

PartUV: Part-Based UV Unwrapping of 3D Meshes

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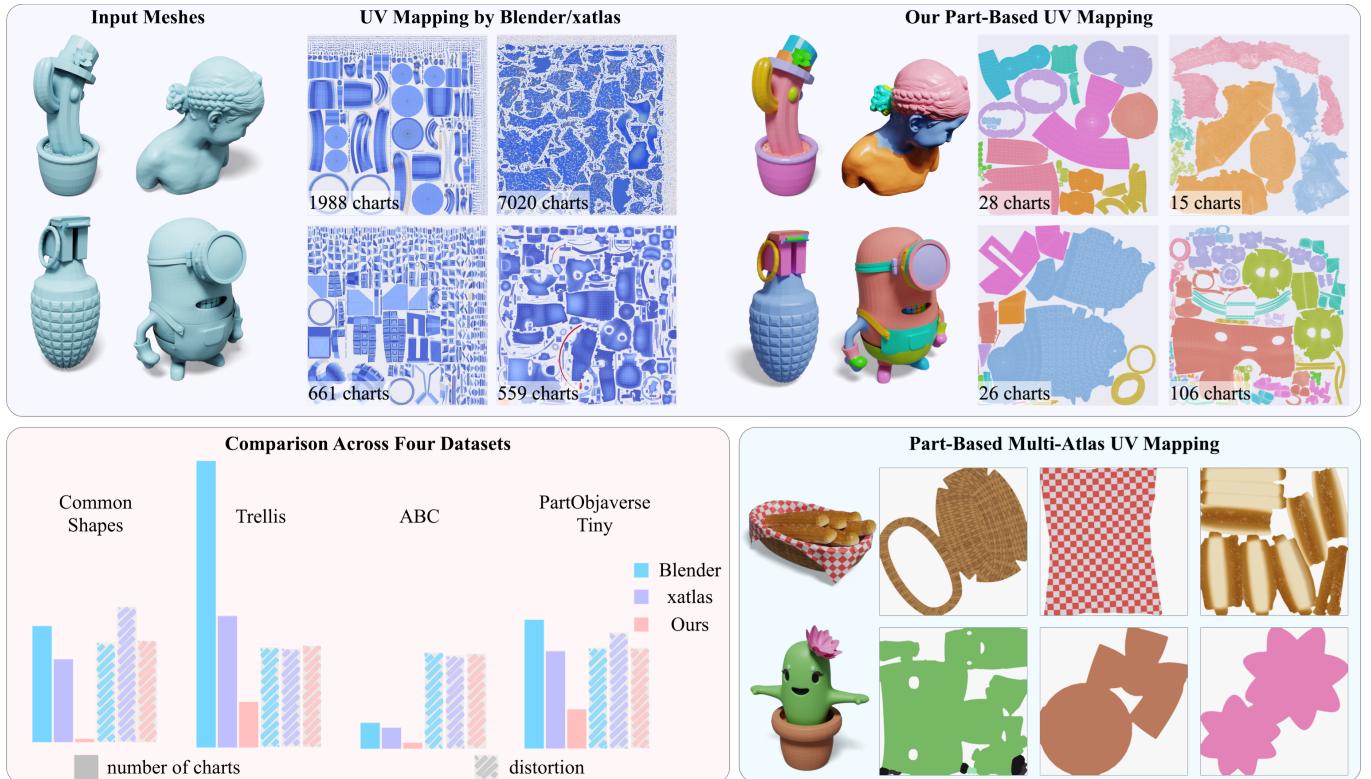


Fig. 1. We propose PartUV, a novel part-based UV unwrapping method for 3D meshes. Unlike traditional approaches that rely solely on local geometric priors and often produce over-fragmented charts, PartUV combines learned part priors with geometric cues to generate a small number of part-aligned charts. We evaluate our method on four diverse datasets—PartObjaverseTiny (man-made) [Yang et al. 2024], Trellis (AI-generated) [Xiang et al. 2024], ABC (CAD) [Koch et al. 2019], and Common Shapes [Jacobson and contributors 2023]—and show that it produces significantly less fragmented UV mappings while maintaining low distortion on par with baseline methods. Leveraging part-aware charts also enables applications such as generating one atlas per part.

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UV unwrapping flattens 3D surfaces to 2D with minimal distortion, often requiring the complex surface to be decomposed into multiple charts. Although extensively studied, existing UV unwrapping methods frequently struggle with AI-generated meshes, which are typically noisy, bumpy, and poorly conditioned. These methods often produce highly fragmented charts and suboptimal boundaries, introducing artifacts and hindering downstream tasks. We introduce PartUV, a part-based UV unwrapping pipeline that generates significantly fewer, part-aligned charts while maintaining low distortion. Built on top of a recent learning-based part decomposition method PartField, PartUV combines high-level semantic part decomposition with novel geometric heuristics in a top-down recursive framework. It ensures

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each chart's distortion remains below a user-specified threshold while minimizing the total number of charts. The pipeline integrates and extends parameterization and packing algorithms, incorporates dedicated handling of non-manifold and degenerate meshes, and is extensively parallelized for efficiency. Evaluated across four diverse datasets—including man-made, CAD, AI-generated, and Common Shapes—PartUV outperforms existing tools and recent neural methods in chart count and seam length, achieves comparable distortion, exhibits high success rates on challenging meshes, and enables new applications like part-specific multi-tiles packing. Our project page is at <https://www.zhaoningwang.com/PartUV>.

CCS Concepts: • Shape modeling → Shape analysis; • Mesh models → Mesh geometry processing; Parametrization; Geometric algorithms.

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1 Introduction

UV unwrapping projects the 3D surface of a mesh onto a 2D plane, assigning every 3D surface point a corresponding 2D UV coordinate. This step is fundamental in 3D-content-creation pipelines because it enables detailed surface information—such as material properties (e.g., base-color, roughness, normal maps), along with auxiliary maps like ambient occlusion and displacement—to be efficiently stored and manipulated in 2D space.

A principal component of UV unwrapping is surface parameterization, which flattens the 3D surface while trying to preserve geometric properties such as angles and areas. For meshes with complex geometry, flattening the entire surface into a single 2D chart introduces large distortion. Consequently, chart segmentation (or seam cutting) is typically used to divide the mesh into multiple charts along strategically placed seams, allowing each chart to be flattened with reduced distortion. Finally, UV packing arranges the resulting charts within the unit square (the UV atlas) to maximize texture-space use.

Although UV unwrapping has been studied extensively, existing methods are typically tuned for well-behaved meshes, such as those created by professional 3D artists. They often fail on more complex, AI-generated meshes. Such meshes, typically extracted from neural-field isosurfaces (e.g., via marching cubes [Lorensen and Cline 1998]), tend to have bumpy surfaces, many small triangles, and poor geometric quality (e.g., disconnected components or holes). On such data, existing methods may time-out or return extremely fragmented atlases in which a single chart holds only one or a handful of triangles. This extreme fragmentation hampers texture painting and editing, introduces texture-bleed and baking or rendering artifacts at chart boundaries, and burdens downstream applications with an unwieldy number of charts.

Some recent approaches mitigate fragmentation [Srinivasan et al. 2024; Zhang et al. 2024; Zhao et al. 2025] by representing the UV mapping using a neural field and optimizing such a field for each 3D shape from scratch. While these methods can effectively control the number of charts generated, they typically run for more than thirty minutes and still exhibit noticeable distortion. Other methods [Li

et al. 2018; Poranne et al. 2017] jointly optimize seam length and distortion but are likewise computationally expensive. Moreover, some existing approaches like [Lévy et al. 2002; Sorkine et al. 2002; Zhou et al. 2004] segment charts or identify seams using heuristics based on local geometric properties, rather than leveraging the concept of geometric or semantic parts. This can lead to unintuitive or suboptimal chart boundaries that split semantically coherent regions across multiple charts, further complicating downstream tasks such as texture authoring, part-based editing, and semantic-aware rendering.

