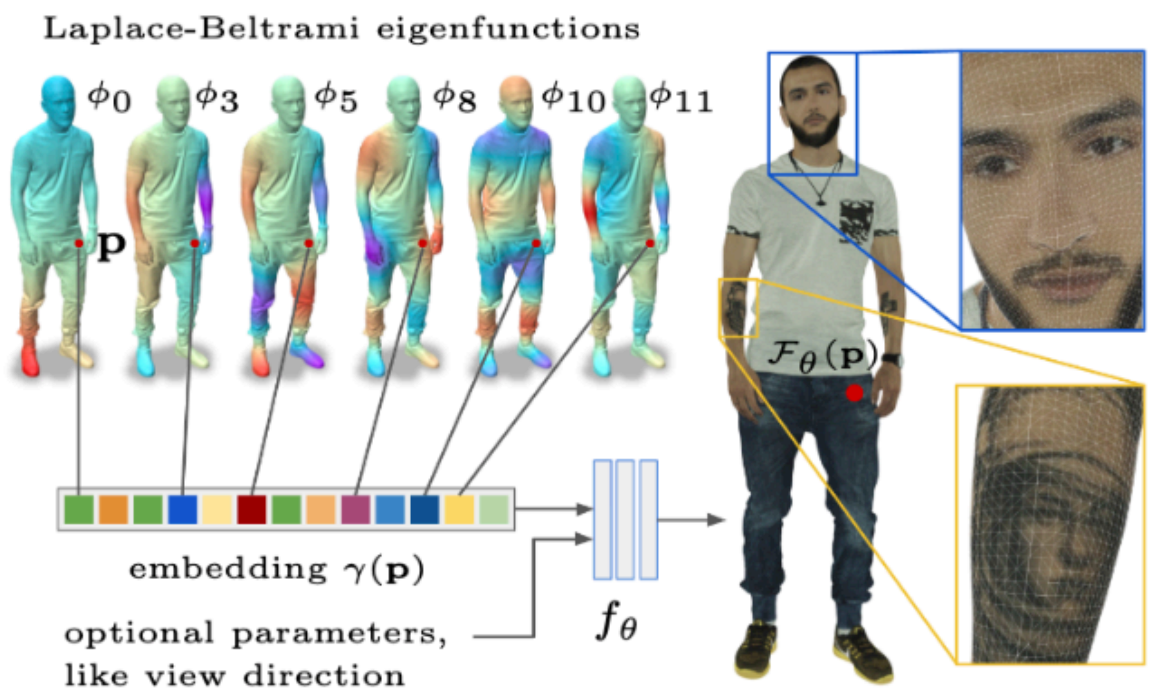
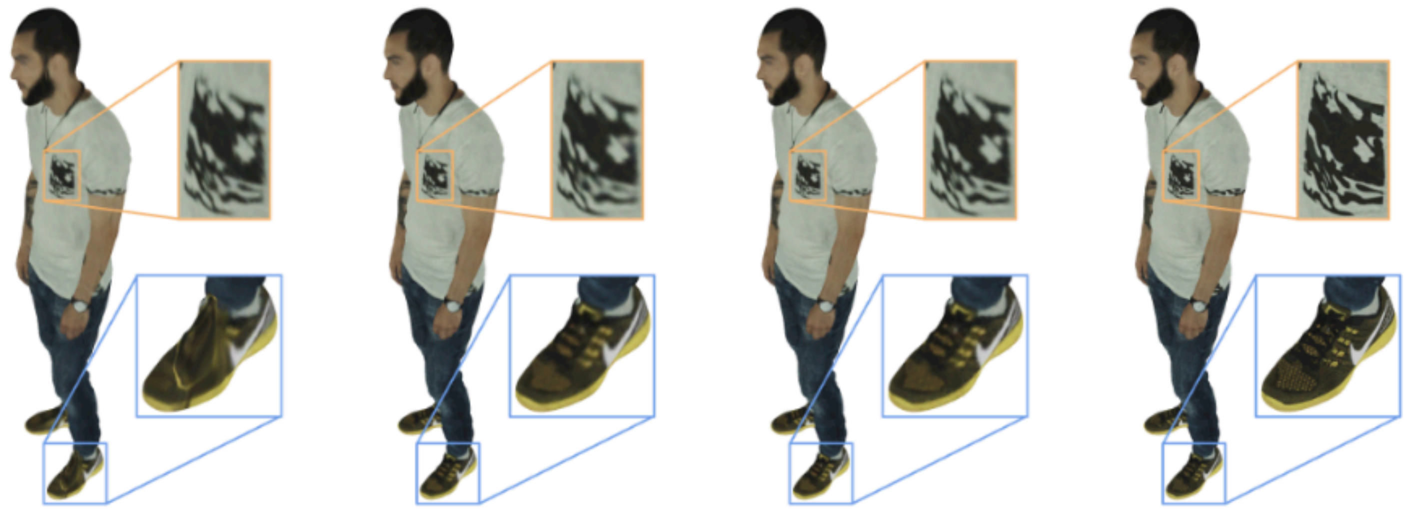
Summary



Intrinsic neural fields offer a novel representation for neural fields on manifolds combining the advantages of neural fields with the spectral properties of the Laplace-Beltrami operator.

