

Reversible Harmonic Maps

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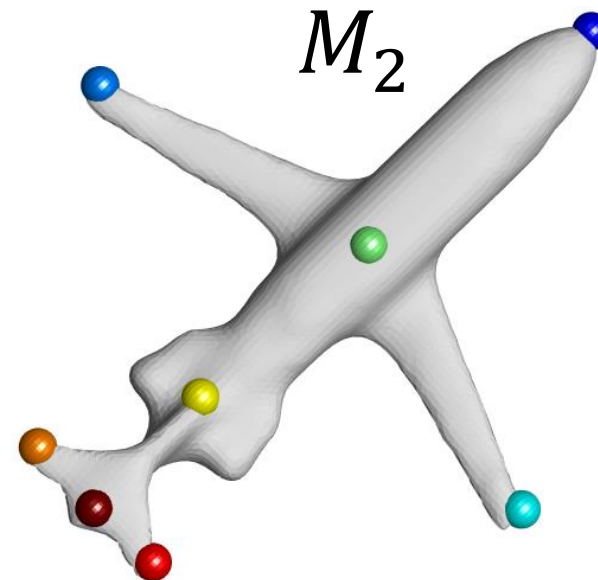
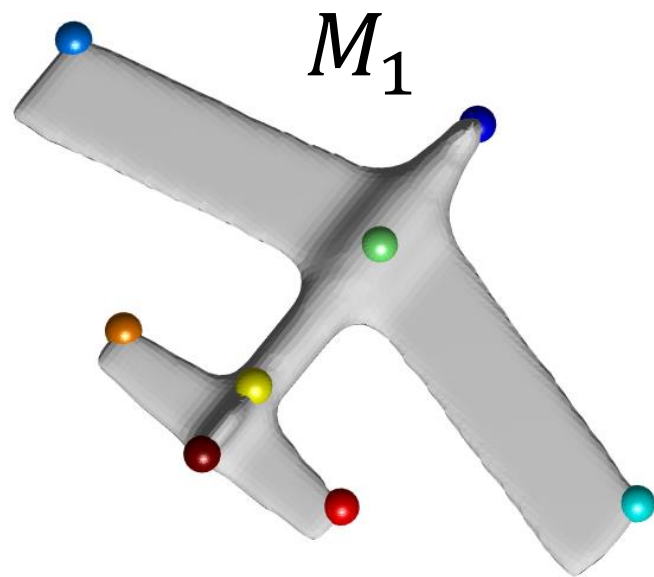
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Our Approach

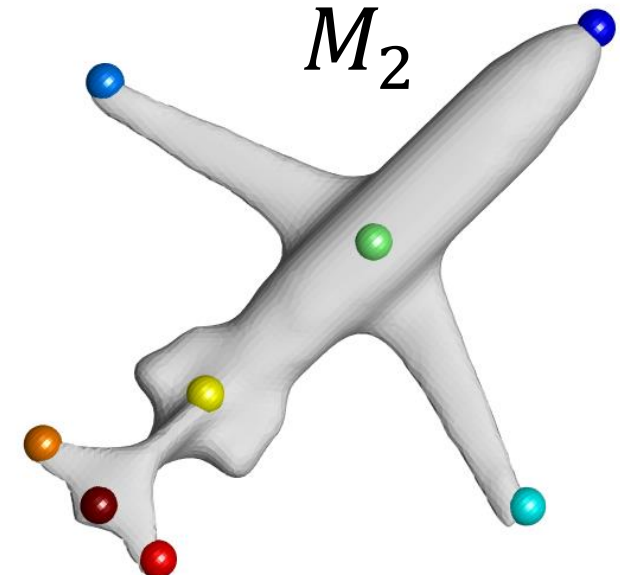
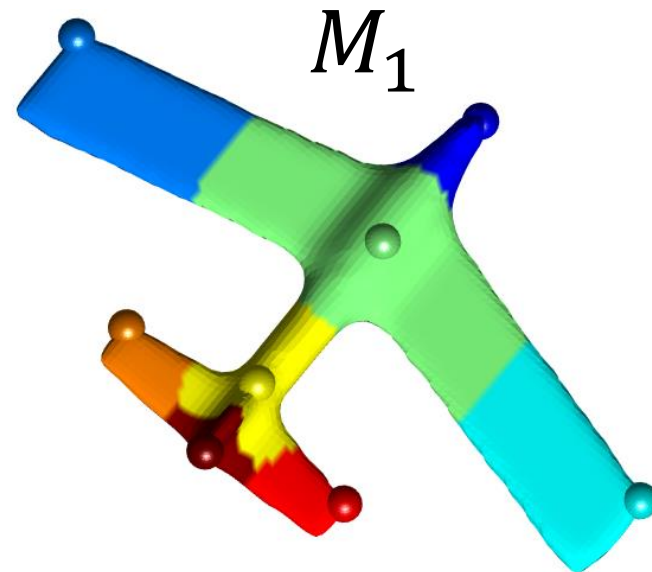
Input: a sparse set of landmarks (p_i, q_i)