In this paper, we introduce PartUV, a part-based UV unwrapping pipeline for 3D meshes that generates UV mappings with a small number of part-aligned charts while maintaining low distortion, as well as robust and efficient processing—typically completed within a few to several tens of seconds. PartUV builds on a recent learning-based method, PartField [Liu et al. 2025], which produces a hierarchical part tree for the input mesh. PartUV also proposes several novel geometric heuristics that further decompose simple local parts into charts that can be flattened with minimal distortion. Combining high-level semantic decomposition from PartField with fine-grained geometric cuts, PartUV employs a top-down recursive search that minimizes chart count while keeping each chart's distortion below a user-specified threshold. PartUV uses established surface parameterization algorithms (e.g., ABF++ [Sheffer et al. 2005]) for chart flattening and proven packing algorithms for optimal atlas layout. To ensure high speed and robustness, the pipeline incorporates extensive parallelization and acceleration strategies, as well as dedicated handling of non-manifold and degenerate cases.

By explicitly incorporating semantic priors, our approach yields several key benefits. First, semantics improve decomposition by reducing excessive reliance on local geometry, which often causes over-segmentation and long runtimes. Second, semantic cues preserve the coherence of object parts, preventing chart boundaries from cutting through meaningful regions (e.g., across the flat surface of a TV screen, as in Figure 7, or a human face), thereby facilitating editing and rendering tasks. Third, semantic grouping naturally supports better chart packing strategies, allowing related charts to be organized together—either within a single atlas (top right of Figure 1) or across multiple atlases (bottom right of Figure 1). This enhances organizational clarity and simplifies the process of locating and editing related charts. Finally, seams guided by semantic boundaries tend to fall in perceptually unobtrusive locations, improving the visual quality of textured models.

We evaluate PartUV on four datasets spanning man-made, AI-generated, CAD models, and common 3D shapes (e.g., Stanford Bunny, XYZ Dragon), and compare it against widely used UV unwrapping tools such as xatlas [Young 2019], Blender [Community [n. d.]], and Open3D [Zhou et al. 2018a], as well as the recent neural-based methods [Srinivasan et al. 2024]. As shown in Figure 1, our method decomposes input meshes into significantly fewer charts—also resulting in shorter seam lengths—while maintaining low angular and area distortion comparable to baseline methods. The incorporation of explicit part priors not only helps the segmented charts better align with part boundaries but also enables new applications, such as packing semantic-aligned parts into separate atlases. Moreover, PartUV maintains a high success rate, handles a wide

range of meshes (including large, complex, and non-manifold ones), and processes each mesh quickly—typically within a few to several tens of seconds.

2 Related Work

2.1 Mesh Parameterization

Disregarding mesh decomposition, mesh parameterization—the process of mapping a 3D mesh to a 2D domain while minimizing various distortion metrics (e.g., isometric, conformal, equiareal)—is a fundamental operation in UV unwrapping [Rabinovich et al. 2017; Sawhney and Crane 2017; Schüller et al. 2013]. Many methods directly optimize UV coordinates based on mesh connectivity by solving linear or nonlinear systems under fixed or free boundary conditions. These include barycentric embeddings like Tutte’s embedding [Tutte 1963], Laplacian eigen-decomposition techniques [Belkin and Niyogi 2003; Mullen et al. 2008; Taubin 1995], and distortion-minimization methods [Ben-Chen et al. 2008; Desbrun et al. 2002; Hormann and Greiner 2000; Ray and Lévy 2003; Sander et al. 2001; Su et al. 2016; Yan et al. 2005; Yueh et al. 2019], such as Least Squares Conformal Maps (LSCM) [Lévy et al. 2002]. Some adopt local/global strategies that combine per-triangle transformations (e.g., rotations) with global stitching [Alexa et al. 2023; Liu et al. 2008; Sorkine and Alexa 2007]. In contrast, Angle-Based Flattening (ABF) methods [Sheffer and De Sturler 2000; Sheffer and de Sturler 2001; Sheffer et al. 2005; Zayer et al. 2007] optimize triangle angles before converting them into UVs, typically offering better angle preservation than LSCM but at higher computational cost due to nonlinear solvers. In this paper, we adopt ABF for base unfolding, integrating it with various mesh decomposition strategies.

2.2 Mesh Segmentation for UV Unwrapping

Mesh segmentation is a key step in UV unwrapping, aiming to divide a complex 3D mesh into simpler patches, or charts, each of which can be flattened with minimal distortion. Existing approaches can be broadly categorized into four main strategies. Top-down methods recursively subdivide the mesh, often using spectral analysis [Liu and Zhang 2007a,b; Pothen et al. 1990] or cuts along feature lines [Zhang et al. 2005] and high-curvature regions [Lavoué et al. 2005]. Bottom-up aggregation [Bhargava et al. 2025; Julius et al. 2005; Kalvin and Taylor 1996; Lévy et al. 2002; Pulla et al. 2001; Sorkine et al. 2002; Takahashi et al. 2011; Yamauchi et al. 2005; Zhou et al. 2004] grows charts from small seeds (e.g., triangles), merging them based on planarity or distortion bounds to maximize chart size under quality constraints. Cut optimization [Carr et al. 2006; Gu et al. 2002; Li et al. 2018; Pietroni et al. 2009; Poranne et al. 2017; Sander et al. 2003; Takahashi et al. 2011] focuses on identifying optimal seam networks that minimize seam length, reduce flattening distortion, or better suit specific parameterization goals. Clustering-based methods [Katz and Tal 2003; Roy 2023] group mesh elements based on geometric similarity to form coherent segments. Commonly used tools such as xatlas [Young 2019], Blender [Community [n. d.]], and Open3D [Zhou et al. 2018a] primarily adopt bottom-up aggregation strategies that rely solely on local geometric properties. In contrast,

PartUV integrates high-level semantic part priors from a learning-based module with novel local geometric decomposition strategies via a top-down recursive tree search.

2.3 Learning-Based Parameterization and Segmentation

Representing UV mappings with neural networks has attracted attention due to their differentiability and composability. Neural Surface Maps [Morreale et al. 2021] pioneered this direction by learning mappings across collections of surfaces. Several approaches jointly optimize UV parameterization and 3D reconstruction from multi-view images using cycle-consistency and distortion-based losses [Das et al. 2022; Xiang et al. 2021]. Others, such as NUVO [Srinivasan et al. 2024], solve for parameterizations directly from sampled 3D points. More recent methods [Zhang et al. 2024; Zhao et al. 2025] design neural networks to emulate physical operations, including face cutting, UV deformation, and unwrapping. However, all the aforementioned techniques typically rely on per-shape optimization, making them computationally expensive and often requiring tens of minutes per shape. A few feedforward models address specific tasks more efficiently, such as intra-category texture transfer [Chen et al. 2022] and low-distortion patch selection [Liu et al. 2023].

To enhance UV chart decomposition, we explore the integration of semantic part priors. Traditional learning-based part segmentation methods [Jiang et al. 2020; Qian et al. 2022; Vu et al. 2022] are restricted to closed-set categories due to the limited scale of part-annotated datasets [Mo et al. 2019; Yi et al. 2016]. Recent approaches [Guo et al. 2024; He et al. 2024; Xu et al. 2023, 2024; Yang et al. 2023; Yin et al. 2024; Zhou et al. 2018a] lifting priors from 2D vision to 3D models [Kirillov et al. 2023; Li et al. 2022] for open-world 3D part segmentation but rely on per-shape optimization, leading to slow runtimes and noise sensitivity. In contrast, a recent method, PartField [Liu et al. 2025], introduces a feedforward model that learns part-aware feature fields for fast, hierarchical 3D part decomposition. While semantic priors intuitively benefit UV unwrapping, naïve integration can yield suboptimal results. PartUV addresses this with a novel top-down strategy that interleaves semantic segmentation and geometric flattening.

