OptCuts: Joint Optimization for Seam Placement and Parameterization of 3D Surfaces

ANONYMOUS AUTHOR(S)

Parameterizing 3D surfaces to the 2D plane with low mapping distortion is a critical problem in computer graphics with many applications including texture mapping, remeshing, and detail transfer. In most practical cases, it is not possible to map 3D surfaces to the 2D plane without introducing discontinuities (seams) and distortion. Most existing techniques follow a two step process - first placing seams and then minimizing distortion - that usually leads to suboptimal results. In this paper, we attack seam placement and parameterization jointly in a single alternating optimization framework, where seams are optimally and progressively introduced or removed (in topology steps) in between distortion minimization (in descent steps). A linear combination of symmetric Dirichlet energy and seam length are taken as our objective, of which the stationary w.r.t. both UV topology and UV coordinates are guaranteed to be reached within a bounded number of alternating iterations per objective, input model, and initial embedding.

Specifically, in descent steps, we minimize symmetric Dirichlet energy using projected Newton method given the current UV topology. In topology steps, we search for a nearby UV topology that locally decrease the objective the most by querying a filtered set of basic topological operations. To be appropriately aggressive on searching in the topological space, we develop an analogous line search method as in continuous settings. Since in application scenarios, an upper bound for distortion or seam length is more intuitive than picking a balancing factor, we also provide a constrained optimization view of this broader problem that seeks stationary w.r.t. both primal (distortion and seams) and dual (balancing factor) variables subject to user specified upper bounds.

Our method automatically produces both visually pleasing and high quality UV maps with low mapping distortion and an optimally sparse set of seams without any user assistance. We also show that given a UV configuration by other methods, our method can improve the distortion and seam placement, and our framework has the potential to handle bijectivity, seamlessness, and user preferences jointly within it as well.

CCS Concepts: • **Computing methodologies → Mesh geometry models**;

Additional Key Words and Phrases: geometry processing, mesh parameterization, seam placement, numerical optimization, ...

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1 INTRODUCTION

2 RELATED WORKS

related methods: AutoCuts [Poranne et al. 2017], Seamster [Sheffer and Hart 2002], geometry images [Gu et al. 2002], Multi-chart geometry images [Snyder et al. 2003], D-Chart [Julius et al. 2005]

components: Bijective parameterization with free boundaries [Smith and Schaefer 2015], projected Newton [Teran et al. 2005], MIPS [Hormann and Greiner 2000],

3 AN ALTERNATING FRAMEWORK OF CONTINUOUS AND DISCRETE OPTIMIZATION FOR MESH PARAMETERIZATION

The most basic and intuitive mesh parameterization objective regarding both seams and distortion is minimizing distortion with as-sparse-as-possible seams introduced. However, seam sparsity usually leads to discontinuous energies w.r.t. UV coordinates $U \in \mathcal{R}^{2n_v}$, which is non-trivial to be considered into existing distortion minimization routines. Instead of progressively approximating seam sparsity energy with a continuous counterpart applying homotopy optimization method as [Poranne et al. 2017], we handle this discrete energy in a combinatoric way - searching in the topological space.

3.1 Formulation

This topological space is a directed graph G_T with its vertices $v_T \in V_T$ being all possible UV topologies of a given 3D surface, and its edges $e_T \in E_T$ are the basic topological operations on a mesh such as vertex split, edge merge, etc, that can transform one UV topology to a nearby topology.

Now, if we consider both distortion and seam in one objective E_w, we can define the value f_v of vertex $v_{T,i}$ as

$$f_v(v_{T,i}) = \min_U E_w$$

and the weights f_w of edge $e_{T,m}$ from $v_{T,i}$ to $v_{T,j}$ could just be defined as

$$f_w(e_{T,m}) = f_v(v_{T,j}) - f_v(v_{T,i})$$

Thus our problem could be written as

$$\min_{U, v_T} E_w$$

which could be stated as to search for a $v_{T,i}$ on G_T where all edges connected to it satisfies $f_w \geq 0$.

