Discretization-Agnostic Deep Self-Supervised 3D Surface Parameterization

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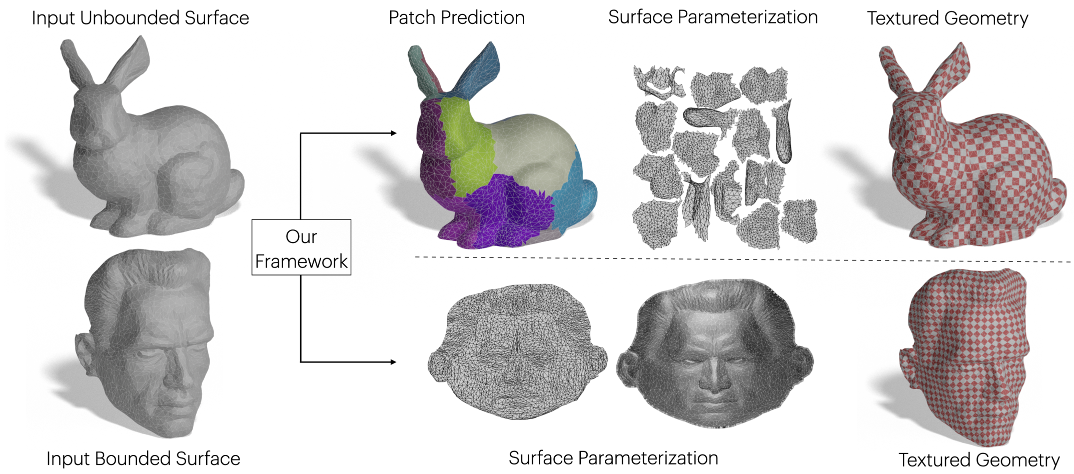

Figure 1: UV parameterization for bounded and unbounded surfaces estimated via our proposed framework.

ABSTRACT

We present a novel self-supervised framework for learning the discretization-agnostic surface parameterization of arbitrary 3D objects with both bounded and unbounded surfaces. Our framework leverages diffusion enabled global-to-local shape context for each vertex to first partition the unbounded surface into multiple patches using proposed self-supervised PatchNet and subsequently perform independent UV parameterization of these patches by learning forward and backward UV mapping for individual patches. Thus, our framework enables learning a discretization-agnostic parameterization at a lower resolution and then directly infer the parameterization for a higher resolution mesh without retraining. We evaluate our framework on multiple 3D objects from publicly available SHREC [Lian et al. 2011] dataset and report superior/faster UV parameterization over conventional methods.

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CCS CONCEPTS

• **Computing methodologies** → **Parametric curve and surface models**; **Neural networks**.

KEYWORDS

UV parameterization, texture mapping, , neural network, self-supervised learning, surface parameterization.

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1 INTRODUCTION

Estimating the UV parameterization of arbitrary 3D surfaces lies at the core of computer graphics and geometry processing domain, with a wide range of applications such as 3D modeling, texture-mapping, remeshing, simulation, etc. Formally, it is defined as the projection of vertices of a tessellated surface (polygon mesh) onto a 2D map (UV plane). Determining the aforementioned mapping is not a trivial task and demands a solution with specific properties. The estimated mapping is expected to be isometric, conformal, and non-overlapping. Existing conventional methods [Lévy et al. 2002; Li et al. 2018; Sander et al. 2001; Sawhney and Crane 2017; Wang et al. 2013] aim to estimate an object-centric mapping with an iterative optimization process, focusing on minimizing an energy function explicitly constructed to retain the desired properties. However, they face scalability issues while dealing with high-resolution object meshes and are also prone to local minima.

With the advent of deep learning, researchers are harnessing the power of neural networks to solve various ill-posed problems, offering tractable solutions. Neural surface parameterization has recently been attempted [Aigerman et al. 2022] but under supervised, data-driven settings, requiring a large amount of training data. Such supervised learning solutions get subjected to data bias and hence suffer from poor generalization to unseen, out-of-distribution samples.