3 Method

3.1 Overview

For a 3D mesh $\mathcal{M} = (V, F)$, PartUV decomposes the mesh faces into a small collection of disjoint charts:

$$F = \bigcup_{k=1}^K C_k, \quad \text{with } C_i \cap C_j = \emptyset \quad (i \neq j), \quad (1)$$

where each **chart** C_k is a connected subset of faces. We utilize an Angle-Based Flattening algorithm(ABF++), to flatten each chart onto a 2D plane, yielding mappings:

$$\phi_k : C_k \longrightarrow \mathbb{R}^2, \quad (2)$$

so that each vertex $v_i \in V$ receives a corresponding 2D UV coordinate $u_i = \phi_k(v_i) \in \mathbb{R}^2$, determined by the chart it belongs.

The primary challenge lies in decomposing the mesh into charts $\{C_k\}$, a task essentially equivalent to identifying optimal seams for mesh segmentation. Many state-of-the-art methods, such as xatlas and Blender’s Smart UV, rely on geometric heuristics—such as



Fig. 2. **Pipeline of PartUV.** Given a mesh M , we first leverage the learning-based method PartField to predict a part-aware feature field. By applying a clustering algorithm to this field, we obtain a hierarchical part tree \mathcal{T} for the input mesh M . We then recursively traverse the part tree \mathcal{T} starting from the root node. For each visited node \mathcal{P} , we apply two novel geometry-based strategies to segment the corresponding part mesh into multiple sets of charts \mathcal{C} . Each chart in the set is then flattened using the ABF algorithm [Sheffer et al. 2005], and its distortion is evaluated. If the distortion exceeds a user-specified threshold τ , we recursively traverse the left and right children of the part tree \mathcal{T} . Otherwise, we adopt the segmented charts and their corresponding UV mappings for the part mesh.

bottom-up greedy chart expansion based on face normals or distortion metrics—to generate these charts. However, these strategies typically produce overly fragmented charts and unintuitive or sub-optimal boundaries, often splitting semantically coherent regions across multiple charts.

In contrast, PartUV adopts a coarse-to-fine, two-stage strategy for mesh decomposition. At a high level, it employs a recent learning-based method called PartField (introduced in Section 3.2) to partition mesh faces into semantically coherent **parts**: $F = \bigcup_{m=1}^M P_m$, where each part P_k exhibits relatively simple geometry—for instance, cylindrical limbs, spherical toes. Subsequently, we introduce two geometry-based heuristics (detailed in Section 3.4) to further segment each part into a small set of **charts**: $P_m = \bigcup_{n=1}^{N_m} C_{m,n}$, ensuring each resulting chart $C_{m,n}$ can be flattened onto a 2D plane with minimal distortion.

To accomplish this, PartUV employs a top-down recursive decomposition search (detailed in Section 3.3) that minimizes the total number of generated charts while ensuring the distortion for each chart remains below a user-specified threshold τ . Since exhaustive decomposition searches can incur substantial computational overhead, we introduce acceleration and parallelization techniques for efficiency. To ensure a complete and robust pipeline, Section 3.5 also describes additional preprocessing and postprocessing procedures, including handling non-manifold and multi-component meshes, as well as performing UV packing.

3.2 Preliminary: PartField

PartField [Liu et al. 2025] trains a feed-forward neural network that takes a 3D mesh as input and predicts a continuous, part-based feature field encoded as a triplane. By leveraging extensive contrastive learning on part-labeled 3D data and large-scale unlabeled 3D data with 2D pseudo part labels, PartField learns general hierarchical concepts of semantic and geometric parts. For any 3D point, we can obtain its high-dimensional part feature by interpolating the

triplane representation. Points whose features are similar—as measured by cosine similarity—are therefore more likely to belong to the same part.

3.3 Top-Down Recursive Tree Search

After obtaining the hierarchical part-based feature field using PartField, we first compute a representative part feature for each triangular face by uniformly sampling s 3D points within the face and averaging their corresponding point features. Next, we construct a hierarchical part tree \mathcal{T} using agglomerative clustering [Johnson 1967] on these face features. In this hierarchical tree structure, the leaf nodes represent individual triangular faces, and the root node encompasses the entire mesh.

A straightforward approach to mesh decomposition might involve using PartField to directly generate a fixed number of parts and attempting to flatten each to 2D individually. Alternatively, one could adaptively traverse \mathcal{T} from the root downward, checking whether each node's corresponding geometry can be flattened into a 2D chart with minimal distortion. However, we observe that relying solely on parts generated by PartField often leads to suboptimal results. This limitation arises because PartField primarily focuses on semantic or coarse geometric partitioning and is less effective for finer-scale, UV-related decompositions—such as accurately segmenting cylindrical or spherical regions into charts that minimize distortion. To address this challenge, PartUV leverages PartField primarily for high-level semantic decomposition into geometrically simpler subparts and employs two geometry-based heuristics (elaborated in Section 3.4) to further divide these semantically meaningful parts into smaller charts amenable to low-distortion flattening. The search algorithm interleaves these two strategies.

Formally, PartUV employs a top-down recursive decomposition search—detailed in Algorithm 1—to optimally balance the chart count against distortion constraints. Given a subtree node \mathcal{P} (initially the root node of the tree \mathcal{T}), a distortion threshold τ , and a

Algorithm 1 PARTTREESearch

Require: \mathcal{P} (a PartField subtree node), distortion threshold τ , chart budget B

Ensure: A $UVChartSet \mathcal{C} = \{C_1, C_2, \dots, C_k\}$ for \mathcal{P} 's mesh, whose charts C_i have distortion $\leq \tau$ and whose total chart count k is $\leq B$; return \perp if no such set exists.

```

1: procedure PARTTREESearch( $\mathcal{P}, \tau, B$ )
2:   if  $B < 1$  then                                 $\triangleright$  budget exhausted
3:     return  $\perp$ 
4:   end if
5:    $\mathcal{H}_1 \leftarrow \text{GENCANDIDATEH1}(\mathcal{P}.mesh, 10)$        $\triangleright$  Heuristic1
6:   for all  $\mathcal{C} \in \mathcal{H}_1$  do     $\triangleright \mathcal{C}$  is one of candidate  $UVChartSet$ 
7:     PARAMETERIZEABF( $\mathcal{C}$ )  $\triangleright$  flatten and compute distortion
8:   end for
9:   if  $\min_{\mathcal{C} \in \mathcal{H}_1} \mathcal{C}.\text{dist} > \tau$  then  $\triangleright$  no admissible H1 candidate
10:     $L \leftarrow \text{PARTTREESearch}(\mathcal{P}.left\_child, \tau, \infty)$ 
11:     $R \leftarrow \text{PARTTREESearch}(\mathcal{P}.right\_child, \tau, \infty)$ 
12:    return  $L \oplus R$        $\triangleright$  merge chart sets from the subtrees
13:   else
14:      $\mathcal{H}_2 \leftarrow \{\text{GENCANDIDATEH2}(\mathcal{P}.mesh, \tau)\}$   $\triangleright$  Heuristic2
15:     PARAMETERIZEABF( $\mathcal{H}_2[0]$ )
16:      $\mathcal{S} \leftarrow \{\mathcal{C} \in \mathcal{H}_1 \cup \mathcal{H}_2 \mid \mathcal{C}.\text{dist} \leq \tau \wedge \text{NoOVERLAP}(\mathcal{C})\}$ 
17:      $\mathcal{C}_{\text{best}} \leftarrow \text{argmin}_{\mathcal{C} \in \mathcal{S}} \mathcal{C}.\text{count}$ 
18:      $\triangleright$  Recurse to determine whether a better solution exists
19:      $B' \leftarrow \min(B, \mathcal{C}_{\text{best}}.\text{count} - 1)$ 
20:      $L \leftarrow \text{PARTTREESearch}(\mathcal{P}.left, \tau, B' - 1)$ 
21:      $R \leftarrow \text{PARTTREESearch}(\mathcal{P}.right, \tau, B' - L.\text{count})$ 
22:      $\mathcal{C}_{\text{comb}} \leftarrow L \oplus R$ 
23:      $\text{is\_valid} \leftarrow \mathcal{C}_{\text{comb}}.\text{dist} \leq \tau \wedge \text{NoOVERLAP}(\mathcal{C}_{\text{comb}})$ 
24:     if  $\mathcal{C}_{\text{comb}}.\text{count} < \mathcal{C}_{\text{best}}.\text{count} \wedge \text{is\_valid}$  then
25:        $\mathcal{C}_{\text{best}} \leftarrow \mathcal{C}_{\text{comb}}$ 
26:     end if
27:     return  $\mathcal{C}_{\text{best}}$ 
28:   end if
29: end procedure