However, computing f_v for one UV topology requires a whole continuous optimization process, and even the number of neighbors of a UV topology is in the scale of n_v^2. Consequently, we construct a search path on G_T by progressively introducing or removing seams, and we only estimate f_w on a local stencil of U for a filtered set of neighbors so that the whole process of continuous optimization is only conducted while necessary:

Let's consider a simple situation, minimizing symmetric Dirichlet energy [Smith and Schaefer 2015]

$$E_{SD} = \frac{1}{n_t|\overline{A}|}\sum_t |A_t|(\sigma_{t,1}^2 + \sigma_{t,2}^2 + \sigma_{t,1}^{-2} + \sigma_{t,2}^{-2})$$

and total seam length

$$E_{se} = \frac{1}{\sqrt{n_t}|\overline{e}|}\sum_{i\in\mathcal{S}} 2|e_i|$$

where a balancing factor $\lambda \in [0,1]$ is controlling the ratio between the two:

$$E_w = \lambda E_{se} + (1-\lambda)E_{SD}$$

We minimize E_w by iteratively alternating between continuous optimization (in descent steps) and discrete optimization (in topology steps):

- In descent steps, we compute $f_v(v_{T,i})$ via projected Newton method [Teran et al. 2005]:
$$f_v(v_{T,i}) = E_{se,i} + \min_U E_{SD}$$
- In topology steps, we estimate $f_v(v_{T,j})$ for a filtered set of neighbors on a local stencil of U as $\hat{f}_v$ and move onto the neighbor $v_{T,i+1}$ with smallest $\hat{f}_v$.

If in a descent step, $f_v(v_{T,i}) \geq f_v(v_{T,i-1})$ is detected, we stop the process by rolling back to $v_{T,i-1}$, which is the stationary of E_w w.r.t. both UV topology and UV coordinates that we are searching for.

3.2 Convergence

As our method is defined to guarantee convergence, we now analyze convergence rate. First, it's easy to see that E_w is monotonically decreasing looking at each end of descent steps. Now we look at descent step i and $i+1$, from $E_w^i \geq E_w^{i+1}$ we have

$$E_{SD}^i - E_{SD}^{i+1} \geq \frac{\lambda}{1-\lambda}(E_{se}^{i+1} - E_{se}^i) \geq \frac{\lambda}{1-\lambda}\frac{1}{\sqrt{n_t}|\overline{e}|}2|e|_{min}$$

if we now only consider splitting operations that keep increasing E_{se}. It's obvious that E_{SD}'s lower bound is defined to be 4. So we have

$$n_{alter} \leq \frac{(1-\lambda)\sqrt{n_t}|\overline{e}|}{2\lambda|e|_{min}}(E_{SD}^0 - 4)$$

The most important hint we can read from this is, to accelerate convergence, we can move through multiple vertices on G_T in each topology step to increase $E_{se}^{i+1} - E_{se}^i$. Consequently, we build an anologous line search method to be appropriately agressive when searching in the topological space so that we won't fall into bad locally optimal UV topologies.

Merge operations should be defined carefully to ensure convergence, and the proof will need updates.

3.3 Potential Extensions

It will be interesting to replace E_{SD} with other types of distortion energies, especially conformal energies like MIPS [Hormann and Greiner 2000] to see how it behaves. Besides, bijectivity could be potentially achieved by augmenting distortion energy with a penalty-based collision handling energy, possibly also assisted by air mesh method [?]. Similarly, seamless properties could also be achieved by augmenting distortion energy with the correspondingly developed new differentiable objectives, and our alternating framework stays the same.

If an objective derived from an application is discontinuous and it could be expressed using mesh topology, then we can simply augment it into E_{se} and tackle it in the topology steps. For example, the smoothness of seams, user preferences on regional seam placement, and properties related to charts should all be able to be considered in this way.

Besides, parallelism not only accelerate our topology steps, but also could improve the results by conducting an either broader or deeper search in the topological space.

4 DESCENT STEPS FOR CONTINUOUS OPTIMIZATION

for each descent step inner iteration j, Newton-type Iteration: compute E_{SD} Hessian proxy P^j using projected Newton compute E_{SD} gradient g^j solve for search direction p^j ($P^j p^j = -g^j$) using PARDISO symmetric indefinite solver compute initial step size α_0^j by avoiding element inversion backtracking line search with Armijo rule update $U^{j+1} = U^j + \alpha^j p^j$ record energy decrease $(1-\lambda_t)\Delta E_{SD}^j$

5 TOPOLOGY STEPS FOR DISCRETE OPTIMIZATION

5.1 Evaluating Topological Operations via Optimization on Local Stencils

Candidate Filtering: for each vertex compute divergence of local gradients independently picking $\sqrt{n_{v,b}^i}$ boundary vertices and $\sqrt{n_{v,i}^i}$ interior vertices with largest divergence as candidates