Our Approach

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- Initialize the map by mapping **geodesic cells** of each landmark p_i to the corresponding landmark q_i :



Our Approach

Input: a sparse set of landmarks (p_i, q_i)

- Initialize the map by mapping **geodesic cells** of each landmark p_i to the corresponding landmark q_i
- Optimize the map with respect to an **energy** that promotes **smoothness** and **bijection**

Discrete Dirichlet Energy

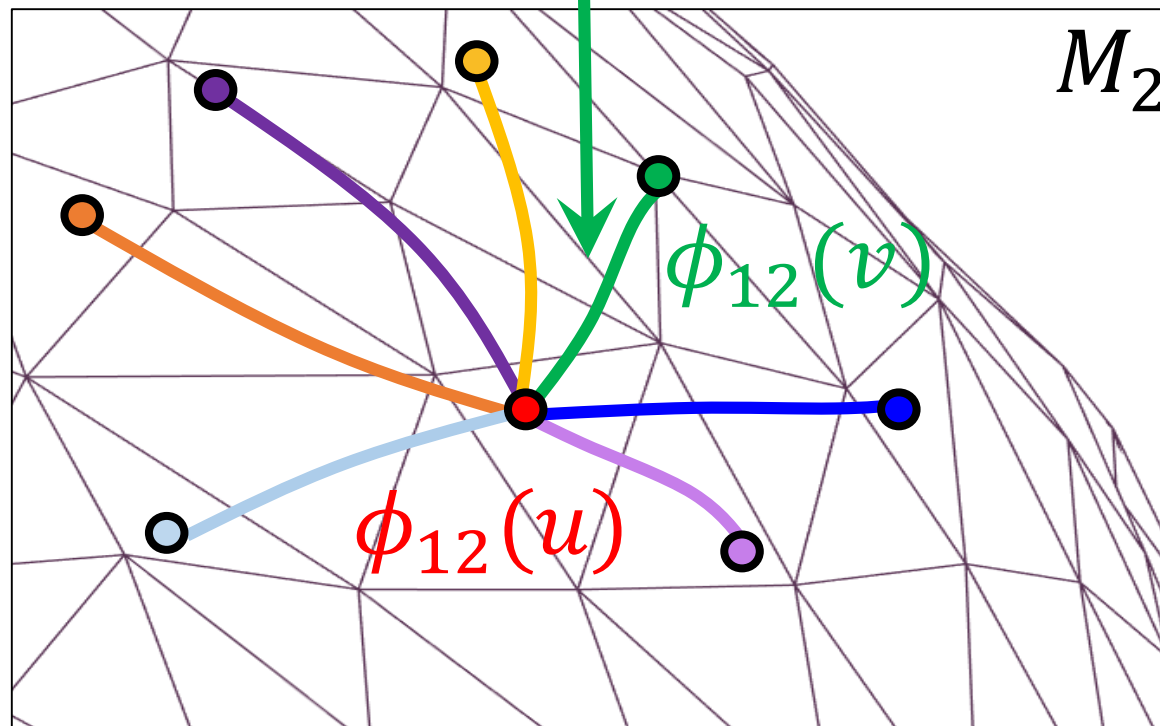
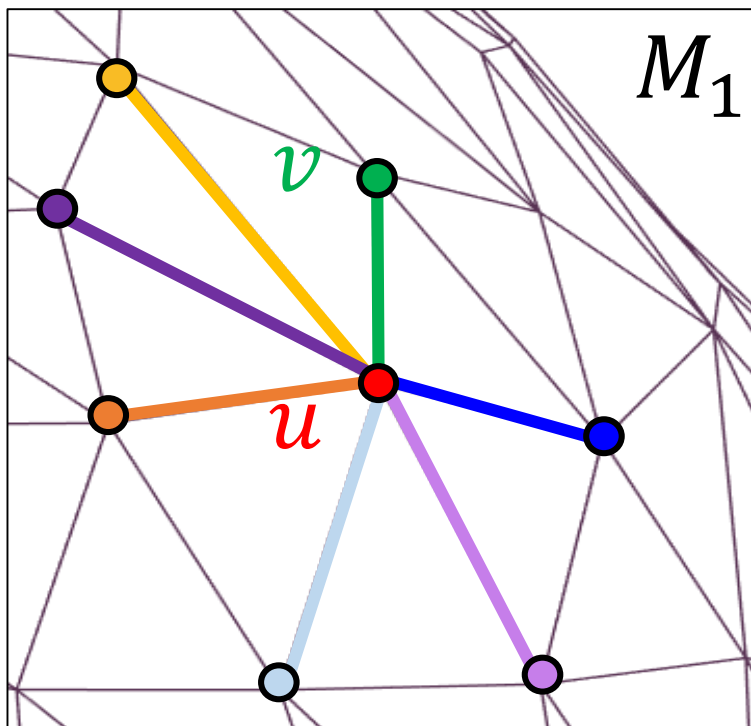
Measures **smoothness** of a map:

$$E(\phi_{12}) = \frac{1}{2} \int_{M_1} |d\phi_{12}|^2$$

A map is **harmonic** if it is a critical point of the Dirichlet energy

Discrete Dirichlet Energy

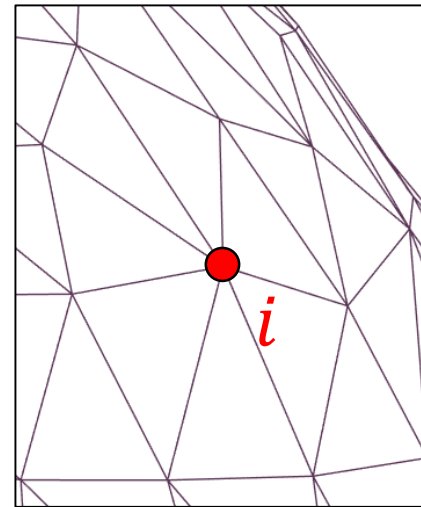
$$E_D(\phi_{12}) = \sum_{(u,v) \in E_1} w_{uv} \underbrace{d_{M_2}^2(\phi_{12}(u), \phi_{12}(v))}_{\text{distance in } M_2}$$



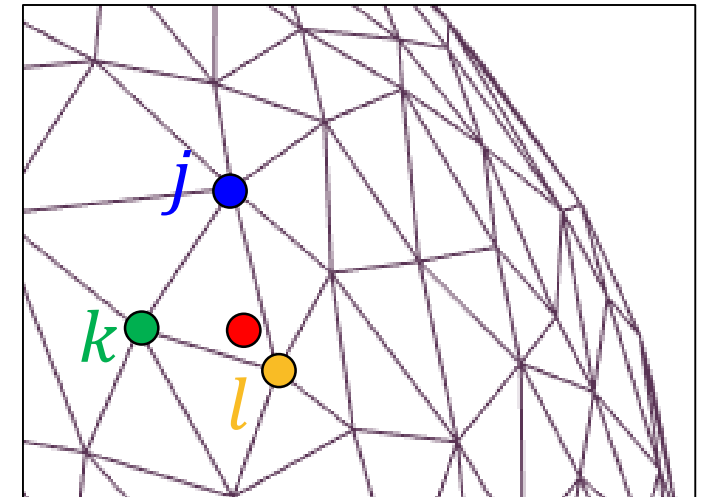
Discrete Precise Maps

Stochastic matrices with barycentric coordinates at each row:

$$P_{12} = \begin{pmatrix} & j & k & l \\ & \vdots & \vdots & \vdots \\ -0.1 & -0.2 & -0.7 & \text{row } i \\ & \vdots & \vdots & \vdots \end{pmatrix}$$



M_1

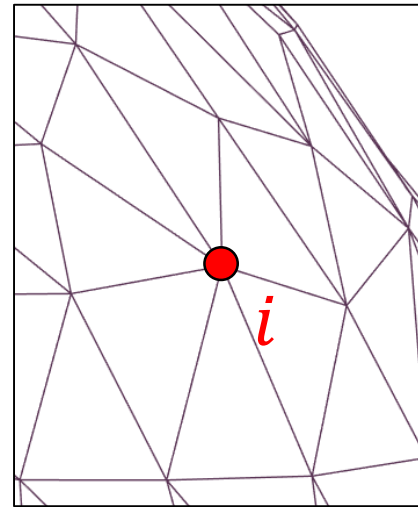


M_2

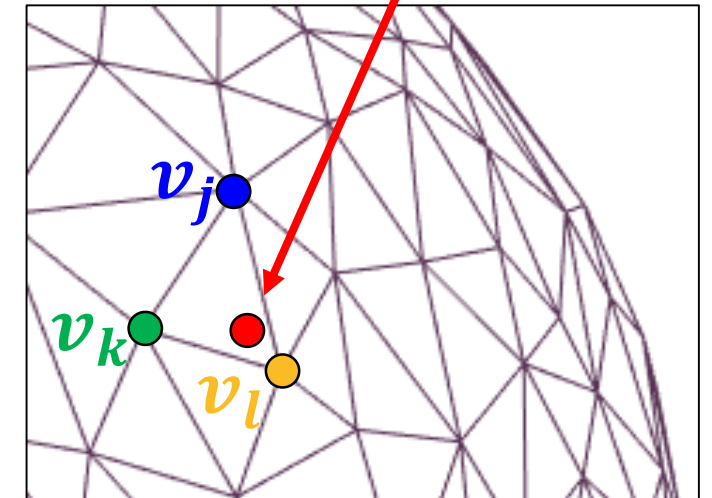
Discrete Precise Maps

Stochastic matrices with barycentric coordinates at each row:

$$\begin{matrix}
 & \begin{matrix} j & k & l \end{matrix} \\
 \begin{matrix} i \\ \vdots \\ \vdots \end{matrix} & \begin{pmatrix} - & - & - \\ 0.1 & 0.2 & 0.7 \\ - & - & - \end{pmatrix} & \begin{pmatrix} -v_j- \\ -v_k- \\ -v_l- \end{pmatrix} \\
 & P_{12} & V_2
 \end{matrix}$$



M_1



M_2

$V_2 \in \mathbb{R}^{n_2 \times 3}$ is a matrix with vertex coordinates of M_2

Discretization – Dirichlet Energy

If we replace the geodesic distances by Euclidean distances, the discrete Dirichlet energy is:

$$E_D^{Euc}(P_{12}) = \|P_{12}V_2\|_{W_1}^2 = \text{Trace}((P_{12}V_2)^T W_1 P_{12}V_2)$$

W_1 is a matrix with $-w_{ij}$ at entry i, j , and the sum of the weights on the diagonal

$$W_1 = \begin{pmatrix} & j & i & k \\ i & -w_{ij} & \sum_v w_{iv} & -w_{ik} \end{pmatrix}$$