```

chart budget B (initially set to ∞), the algorithm searches for a valid chart decomposition of \mathcal{P} 's mesh that satisfies three key conditions: each chart has a distortion of at most τ , no charts overlap in 2D, and the total number of charts does not exceed B . If no feasible decomposition exists, the algorithm returns failure (\perp).

Specifically, the algorithm begins by generating candidate chart decompositions for node \mathcal{P} 's mesh using a primary geometric heuristic (Heuristic1). Each candidate chart set $\mathcal{C} = \{C_i\}$, consisting of up to t charts, is flattened using Angle-Based Flattening (ABF), and its distortion is evaluated. If none of the candidate decompositions with up to t charts from Heuristic1 satisfy the distortion constraint (i.e., $\delta_{\min} > \tau$), the algorithm utilizes the PartField tree to divide the mesh and recursively searches both the left and right child subtrees without budget constraints, then merges their respective optimal chart sets.

Conversely, if an admissible candidate decomposition is found through Heuristic1, we further refine it using a secondary heuristic (Heuristic2) designed to potentially yield fewer charts. Among these

candidates, we select the best solution $\mathcal{C}_{\text{best}}$ with the minimal chart count that satisfies the distortion and overlap constraints.

Before accepting this solution, the algorithm performs a final check by recursively exploring the left and right child nodes of the PartField subtree, using a reduced chart budget (B'), which is derived from the best candidate's chart count minus one. If the combined solution from this subtree search yields a valid and superior decomposition (i.e., fewer charts than $\mathcal{C}_{\text{best}}$), it replaces the previously identified best solution. The chart budget B prevents the search from going too deep. As the search progresses, B tightens, and recursion stops when candidates exceed it. In practice, the search rarely goes very deep.

By strategically interleaving hierarchical semantic guidance from PartField with fine-grained geometric heuristics and systematic recursive exploration, our proposed decomposition search achieves semantically coherent, distortion-bounded, and notably compact mesh parameterizations—characterized by a small number of charts.

3.4 Geometry-Based Part Decomposition

In this section, we introduce two heuristics, *Normal* and *Merge*, to further decompose a part P_m generated by PartField and exhibiting simple geometry. The goal is to divide P_m into multiple charts, denoted as $P_m = \bigcup_{n=1}^{N_m} C_{m,n}$, such that each chart can be flattened to 2D with low distortion.

The first heuristic, referred to as *Normal* (line 5 in Algorithm 1), is based on face normals. We apply an agglomerative clustering algorithm [Johnson 1967] to the face normals of P_m 's mesh, partitioning its triangle faces into charts, where each chart is composed of connected faces with similar normals. This clustering is performed once for P_m , producing t candidate decompositions with 1 to t charts (we use $t = 10$ in our experiments). For each candidate decomposition, we apply the Angle-Based Flattening (ABF) algorithm to flatten the charts and evaluate distortion. Since ABF aims to preserve angles, we quantify distortion using an area stretch metric, defined as:

$$\text{distortion}(\mathcal{C}) = \max_{C \in \mathcal{C}} \left(\frac{1}{|C|} \sum_{f \in C} \max \left(\text{stretch}(f), \frac{1}{\text{stretch}(f)} \right) \right), \quad (3)$$

where C denotes a single chart composed of multiple connected faces, and \mathcal{C} denotes the set of all charts in the decomposition. The stretch of a triangle face f is computed as:

$$\text{stretch}(f) = \frac{\text{area}2D(f)}{\text{area}3D(f)} \left/ \left(\frac{1}{|C|} \sum_{f' \in C} \frac{\text{area}2D(f')}{\text{area}3D(f')} \right) \right. \quad (4)$$

Note that both PartField and the *Normal* heuristic employ the agglomerative clustering algorithm to group faces into parts or charts. The key difference lies in the features used: PartField utilizes learned high-level part features, while heuristic *Normal* relies on low-level geometric face normals. These two strategies are thus consistent in spirit and complementary in practice.

The *Normal* heuristic is simple, fast, and often yields satisfactory results. However, we also propose a second, more computationally expensive heuristic, called *Merge* (line 14 in Algorithm 1), which may produce decompositions with fewer charts. Given a part P_m , the *Merge* heuristic begins by computing its oriented bounding box (OBB). It then assigns each triangle face a label from 1 to 6, corresponding to the OBB face normal with which the triangle's

normal is most closely aligned. Using both face connectivity and these labels, we segment the faces into multiple connected components. These components are then sorted by size (small to large), and we iteratively attempt to merge each component with its adjacent neighbors, starting from the one with the longest shared edges. For each merge attempt, we temporarily merge two components and apply ABF to flatten the combined chart. The merge is accepted if the resulting chart satisfies the distortion threshold and is free of overlaps. This merging process continues until no further valid merges can be made, after which the final chart set is returned. Since the *Merge* heuristic often begins with many small components and performs multiple ABF calls during its iterative merging process, it is significantly more expensive than the *Normal* heuristic. However, it may yield better decompositions with fewer charts. Therefore, we only invoke the *Merge* heuristic when the *Normal* heuristic returns a valid (admissible) decomposition.

3.5 Runtime Optimization and Pre- and Post-processing

Runtime Optimization To ensure efficiency despite the computational cost of recursive decomposition and repeated ABF invocations, we adopt two key strategies during the decomposition process. First, we parallelize all recursive calls to the left and right subtrees during the top-down search, allowing the algorithm to exploit multi-core processing and significantly accelerate the overall decomposition. Second, to avoid the high cost of repeatedly invoking Angle-Based Flattening (ABF) on dense meshes, we employ a GPU-accelerated mesh simplification algorithm [Oh et al. 2025] to generate low-resolution approximations of candidate charts. During simplification, the chart boundary is kept fixed to preserve the geometric structure relevant to UV mapping. These simplified charts are used to estimate distortion metrics quickly (i.e., surrogate distortion) during intermediate evaluations. Once the final chart set is determined, ABF is applied to the original high-resolution mesh to produce accurate UV coordinates and distortion measurements.

Non-Manifold and Multi-Component Meshes Since the ABF algorithm assumes each input chart is a manifold and connected surface, additional processing is required when handling non-manifold or multi-component meshes. For non-manifold meshes, we detect all non-manifold edges—i.e., edges shared by more than two faces—and resolve them by duplicating the shared vertices and splitting each such edge into $N - 1$ distinct edges, where N is the number of incident faces, thereby converting the structure into a manifold form suitable for flattening. For meshes containing multiple connected components, we initially proceed with the proposed PartField-guided hierarchical decomposition. If a part mesh consists of disconnected components, we skip heuristic-based decomposition at that level and instead recursively explore the left and right subtrees of the PartField hierarchy. However, if PartField fails to further segment the multiple components after reaching a predefined recursion depth, we fall back to applying the geometric heuristics and ABF flattening to each connected component at that level individually, in order to avoid excessively fragmented decomposition.