In this paper, we present a novel, self-supervised framework for learning the discretization-agnostic surface parameterization of arbitrary 3D objects with both bounded and unbounded surfaces as shown in Figure 1. First, to handle unbounded surfaces (e.g., a sphere) or surfaces with regions of extreme extrinsic-curvature, we propose a learning-based partitioning of the given surface into multiple bounded patches, which are independently parameterized. To this end, we employ a self-supervised network that assigns each 3D point of the surface to one of the patches, trained using losses based on local features (such as face-normals) and geodesic relationships within the patch.

Subsequently, we propose to learn the surface parameterization of an arbitrary (bounded) 3D surface to a UV plane using a *Multi-layer Perceptron* (MLP). More specifically, given a *bounded* 3D surface (patch), we train the forward MLP to predict per-point UV coordinates independently. In order to ensure a meaningful UV mapping, we enforce cycle-consistency loss between the input and reconstructed surface by learning a backward mapping (UV-to-3D) MLP. Additional losses are employed to achieve desired properties of surface parameterization, i.e., isometric, conformal, and area-preserving. A diffusion process [Sharp et al. 2020] over the mesh provides multi-scale characterization of the underlying surface, entailing a global-to-local context for each of the vertex and hence DiffusionNet backbone is used for PatchNet, and similarly, respective features are appended while learning surface parameterization in order to achieve discretization-agnostic UV mapping. A key advantage of learning a discretization-agnostic parameterization is that we can learn on meshes at a lower resolution and then directly infer the parameterization for high resolution meshes without retraining, as shown in Figure 3.

2 RELATED WORK

Conventional methods for mesh parameterization can be categorised as *single-patch, fixed boundary* methods, e.g., harmonic parameterization [Wang et al. 2013], *single-patch, free boundary* methods, e.g., LSCM [Lévy et al. 2002]; and *global parameterization* methods, e.g., Voronoi atlas parameterization [Sander et al. 2001]. Global parameterization methods can deal with meshes of arbitrary genus. They achieve this by either partitioning the unbounded mesh into multiple bounded patches or detecting one or more seams to cut the mesh, making it bounded. Boundary-First Flattening [Sawhney and Crane 2017] and OptCuts [Li et al. 2018] fall into this class.

Neural parameterization methods have been gaining popularity over the past few years due to their ability to address ill-posed problems. AtlasNet [Groueix et al. 2018], and DGP [Williams et al. 2018] propose a way of surface reconstruction and parameterization

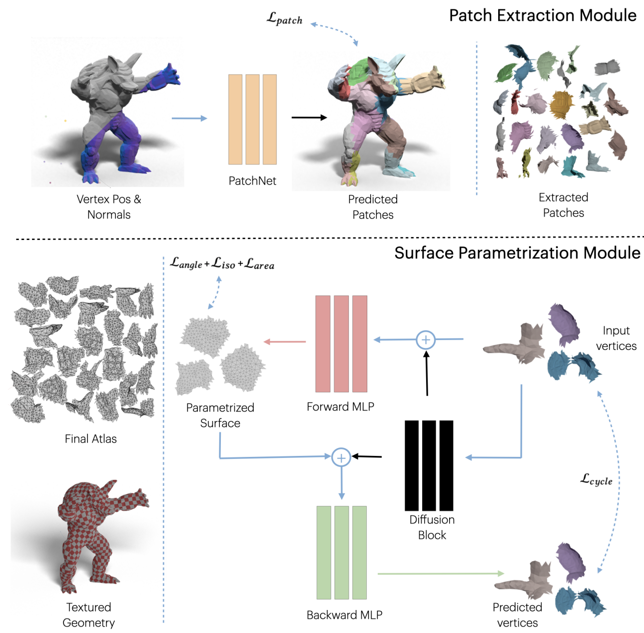

Figure 2: The outline of proposed framework.

by training a neural network to represent a single UV chart over the reconstructed surface. Both the methods use a fixed number of patches for the surface parameterization but require a different neural network for every patch, which is an overkill and difficult to scale up. A recent work AUV-Net [Chen et al. 2022] takes a point cloud as input and learns parameterization of aligned surfaces (e.g., faces and humans in T-poses) using a cycle-loss, but requires all the meshes to have similar topology and same orientation to enable learning. Moreover, the proposed two-patch estimation method is very naive and cannot scale to an arbitrary number of patches. Another recent method [Aigerman et al. 2022] learns intrinsic mapping of arbitrary surfaces in a supervised setup, where a conventional method acts as the ground truth. However, it can only deal with bounded surfaces and does not provide its provision for unbounded surfaces (e.g., spheres).