Discrete Dirichlet Energy

We use a *high dimensional embedding* where Euclidean distances approximate geodesic distances (MDS)

$$X_2 \in \mathbb{R}^{n_2 \times 8}$$

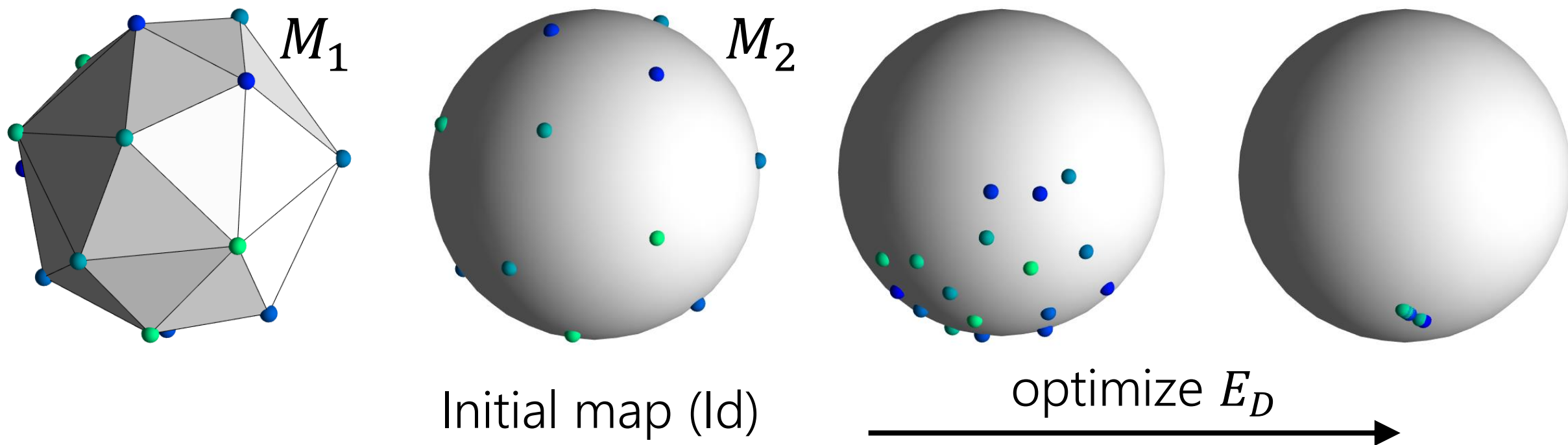
Then the discrete Dirichlet energy is approximated by:

$$E_D(P_{12}) = \|P_{12}X_2\|_{W_1}^2$$

Minimizing the Dirichlet Energy

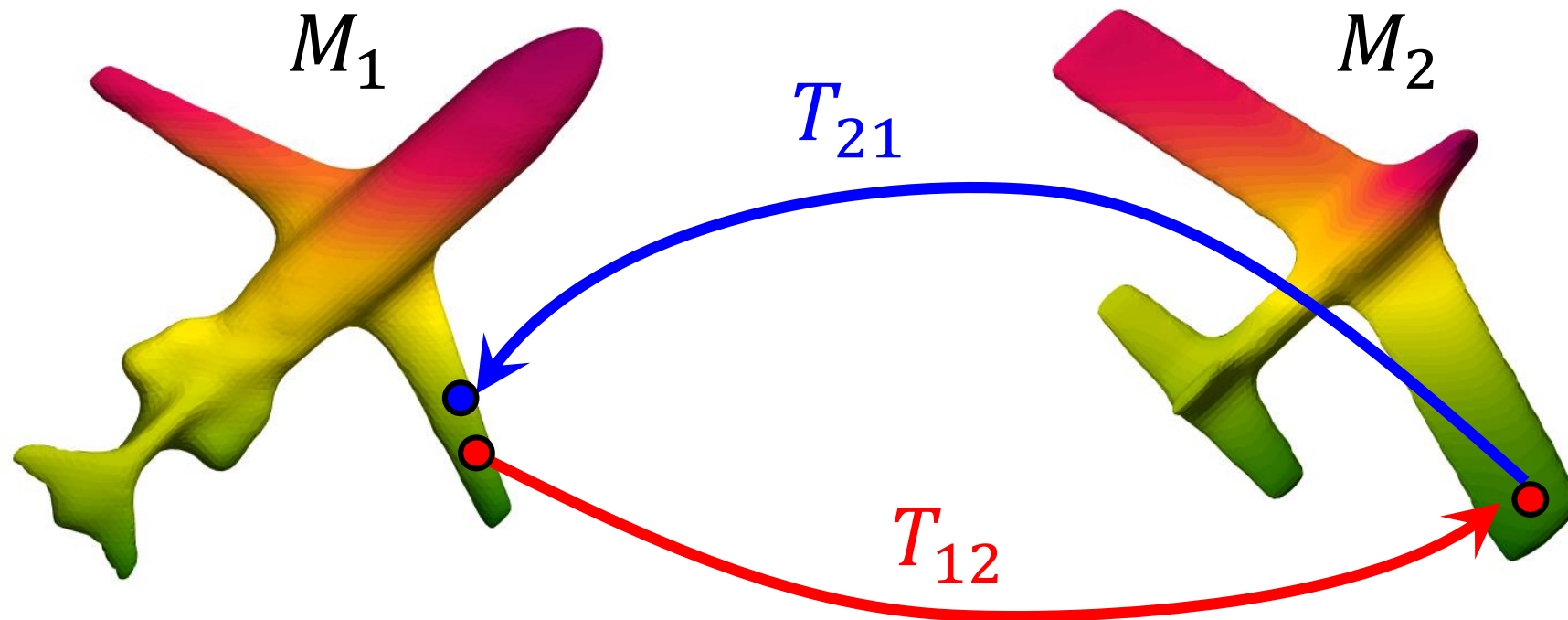
A map that maps all vertices to a single point is harmonic

Minimizing the harmonic energy “shrinks” the map:



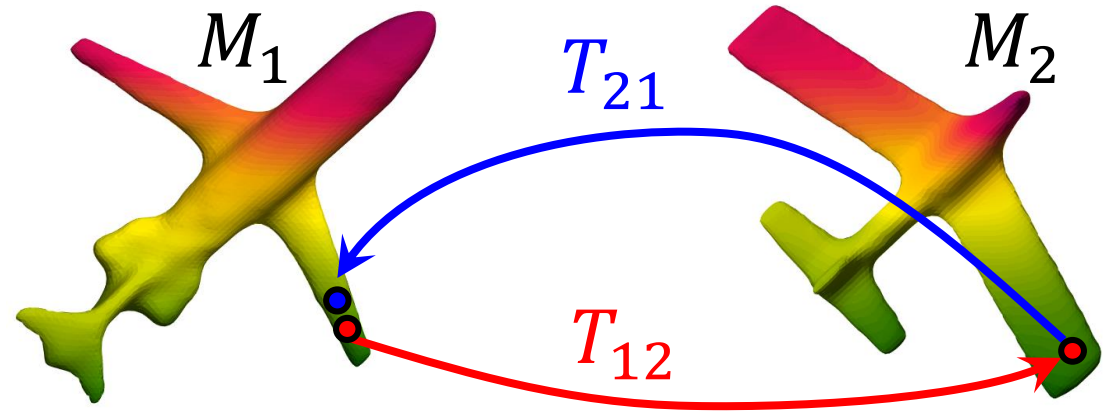
Reversibility

- We add a **reversibility term** to prevent the map from shrinking



Reversibility

Continuous setting:

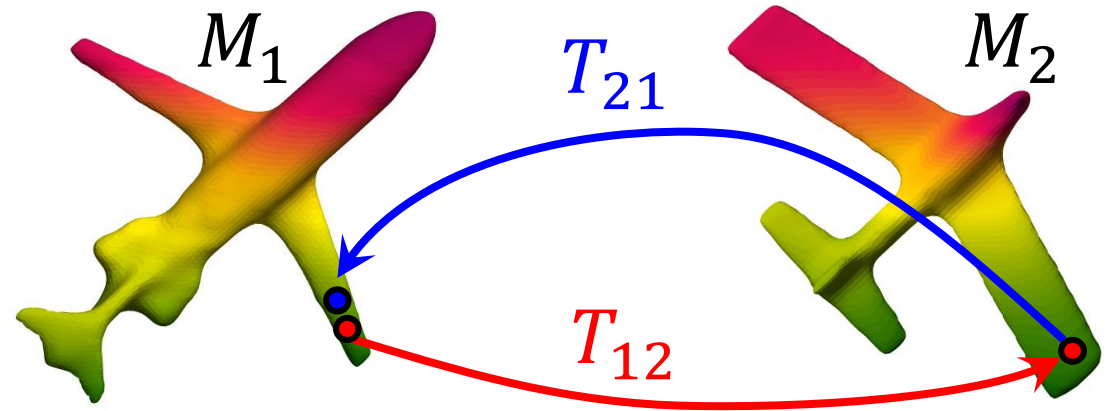


$$E_R(T_{12}, T_{21}) = \sum_{v \in V_1} d_{M_2}(v, T_{21}(T_{12}(v))) + \sum_{v \in V_2} d_{M_1}(v, T_{12}(T_{21}(v)))$$

The term $E_R(T_{12}, T_{21})$ promotes *injectivity* and *surjectivity*

Reversibility

Discrete setting:



$$E_R(P_{12}, P_{21}) = \|P_{21}P_{12}X_2 - X_2\|_{M_2}^2 + \|P_{12}P_{21}X_1 - X_1\|_{M_1}^2$$

Again we use X_1, X_2 the high dimensional embedding of each shape to approximate geodesic distances

Total Energy

We combine the Dirichlet energy and the reversibility term:

$$E(P_{12}, P_{21}) = \alpha E_D(P_{12}) + \alpha E_D(P_{21}) + (1 - \alpha) E_R(P_{12}, P_{21})$$

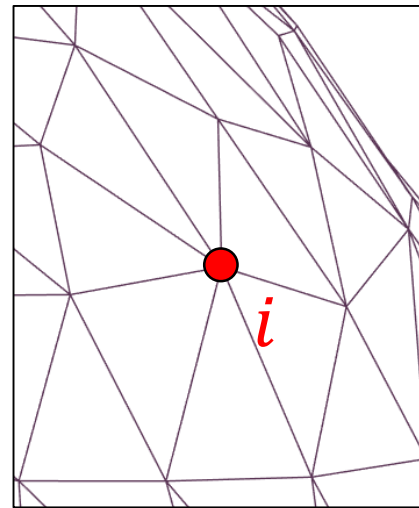
The parameter α controls the trade off between the terms

$$E(P_{12}, P_{21}) = \alpha E_D(P_{12}) + \alpha E_D(P_{21}) + (1 - \alpha) E_R(P_{12}, P_{21})$$

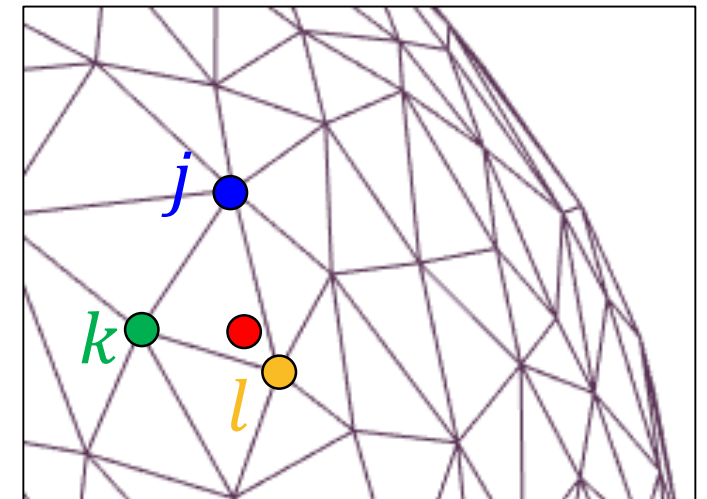
Optimization

All the terms are quadratic, but P_{12}, P_{21} are constrained to the feasible set of precise maps

$$P_{12} = \begin{pmatrix} & j & k & l \\ & \vdots & & \\ -0.1 & -0.2 & -0.7 & \\ & \vdots & & \end{pmatrix} \text{row } i$$