UV Packing While our primary focus is on decomposing 3D meshes into charts and generating corresponding low-distortion 2D parameterizations, our method is fully compatible with a variety of existing

UV packing algorithms. A distinguishing feature of our approach is that chart decompositions are grouped based on semantically meaningful parts, enabling more structured and application-aware packing strategies. For example, charts belonging to the same part can be grouped together during packing. Alternatively, part groups can be packed into an arbitrary number of UV atlas squares (e.g., multiple $[0, 1]^2$ spaces) with a semantically balanced distribution across atlases. This semantic hierarchy not only improves organizational clarity but also benefits downstream applications such as texture painting or editing, where charts belonging to the same part remain spatially close and are easier to manipulate collectively.

4 Experiments

4.1 Implementation Details and Evaluation Setup

Implementation Details. We train PartField [Liu et al. 2025] on Objaverse [Deitke et al. 2022] using 8 NVIDIA H100 GPUs for 15 days. During inference, we sample 10 points per face and average their features for face clustering and part tree construction. The core pipeline of PartUV is implemented in C++17, and we use UVPackmaster [Łukasz Czyż 2025] for final group-based UV packing. A distortion threshold of 1.25 is used in all experiments. For ABF++, we run 5 iterations per call, and follow Blender to set the gradient early-stop condition. Mesh simplification is controlled by a curvature-related threshold of $1e-4$ and a maximum iteration count of 1,000. All parameters are fixed across experiments. All methods are evaluated on a cluster node with a 96-core Intel® Xeon® Platinum 8468 CPU and an NVIDIA H100 GPU.

Evaluation Datasets. To comprehensively evaluate the approaches across diverse mesh sources, qualities, and styles, we use four datasets: (a) *Common Shapes* [Jacobson 2013], a GitHub repository of 24 widely used models in graphics (e.g., Bimba, Igua, Stanford Bunny) with provided processed .obj files; (b) *PartObjaverseTiny* [Yang et al. 2024], a 200-shape subset of Objaverse [Deitke et al. 2022] featuring high-quality, man-made meshes with multiple components and smooth surfaces; (c) *ABC* [Koch et al. 2019], a CAD dataset of mechanical models combining sharp and smooth features—we use the first 100 meshes from its initial batch; and (d) *Trellis* [Xiang et al. 2024], which includes 114 AI-generated meshes from a recent 3D diffusion-based generative model. These meshes are typically noisy and geometrically low-quality, posing greater challenges than human-made counterparts.

Evaluation Metrics. We evaluate the quality of the generated UV maps from four perspectives: (1) *Number of Charts*: For each shape, we count the number of charts and report both the average and median values across the dataset. (2) *Seam Length*: We compute the seam length by summing the lengths of all chart boundary edges, with UV coordinates normalized to a $[0, 1]$ grid. The median value is reported across the dataset. (3) *Angular (Conformal) Distortion*: We compute the cosine between the tangent and bitangent vectors of each face. The distortion for a shape is defined as one minus the average cosine across all faces [Srinivasan et al. 2024]. We report the average distortion across the dataset. (4) *Area (Equiareal) Distortion*: We compute both *area distortion* and *overall area distortion*. *Area distortion* is defined as in Equation 3, based on the chart with the highest distortion in each shape. *Overall area distortion* is computed



Fig. 3. Quantitative comparison between Blender [Community [n. d.]], xatlas [Young 2019], and PartUV. Unlike Blender and xatlas, which rely solely on local geometric properties for UV unwrapping, PartUV integrates high-level semantic priors with low-level geometric heuristics, enabling part-based chart decomposition. As a result, it produces significantly fewer charts, with boundaries that better align with semantic parts.

by aggregating all triangles across all charts, calculating individual distortions, and averaging them. For both metrics, we first compute per-shape values and then average them across the dataset. All triangle-level distortion values are clipped to a maximum of 10. Notably, *overall area distortion* may be smoothed by the number of faces, while *area distortion* more effectively highlights problematic regions in the UV maps. We did not report stretch L_2 and L_∞ [Sander et al. 2001] since they are per-triangle metrics that can diverge to infinity when triangles flip or have near-zero area—issues that are common in baselines such as xatlas, making direct comparison less meaningful.

4.2 Comparison with Baselines

Baselines. We compare PartUV with commonly used tools—Blender’s Smart UV Project [Community [n. d.]], xatlas [Young 2019], and Open3D—as well as optimization-based methods, including Nuvo [Srinivasan et al. 2024] and OptCuts [Li et al. 2018].

Blender, xatlas, and Open3D decompose meshes into charts using bottom-up strategies guided by local geometric priors. Blender clusters triangles based on mesh normals and flattens each chart using simple planar projection. xatlas employs a greedy algorithm that balances geometric deviation, UV distortion, and seam cost, followed by Least Squares Conformal Maps (LSCM) [Lévy et al.

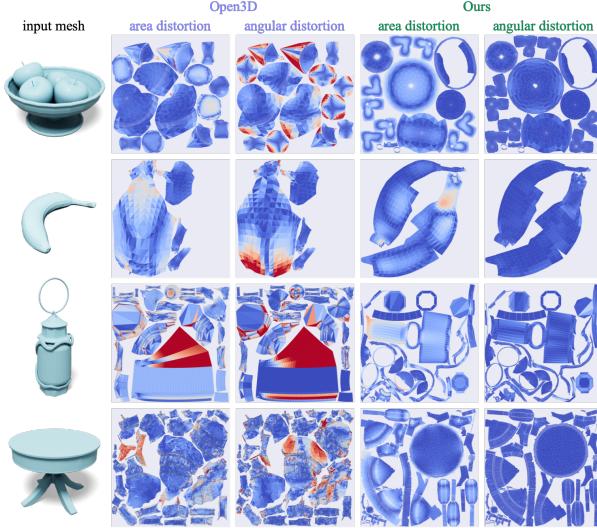


Fig. 4. Open3D not only suffers from a limited success rate but also produces results with large distortion, which may reduce their practical utility.

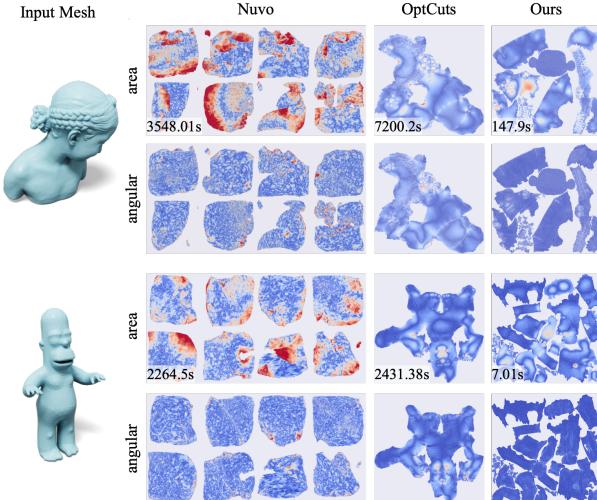


Fig. 5. Nuvo and OptCuts incur significantly longer optimisation times for each shape. Nuvo’s results also exhibit large distortion.

2002] for flattening. Open3D builds on Microsoft’s UVAtlas [Corporation 2023; Sander et al. 2002; Zhou et al. 2004], which uses region growing guided by the isometric stretch metric and flattens charts with LSCM. Among optimization-based methods, Nuvo [Srinivasan et al. 2024] learns a continuous UV mapping via a neural field by minimizing distortion losses with various regularizations. OptCuts jointly optimizes surface cuts and distortion under a global bijectivity constraint. Both methods require significantly longer runtimes per mesh.