3 METHOD

We now describe the proposed framework in detail. The input to our framework is a mesh $\mathcal{M} = \{\mathcal{V}, \mathcal{F}, \mathcal{N}_V\}$, where $\mathcal{V}$, $\mathcal{F}$ and $\mathcal{N}_\mathcal{V}$ are the sets of vertex positions, faces and vertex-normals respectively. Our framework consists of two modules: (i) Patch extraction module and (ii) Surface parameterization module.

3.1 Patch Extraction Module

Handling surfaces with regions of high extrinsic curvature or unbounded topology requires the 3D manifold to be partitioned into multiple bounded patches to minimize distortion and overlap. Each patch is defined as $\mathcal{P}_k = \{\mathcal{V}_k, \mathcal{F}_k, \mathcal{N}_{Fk}\}$ ($k = 1, 2, \dots K$), where $\mathcal{V}_k \subseteq \mathcal{V}$ is the set of vertices belonging to $\mathcal{P}_k$. $\mathcal{F}_k \subseteq \mathcal{F}$ is the set of faces defined on $\mathcal{V}_k$ and $\mathcal{N}_{Fk} \subseteq \mathcal{N}_F$ is the associated set of face-normals. We propose PatchNet with parameters ϕ_{patch}, which

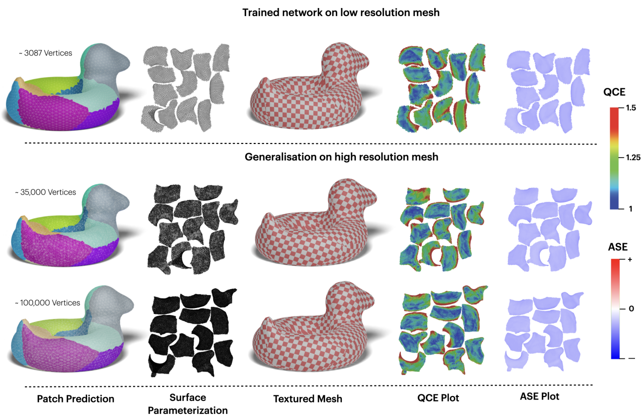

Figure 3: Discretization-agnostic UV parameterization.

learns to assign each vertex of $\mathcal{M}$ to one of the K patches, as shown in Figure 2. Here, K is a controllable parameter and can vary based on the acceptable amount of distortion in the input mesh. To learn the parameters ϕ_{patch} we minimize the following cosine similarity constraint on the estimated patches:

$$\mathcal{L}_{cos} = \sum_{k=1}^{K} \frac{1}{|\mathcal{F}_k|} \left[1 - \left(\sum_{i,j \in \mathcal{F}_k} (\hat{n_i}^T \hat{n_j}) \right) \right]^2 \tag{1}$$

where $i, j \in \mathcal{F}_k$ are the pair of faces with unit normal vectors $\hat{n_i}, \hat{n_j} \in \mathcal{N}_{Fk}$, respectively, and $|\mathcal{F}_k|$ is the number of faces in that patch. The above constraint has the effect of producing locally flat patches. However, it is possible that geodesically far apart triangles with high cosine similarity will be assigned to the same patch, which is undesirable. To circumvent such disjoint assignments, we minimize the following additional constraint:

$$\mathcal{L}_{geo} = \sum_{k=1}^{K} \frac{1}{|\mathcal{P}_k|} \left(\sum_{i,j \in \mathcal{V}_k} g(i,j) \right) \tag{2}$$

where $g(i, j)$ denotes the geodesic distance between the pair of vertices i & j within the patch and $|\mathcal{P}_k|$ is the number of vertices in that patch. We model PatchNet using DiffusionNet [Sharp et al. 2020] architecture in order to achieve multi-scale characterization of the underlying surface, entailing a global-to-local context for all the vertices. Input to PatchNet is the vertices $\mathcal{V}$ and vertex-normals $\mathcal{N}_V$ and the output is predicted assignment probability for all the vertices to each of the K patches. Subsequently, per-face probabilities are obtained by taking the mean probabilities of the corresponding face vertices. We further consolidate the per-face probabilities by taking an average over neighboring faces and then each face is assigned to the patch with the highest probability. Note that, in case of bounded surface with extrinsic curvature of low-variability, the whole mesh can be considered as a single patch. The combined objective function for patch extraction becomes $\mathcal{L}_{patch} = \lambda_{cos}\mathcal{L}_{cos} + \lambda_{geo}\mathcal{L}_{geo}$.