Texture Reconstruction



NeuTex[3] TF[2]+RFF[1] Ours GT

We can also consider optional parameters, such as view dependence:

Baseline Ours GT Image

Neural Tangent Kernel Analysis

We define a kernel

$$k : \mathcal{M} \times \mathcal{M} \to \mathbb{R}$$

to be **stationary** if it can be written as

$$k(\mathbf{p}, \mathbf{q}) = \sum_i \hat{k}(\lambda_i)\phi_i(\mathbf{p})\phi_i(\mathbf{q}) \quad (4)$$

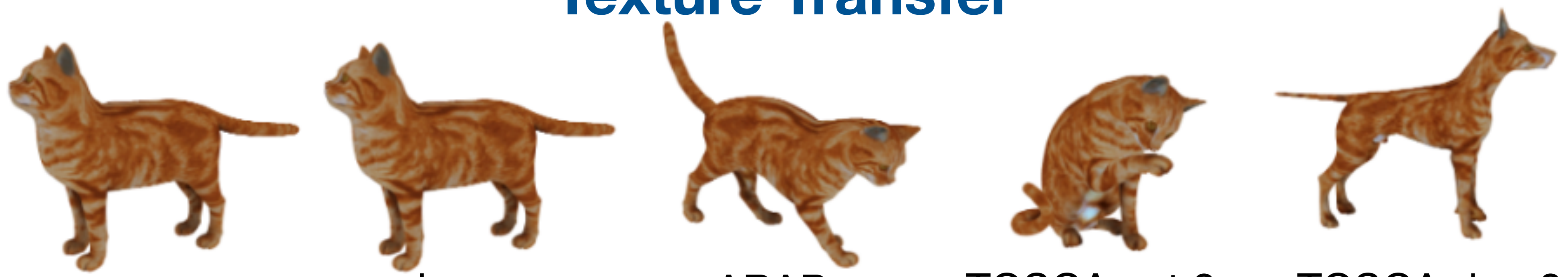
XYZ RFF Ours

Theorem 1. *Let $\mathcal{M}$ be $\mathbb{S}^n$ or a closed 1-manifold. Let $(\lambda_i, \phi_i)_{i=1,\ldots,d}$ be the positive, non-decreasing eigenvalues with associated eigenfunctions of the Laplace-Beltrami operator on $\mathcal{M}$. Let $a_i \geq 0$ be coefficients s.t. $\lambda_i = \lambda_j \Rightarrow a_i = a_j$, which define the embedding function $\gamma : \mathcal{M} \to \mathbb{R}^d$ with $\gamma(\mathbf{p}) = (a_1\phi_1(\mathbf{p}), \ldots, a_d\phi_d(\mathbf{p}))$. Then, the composed neural tangent kernel $\mathrm{k}_{NTK} : \mathcal{M} \times \mathcal{M} \to \mathbb{R}$ of an MLP with the embedding γ is stationary as defined in Eq. 4.*

Contributions

- A novel and versatile **representation for neural fields on manifolds**.
- We extend the **neural tangent kernel analysis** of Fourier features[1] to the manifold setting.
- We show state-of-the-art quality for **high-fidelity texture reconstruction**.
- We demonstrate the versatility of our method through **various applications**: texture transfer, texture reconstruction with view dependence, and discretization-agnostic learning on meshes and point clouds.

Texture Transfer



source dense ARAP TOSCA cat 2 TOSCA dog 0

Discretization-Agnostic Learning

original iso dense qes cloud↓

Evaluations: Texture Reconstruction

		NeuTex[3]	TF[2]+RFF[1]	Ours
cat	PSNR↑	31,96	34,39	**34,82**
	DSSIM↓	0,212	0,097	**0,095**
	LPIPS↓	0,266	0,205	**0,153**
human	PSNR↑	29,22	32,26	**32,48**
	DSSIM↓	0,306	0,129	**0,121**
	LPIPS↓	0,669	0,336	**0,306**

Demo

Code Paper Data

[1]Tancik, M., Srinivasan, P.P., Mildenhall, B., Fridovich-Keil, S., Raghavan, N., Singhal, U., Ramamoorthi, R., Barron, J.T., Ng, R. Fourier Features let networks learn high frequency functions in low dimensional domains. *Conference on Neural Information Processing Systems (NeurIPS)*, 2020
[2]Oechsle, M., Mescheder, L.M., Niemeyer, M., Strauss, T., Geiger, A. Texture Fields: Learning texture representations in function space. *IEEE International Conference on Computer Vision (ICCV)*, 2019
[3]Xiang, F., Xu, Z., Hasan, M., Hold-Geoffroy, Y., Sunkavalli, K., Su, H. NeuTex: Neural texture mapping for volumetric neural rendering. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021