Results. As shown in Table 1, Blender and xatlas often produce over-fragmented charts, whereas PartUV generates UV maps with significantly fewer charts. For instance, on the Common Shapes dataset, PartUV uses only 1/31 as many charts as Blender. Consequently, it also results in shorter seam lengths. PartUV maintains low levels of both angular and area distortion, while xatlas may

Table 1. Quantitative comparison between Blender [Community [n. d.]], xatlas [Young 2019], and PartUV.

dataset	method	success	average	median	median	overall	time		
		rate (%)	# of charts ↓	# of charts ↓	seam length ↓	angular distort. ↑	area distort. ↓	area distort. ↓	distort. ↓
Common Shapes (24 shapes)	Blender	100.0	1360.3	332.5	44.7	0.906	1.172	1.102	0.3
	xatlas	100.0	974.8	301.0	42.9	0.987	1.885	1.504	77.9
	Ours	100.0	43.6	15.0	16.8	0.982	1.404	1.131	54.0
Trellis (114 shapes)	Blender	100.0	3352.9	1957.0	94.5	0.921	1.252	1.107	1.1
	xatlas	100.0	1541.6	895.0	91.2	0.984	2.357	1.093	13.1
	Ours	100.0	538.8	221.5	55.9	0.961	1.300	1.135	41.9
ABC (100 shapes)	Blender	100.0	305.3	78.0	25.0	0.992	1.122	1.067	0.7
	xatlas	100.0	249.6	56.0	26.5	1.000	1.192	1.030	31.0
	Ours	100.0	74.0	18.0	19.8	0.999	1.175	1.058	43.1
Part Objaverse Tiny (200 shapes)	Blender	100.0	1509.2	647.5	70.2	0.925	1.325	1.115	0.2
	xatlas	100.0	1142.1	491.5	67.0	0.982	1.728	1.286	4.4
	Ours	100.0	463.3	155.5	39.3	0.954	1.271	1.112	21.0

Table 2. Quantitative comparison between Open3d [Zhou et al. 2018b] and PartUV. Note that Open3d has a limited success rate, and the reported numbers are averaged over the easier cases it successfully completes. Despite this, Open3d still exhibits large distortion.

dataset	method	success	average	overall	average	median	median	time	
		rate (%)	angular distort. ↑	area	# of distort. ↓	# of charts ↓	area		
Common Shapes	Open3d	79.2	0.852	1.509	1.191	19.8	12.0	11.8	19.8
	Ours	100.0	0.987	1.281	1.128	24.4	12.0	15.1	52.3
Trellis	Open3d	39.5	0.859	1.931	1.264	79.8	40.0	25.9	24.1
	Ours	100.0	0.984	1.308	1.144	97.9	51.0	27.4	23.7
ABC	Open3d	83.0	0.878	1.459	1.162	15.0	8.0	9.3	17.6
	Ours	100.0	0.994	1.171	1.062	35.0	15.0	18.6	39.6
PartObjaverse Tiny	Open3d	52.5	0.799	2.772	1.295	161.5	80.0	25.6	10.0
	Ours	100.0	0.957	1.254	1.117	227.1	91.0	30.6	14.0

Table 3. Quantitative comparison between Nuvo [Srinivasan et al. 2024] and PartUV.

dataset	method	success	average	overall	average	median	median	time
		rate (%)	angular distortion ↑	area	# of distortion ↓	# of charts ↓	area	
Common Shapes	nuvo	100.0	0.802	2.722	1.940	17.0	2908.8	52.3
	Ours	100.0	0.987	1.281	1.128	24.4	12.0	

exhibit large area distortion on certain challenging shapes. Despite utilizing a more exhaustive decomposition search and a computationally expensive ABF flattening algorithm to achieve higher quality, PartUV maintains a runtime comparable to xatlas, typically completing in tens of seconds. See Figure 3 for a qualitative comparison, where PartUV leverages semantic part information to produce chart boundaries that align more closely with object semantics.

We report the comparison results with Open3D separately in Table 2 due to its failure to complete some shapes within a reasonable time. For example, on the challenging Trellis dataset, it achieves a success rate of only 39.5%. In Table 2, we report the average performance only over the easy cases that Open3D successfully processes. For these cases, Open3D achieves a similar number of charts and seam lengths compared to our method. However, this comes at the cost of significant distortion. For instance, while Blender, xatlas, and PartUV all achieve angular distortion scores mostly above 0.95 across all datasets, Open3D consistently falls below 0.9 and even 0.8 in some cases. A similar phenomenon is observed for area distortion. Please refer to Figure 4 and Figure 6 for qualitative examples, where Open3D produces large distortions, rendering the UV mappings less suitable for practical applications.



Fig. 6. Texture-map comparison among Blender, xatlas, and our PartUV.

Compared to Nuvo and OptCuts, we observe that although both methods effectively reduce the number of charts, they typically require significantly longer optimization times—often exceeding 30 minutes or even several hours. Moreover, Nuvo leads to substantially higher distortion, as shown in Table 3 and Figure 5. While OptCuts achieves low distortion, its success rate is limited: it produces outputs for only 9 out of 24 shapes in the Common Shapes dataset. Additionally, neither method incorporates the concept of semantic parts during optimization.

See supplementary material for additional qualitative examples UV efficiency comparisons, and analysis of Open3D results.

4.3 Applications and Analysis

In this section, we demonstrate the benefits of using our PartUV: **Texture Editing and Replacement.** Since our UV mappings are less fragmented, texture maps can be more effectively edited or modified in 2D space. In Figure 7, we show that our UV maps enable clean placement of conference logos, whereas the UV maps generated by Blender or xatlas fail to do so due to their overly fragmented layouts. Figure 8 further showcases an application where the texture is replaced with various tiling patterns. Because xatlas and Blender often produce numerous small charts containing only a few triangles, noticeable artifacts appear on the mesh surface. In contrast, our method preserves significantly better visual quality.

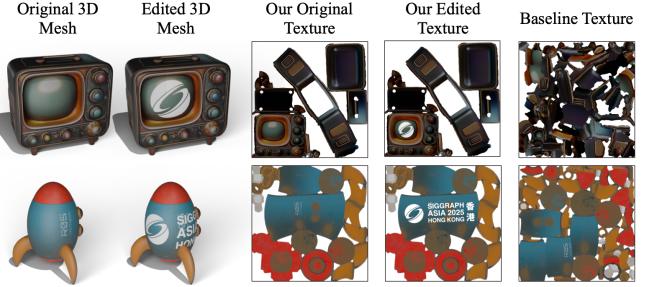


Fig. 7. Unlike our baselines, which generate over-fragmented UV maps that hinder 2D texture editing, PartUV produces significantly fewer charts with part-aligned boundaries, enabling more effective 2D operations.

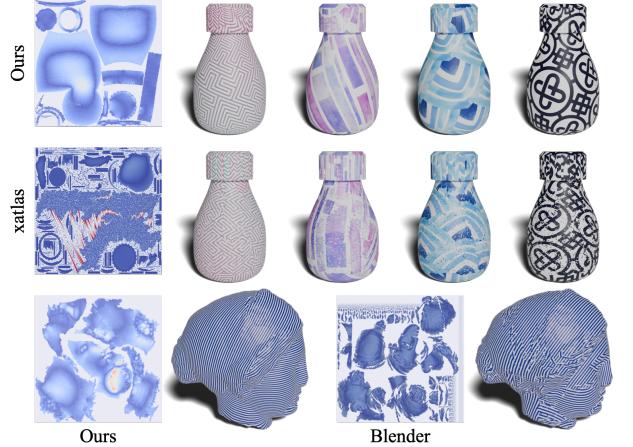


Fig. 8. Our UV map enables easy texture replacement, whereas xatlas / Blender maps cause severe artefacts due to over-segmentation.

Texture Compression. UV maps always require padding between charts. When the UV layout is over-segmented, more padding is needed, which increases the risk of color bleeding. In Figure 10, we demonstrate that reducing the UV map resolution from 1024 to 128—a common setting in mobile games—results in noticeable color bleeding for textures generated by xatlas and Blender. In contrast, PartUV is free from such issues.