3.2 Surface Parameterization Module

Each patch $\mathcal{P}_k = \{\mathcal{V}_k, \mathcal{F}_k, \mathcal{N}_k\}$ is treated as a separate bounded surface and is independently parameterized. Let $f : \mathbb{R}^3 \to \mathbb{R}^2$ be the mapping of each vertex $v \in \mathcal{V}_k$ to a 2D point u on the UV plane. We propose to represent f using a *forward* mapping network MLP_f with learnable parameters ϕ_f. First, the set of vertices $\mathcal{V}_k$ for the given patch is passed to the diffusion block to get a global shape encoding $\psi \in \mathbb{R}^{128}$. Per-vertex input given to MLP_f is $z \in \mathbb{R}^{131}$ (v concatenated with ψ) and the output is $u \in \mathbb{R}^2$ (UV coordinate), i.e. $u = MLP_f(z)$. Since we don't have corresponding ground truth UV coordinates, we resort to a self-supervised cycle-consistency loss. We employ another $MLP_{f^{-1}}$ with learnable parameters $\phi_{f^{-1}}$ to represent the *backward* mapping $f^{-1} : \mathbb{R}^2 \to \mathbb{R}^3$. $MLP_{f^{-1}}$ takes u as input and predicts its corresponding 3D position, which ideally should match with the input vertex position v . We enforce this consistency by minimizing the following cycle loss:

$$\mathcal{L}_{cycle} = \frac{1}{|\mathcal{V}_k|} \sum_{v \in \mathcal{V}_k} \left(v - MLP_{f^{-1}}(u) \right)^2 \tag{3}$$

Note that due to presence of non-linear activation functions in MLP_f and $MLP_{f^{-1}}$, the condition $\phi_f . \phi_{f^{-1}} = I$ need not ehold. Per-vertex prediction can be noisy, resulting in an irregular UV space. Conditioning the MLPs with the diffusion-based global shape-encoding ψ regularizes the UV prediction and improves the output of $MLP_{f^{-1}}$. We further add losses to enforce desired properties of surface parameterization, namely, L_{iso} provides isometric behaviour, L_{angle} preserves angles of the faces and L_{area} preserves face-area (neglecting uniform scaling). The final objective function for surface parameterization is given as:

$$\mathcal{L}_{uv} = \lambda_1 \mathcal{L}_{cycle} + \lambda_2 \mathcal{L}_{iso} + \lambda_3 \mathcal{L}_{angle} + \lambda_4 \mathcal{L}_{area}. \tag{4}$$

4 RESULTS & EVALUATION

We compute Quasi-Conformal Error (QCE) and Area Scale Error (ASE) on the final texture atlas for quantitative and qualitative evaluation. Please refer to supplementary for their description.

Qualitative Comparison: We compare our framework with BFF[Sawhney and Crane 2017] and OptCuts[Li et al. 2018] in Figure 4. As shown our framework performs on-par with these methods on varying geometrical shapes.

Quantitative Comparison: In Table 1, we compare our framework with BFF[Sawhney and Crane 2017] and Opt-Cuts[Li et al. 2018]

	BFF		OptCuts		Ours	
Class	QCE↓	|ASE|↓	QCE↓	|ASE|↓	QCE↓	|ASE|↓
Laptop	1.046	2.052	**1.045**	**2.005**	1.196	2.420
Pliers	**1.112**	1.909	1.128	**1.391**	1.274	2.895
Rabbit	**1.132**	2.116	1.160	**2.062**	1.183	0.992
Scissors	1.156	1.456	**1.122**	**1.276**	1.261	2.728
Bird	2.130	**1.103**	**1.129**	1.928	1.262	1.996

Table 1: Comparison of QCE and ASE metrics with BFF [Sawhney and Crane 2017] and OptCuts [Li et al. 2018] on SHREC dataset.