Local Evaluation: for each candidate vertex if on boundary for each interior incident edge split and compute $\Delta E_{SD,l}$ locally compute $\Delta E_{w,l} = (1-\lambda_t)\Delta E_{SD,l} + \lambda_t \Delta E_{se}$ else for each pair of incident edges forming a smooth path split and compute $\Delta E_{SD,l}$ locally compute $\Delta E_{w,l} = 0.5((1-\lambda_t)\Delta E_{SD,l} + \lambda_t \Delta E_{se})$

split the vertex with largest $|\Delta E_{w,l}|$ turn on fracture propagation

try larger stencils

enable merge operation

5.2 Line Search in Topological Space

Current Fracture Propagation: if fracture propagation is on for each fracture tail vertex k for each interior incident edge of k split and compute $\Delta E_{SD,l}$ locally compute $\Delta E_{w,l} = (1-\lambda_t)\Delta E_{SD,l} + \lambda_t \Delta E_{se}$ if the largest $|\Delta E_{w,l}|$ is larger than $|(1-\lambda_t)\Delta E_{SD}^j|$ propagate fracture by splitting the vertex else turn off fracture propagation for the rest of the current descent step

6 WEIGHTING THE OBJECTIVE AUTOMATICALLY BY INTRODUCING A DUAL PROBLEM

At each inner iterate $k+1$, we fix some λ^{k+1} and minimize the bi-objective

$$\min_{T,V} E_{SE}(V,T) + \lambda^{k+1} E_{SD}(V,T)$$

How do we get λ^{k+1}?

Our overall minimization is inequality constrained with a specified upper bound $b \in \mathbb{R}_+$ on distortion. (L2 norm on SD energy for now - pretty easy to modify to an extremal measure if we want later on.)

Our model problem minimization is then

$$\min_{T,V} E_{SE}(V,T) : b - E_{SD}(V,T) \geq 0$$

Or, equivalently,

$$\min_{T,V} \max_{\lambda \geq 0} E_{SE}(V,T) + \lambda\big(E_{SD}(V,T) - b\big)$$

Of course this is nonsmooth in λ since it does not take into account very nicely the fact that per-iteration we will start away from feasibility and want to iteratively improve both our primal variables $\{V,T\}$ and our dual variable λ. So to smoothly update to a current λ^{k+1} from a previous estimate λ^k we will add a regularizer $R(\lambda, \lambda^k)$ to make sure λ iterates behave themselves reasonably. For now lets stick with something simple: a quadratic regularizer should do the trick $R = \frac{1}{2\kappa}(\lambda - \lambda^k)^2$.

For iteration $k+1$ this gives us

$$\min_{T,V} \max_{\lambda \geq 0} E_{SE}(V,T) + \lambda\big(E_{SD}(V,T) - b\big) - \frac{1}{2\kappa}(\lambda - \lambda^k)^2$$

And now we can first solve closed form for λ as

$$\lambda^{k+1} \leftarrow argmax_{\lambda \geq 0} E_{SE}(V,T) + \lambda\big(E_{SD}(V,T) - b\big) - \frac{1}{2\kappa}(\lambda - \lambda^k)^2$$

giving us

$$\lambda^{k+1} \leftarrow \max\big(0, \kappa\big(E_{SD}(V,T) - b\big) + \lambda^k\big)$$

We then can solve the inner iteration (with both discrete topology steps and smooth steps) with the energy

$$\min_{T,V} E_{SE}(V,T) + \lambda^{k+1} E_{SD}(V,T)$$

Followed by the next update of dual variable λ.

(Notice that throughout the above we can define a progressive λ without needing to employ subgradients to reason about nonsmoothness in our sparsity energy.)

R is to iteratively solving for λ so that it could have intermediate values between 0 and ∞. Then starting from full mesh, λ will first increase as bound is not reached, and then it will decrease when bound is reached. But currently we don't have merge to increase E_{SE} and decrease E_{SD}, so our process will stop right after it reaches the bound. The bound is obvious to be reached, how do we know the path of λ is great? If we have merge, then will the optimization converge on all T, V, λ?

7 RESULTS AND DISCUSSION

quality and timing comparison with previous methods

show improvements starting from results given by previous methods

8 CONCLUSIONS AND FUTURE WORKS

multiple cut initiation in one topology step by global stretch analysis?

how to deal with closed surfaces (what will be the initial cuts for the initial embedding)?

try conformal energy like MIPS

bijectivity, seamless, and other augmentation of continuous energy?

handle user preferences on seam placement

seam smoothness, patch related discrete energy?

start and solve in 3D by reducing curvature so that the need for initial embedding could be eliminated, and the result is only "biased" by it's 3D shape, which is the most reasonable bias

taking advantage of parallelism to look both broader and deeper when searching in topological space, very useful for practical implementations

if the user won't mind getting a slightly different triangulation, we could also create fractures in the interior of an element and locally remesh the stencil

given a symmetric shape, whether symmetrically triangulated or not, does our method preserve symmetry in UV space?

9 ACKNOWLEDGEMENTS

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