Multi-Atlas Wrapping. As shown in Figure 1 and Figure 9, PartUV supports part-based UV packing. Given the desired number of atlases, it can automatically extract semantic-meaningful parts and pack across separate atlases, facilitating downstream applications such as texture editing.

Adaptive Threshold Adjustment. PartUV allows users to specify a distortion threshold τ , enabling adaptive control over the trade-off between the number of charts and the distortion in the generated UV maps, as shown in Figure 11.

4.4 Ablation Studies

PartField. We integrate semantic part priors with geometric heuristics through an adaptive recursive tree search. A naive way to combine them is to first use PartField to decompose the shape into a fixed set of 20 parts, and then further decompose each part using the two heuristics. As shown in Table 4(a), this naive combination results in high distortion, as some parts may remain too complex to

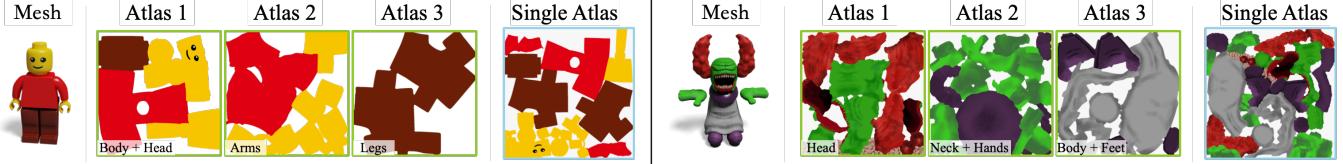


Fig. 9. Our part-based UV unwrapping can pack all charts into a single atlas or multiple atlases by semantic part, aiding tasks such as 2-D editing.

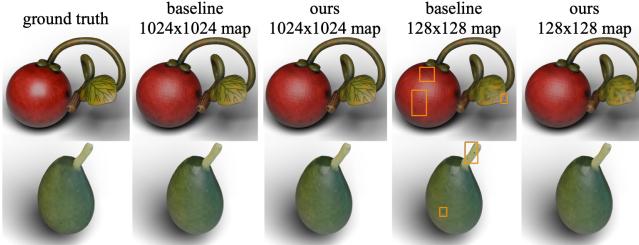


Fig. 10. xatlas and Blender generate over-fragmented UV maps that may introduce color bleeding, especially with low-resolution texture maps (e.g., in mobile games). In contrast, our results are free from such issues.

Table 4. Ablation study conducted on the Trellis dataset.

id	version	average	median	area	angular	seam	time
		# charts ↓	# charts ↓	distort.↓	distort.↑	length ↓	
a	fixed 20 parts	397.02	223.00	2.18	0.9687	66.42	207.75
b	replace PF feat. with face normal	574.43	259.50	1.28	0.9708	64.46	83.67
c	no merge	763.74	270.50	1.30	0.9607	62.75	38.00
d	no recursion	928.23	237.00	1.31	0.9630	59.17	40.66
e	no distortion surrogate	575.31	216.50	1.24	0.9632	57.88	61.48
f	full	538.81	221.50	1.30	0.9609	57.92	41.88

be flattened with low distortion. We also experimented with replacing the PartField features with face normals and then applying the original recursive tree search. As shown in Table 4(b), this variant doubles the runtime, increases the number of charts, and produces chart boundaries that no longer align with semantic parts.

Merge Heuristic. We propose an innovative geometry-based heuristic, *Merge*, for chart decomposition. When this heuristic is removed and only the *Normal* heuristic is used (Table 4(c)), we observe an increase in the number of charts.

Recursion. As shown in Alg. 1, Line 18, we do not immediately return the first solution found but continue the search to find potentially better solutions. When this strategy is removed (Table 4(d)), we observe a significant increase in the number of charts.

Distortion Surrogate. To accelerate the search, we first simplify the mesh during intermediate iterations and then apply the ABF algorithm to the simplified mesh to compute an approximate distortion, which helps guide the search more efficiently. When this strategy is removed (Table 4(e)), we observe an increase in runtime.

We show more ablations and visualizations, including comparisons of different flattening algorithms, in the Appendix.

4.5 95th Percentile Distortion Metrics

To evaluate worst-case behavior, we additionally report 95th-percentile distortion metrics and compare them with baseline methods on four datasets. As shown in Table 5, we consider two metrics: *distortion 95th-shape*, defined as the 95th-percentile area distortion across all shapes in a dataset, and *distortion 95th-chart*, which first computes the 95th-percentile area distortion across all charts within a shape and then averages the results over all shapes in the dataset. As the

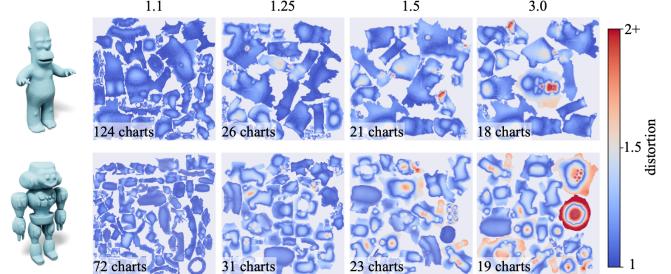


Fig. 11. PartUV lets users set a distortion threshold, flexibly controlling both distortion and chart count.

Table 5. 95th-percentile area distortion metrics across four datasets.

Dataset	Metric	Blender	xatlas	ours
ABC	distortion 95th-shape ↓	1.175	1.726	1.273
	distortion 95th-chart ↓	1.093	1.041	1.133
Common Shapes	distortion 95th-shape ↓	1.885	1.504	1.404
	distortion 95th-chart ↓	1.139	1.131	1.169
PartObjaverseTiny	distortion 95th-shape ↓	1.728	1.286	1.271
	distortion 95th-chart ↓	1.132	1.079	1.116
Trellis	distortion 95th-shape ↓	1.319	4.701	1.442
	distortion 95th-chart ↓	1.120	1.099	1.220

table shows, our method consistently yields low 95th-percentile distortion values, with a maximum of 1.442, whereas baseline methods often produce much higher distortions (e.g., 4.701, 1.885, 1.728). These results demonstrate that our approach achieves more robust and stable performance under challenging cases.

5 Discussion on Failure Cases

Our method struggles with poor input mesh topology. For example, it cannot handle 3D meshes containing self-intersections. In such cases, the algorithm may recurse deeply in an attempt to resolve the intersections, which can lead to fragmented charts. Moreover, when input meshes are extremely fragmented—for instance, those with over 1000 components—the unwrapping results also become highly fragmented. In these cases, remeshing may be required before UV unwrapping. However, our method performs well on general meshes with few components and does not require meshes to be watertight or manifold.

6 Conclusion

In this paper, we propose PartUV, a novel framework for UV unwrapping that strategically integrates semantic part priors from learning-based methods with two novel geometric heuristics. PartUV outperforms existing approaches by generating significantly fewer charts, low distortion, and chart boundaries that align with semantic parts. We demonstrate the advantages of this pipeline through several applications.

Appendix

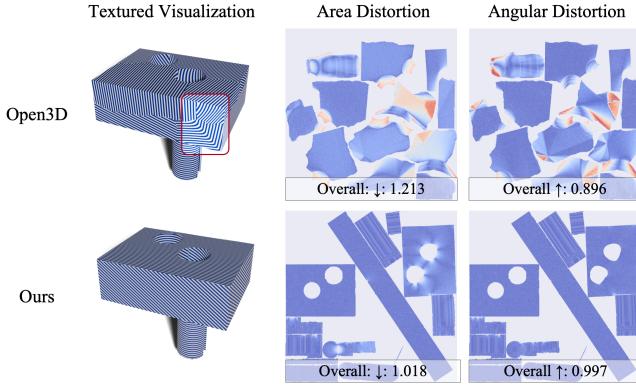


Fig. 12. A demonstration of effects from Open3D’s higher distortion results, creating curved (from angular distortion) and uneven (from area distortion) stripes.