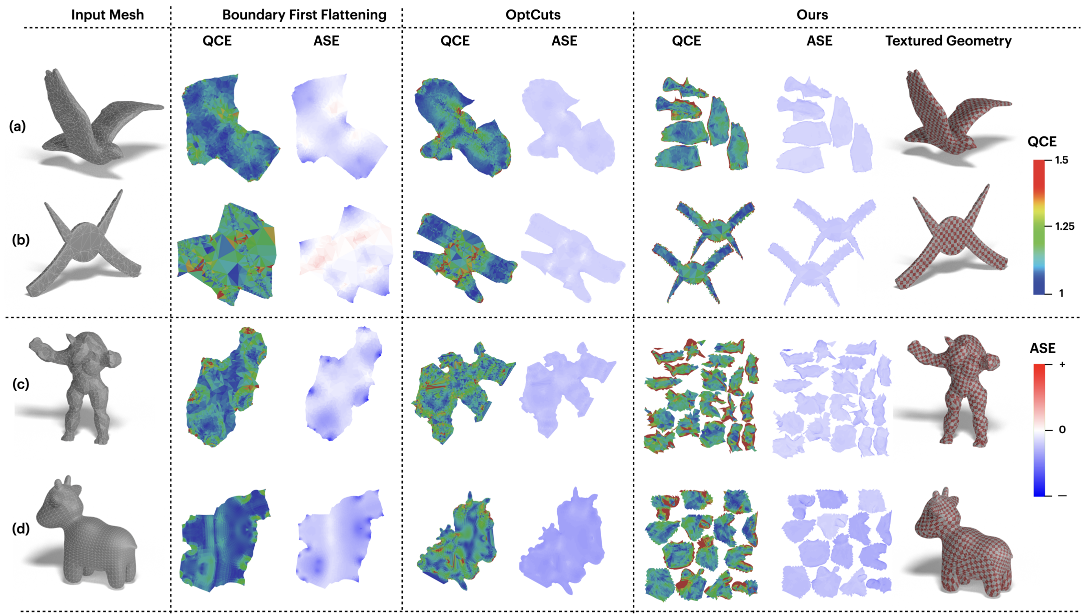

Figure 4: Comparison of error plots for QCE and ASE with other methods. First two categories (a) bird & (b) pliers are taken from SHREC dataset while later two (c) & (d) are Armadillo and Spot.

on a few classes of SHREC [Lian et al. 2011] dataset using QCE and ASE metric. For each mentioned class, we train our network on 16 meshes and compute errors on 4 test sample meshes. Please note that, instead of purely object-centric learning, here we compare on a category-specific generalized network, and our performance is comparable to other object-centric methods. Such generalization can be attributed to intrinsic characterization encoded in diffusion features used in our surface parametrization module.

Discretization-agnostic Learning: Figure 3 shows the discretization-agnostic learning capability of our framework. We train on a mesh with only $\sim 3K$ vertices and then directly infer at high resolutions ($\sim 35K$ and $\sim 100K$ vertices). Please note that the error values for high-resolution meshes stay close to the low-resolution mesh as can be observed in the error plots.

More importantly, discretization-agnostic learning allows us to reduce the computation time with significant amount when compared to other methods. Specifically, we train our method on the decimated Stanford's Armadillo mesh with $\sim 2K$ vertices, and compare our computation time with other two methods at higher resolution ($\sim 30K$ and $\sim 100K$) as shown in Table 2.

Please refer to our supplementary for implementation details and detailed ablative studies.

5 CONCLUSION

We proposed a novel self-supervised learning based framework for surface parameterization of bounded as well as unbounded surfaces. Our framework enables discretization-agnostic learning thereby significantly improving our inference time performance on high resolution meshes.

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Resolution	BFF	OptCuts	Ours
$30K$	17.41 sec	> 10 min	**2.92 sec**
$100K$	61.04 sec	> 10 min	**5.02 sec**

Table 2: Comparison of computation time for Stanford's Armadillo.

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