Table 6. Efficiency (\uparrow) comparison across methods

	ours	Blender	Open3D	xatlas
Part-Objaverse-Tiny	0.606	0.514	0.332	0.666
Trellis	0.571	0.430	0.242	0.619
ABC	0.568	0.554	0.490	0.646
Common Shapes	0.575	0.460	0.461	0.561

A1 Additional Results and Comparisons

A1.1 More Qualitative Results

In the supplementary material, we provide an HTML file containing more qualitative and quantitative comparisons between our method and our baselines. The examples are gathered across the four datasets we used in the main paper. The metrics are computed and reported for individual shapes.

A1.2 Efficiency

As we create the UV map with regard to semantic features and groups, it may raise doubts regarding the final efficiency of the resulting UV maps. In Table 6, we show the comparison of the average efficiency of valid results between our method and the baselines. In our experiments, we always group the charts from the same parts when packing, and we use UVPackMaster [Łukasz Czyż 2025] to get the final packed UV map. We set the "heuristic search" time to 3 seconds for UVPackMaster, while most meshes finish within microseconds. We define efficiency as the total area of valid 2D faces within the normalized 0–1 UV space. It can be seen that our method does not hurt the overall efficiency, and it remains competitive compared to our baseline methods.

A1.3 Analysis and Visualization of Open3D Results

In our experiments, particularly on the more challenging meshes, Open3D frequently crashed or exceeded the allotted time budget.

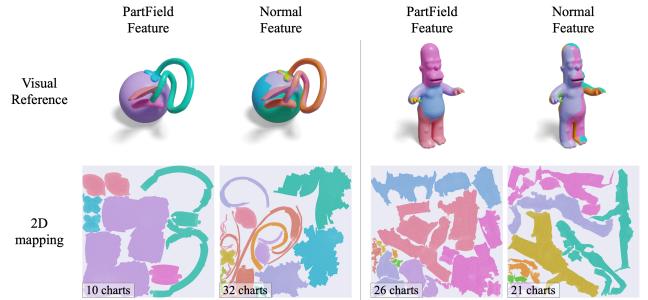


Fig. 13. When using the face normals as agglomerative features for top-down tree construction, the pipeline generates messier results with no semantic alignment.

We designate a shape as timed-out when its runtime surpasses 30 seconds plus three times the longest runtime among other methods on the current shape.

Even for the shapes where Open3D successfully produces a UV map, the results still exhibit notable shortcomings. At first glance, Open3D seemingly generates results with chart numbers similar to our method, albeit with slightly higher distortion. However, such differences in distortion can significantly affect downstream tasks. In Fig. 12, we show one example from the ABC dataset, which Open3D creates a layout with a similar chart number with ours. However, with 0.2 difference in area distortion and 0.1 difference in angular distortion, the deformation of the texture is clearly noticeable. In particular, when using a striped texture, angular distortion leads to curved lines (bottom half of highlighted region), while area distortion causes uneven width (top half of highlighted region)—both prominently visible in the red-marked rectangle of the figure, not to mention the seams that disregard underlying geometric features. In contrast, our results exhibit minimal distortion, maintain the regularity of the shape, and feature seams that largely respect the underlying geometric structure.

A2 Additional Ablation Results

A2.1 Replacing PartField feature with Face Normals

In our main pipeline, we create a top-down tree of faces with agglomerative clustering of PartField-predicted features. A simpler alternative would be replacing such features with face normals. In Fig. 13, we provide some visual examples of meshes using normal as Agglomerative features versus using the PartField-predicted ones. It can be seen that using normal is substantially prone to producing curly shapes, like the cherry on the left. Moreover, though being able to predict a similar number of charts under the same heuristic settings, using normal as the agglomerative features leads to way less organized and neat UV layouts, as exemplified on the right of the figure.

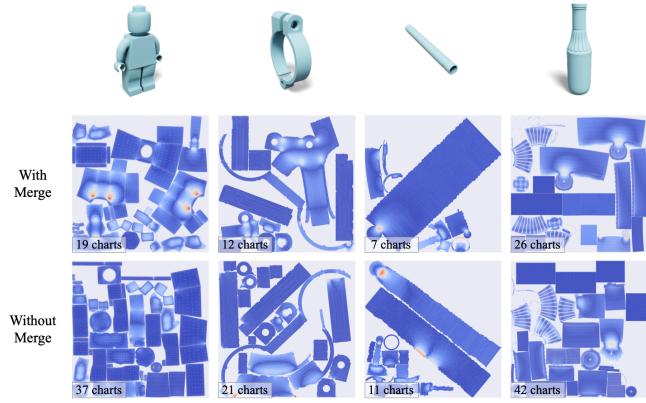


Fig. 14. Visual comparison of with and without the merge heuristics.

Table 7. Comparison between using ABF++ (Ours) and LSCM (Ours-LSCM) in our pipeline.

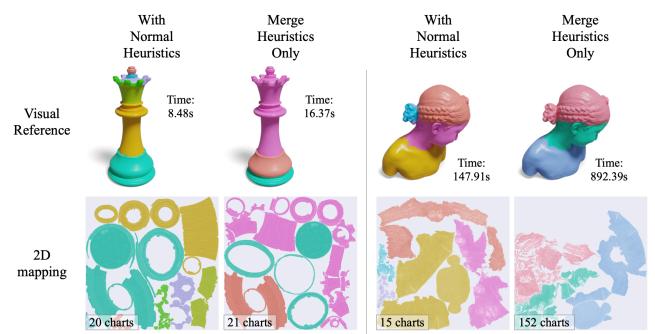
	average # charts ↓	median # charts ↓	area distort. ↓	seam length ↓	time (s)
Ours-LSCM	1154.12	363.00	1.27	65.48	58.61
Ours	538.81	221.50	1.30	57.92	41.88

A2.2 Without Merge Heuristic

In the main manuscript, we propose two heuristics used to unwrap a part into charts, *Normal* and *Merge*. Despite the higher cost of computation, *Merge* often produces more visually appealing UV maps with fewer charts. As illustrated in Fig. 14, the *Merge* heuristic can usually unwrap the part in an "unfolding" manner, creating less number of charts with a neater layout, comparing under the same distortion threshold requirements with using only the *Normal* Heuristics.

A2.3 Without Normal Heuristic

With two heuristics included in the pipeline, one can also opt to use only the *Merge* throughout the pipeline. We show several example results in Fig. 15. Due to its high computational cost, using only *Merge*, especially at the beginning, incurs substantial runtime overhead. To be precise, the *Merge* heuristic would compute an oriented bounding box (OBB) and use projection to get initial charts, and it could get hundreds of charts from a bumpy input. Trying to merge all of them would introduce significant overhead for such bumpy/uneven meshes. For example, on the bimba mesh on the right side of the figure, the runtime increases from 147 seconds to over 892 seconds. Moreover, due to its bumpy geometry, the merging process often results in overlapping, leading to an increase in the number of charts. In essence, *Merge* could yield better results, but only on simpler shapes. Therefore, it is most effective as a complement to the *Normal* heuristic and should be invoked only when *Normal* produces a sufficiently good result.

Fig. 15. Using only *Merge* heuristic from the beginning would incur more runtime, and more fragmented charts on bumpy meshes.

A2.4 Using LSCM instead of ABF++

In our main pipeline, we adopt ABF++ [Sheffer et al. 2005] as the primary flattening algorithm due to its fast performance and low-distortion mappings. Most of our baselines utilize LSCM [Lévy et al. 2002], which generally offers faster runtimes thanks to its linear energy formulation. However, despite its speed, LSCM generally produces inferior mapping results compared to ABF++. Such sub-optimal outputs can trigger additional recursions in our pipeline, resulting in increased runtimes and more fragmented UV charts. As shown in Table 7, using LSCM ultimately leads to both higher runtime and a larger number of charts on the Trellis dataset.

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