M_1



M_2

Optimization

We know how to optimize functions of the form:

$$\arg \min_{P_{12} \in S} \|P_{12}A - B\|^2$$

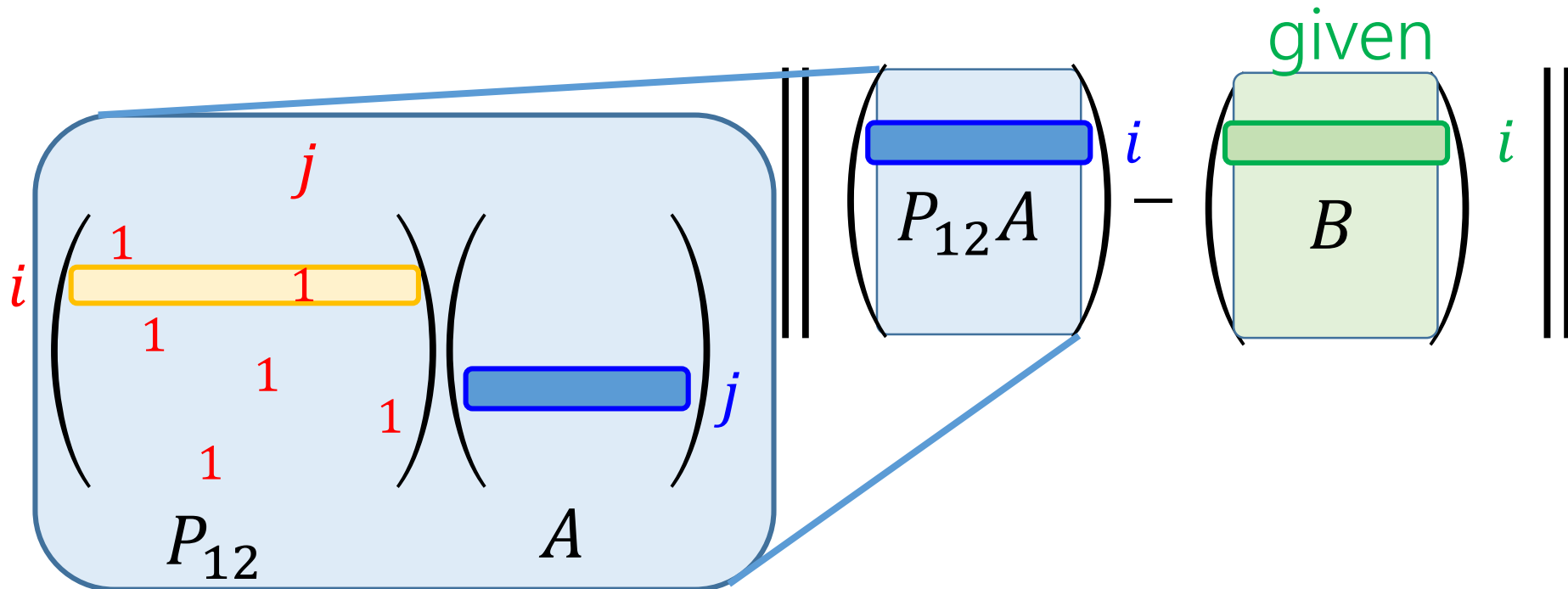
S is the feasible set of precise maps

Optimization

$$P_{12}^* = \arg \min_{P_{12} \in S} \|P_{12}A - B\|_{M_1}^2$$

If we constrain to **vertex-to-vertex** maps (subset of feasible set):

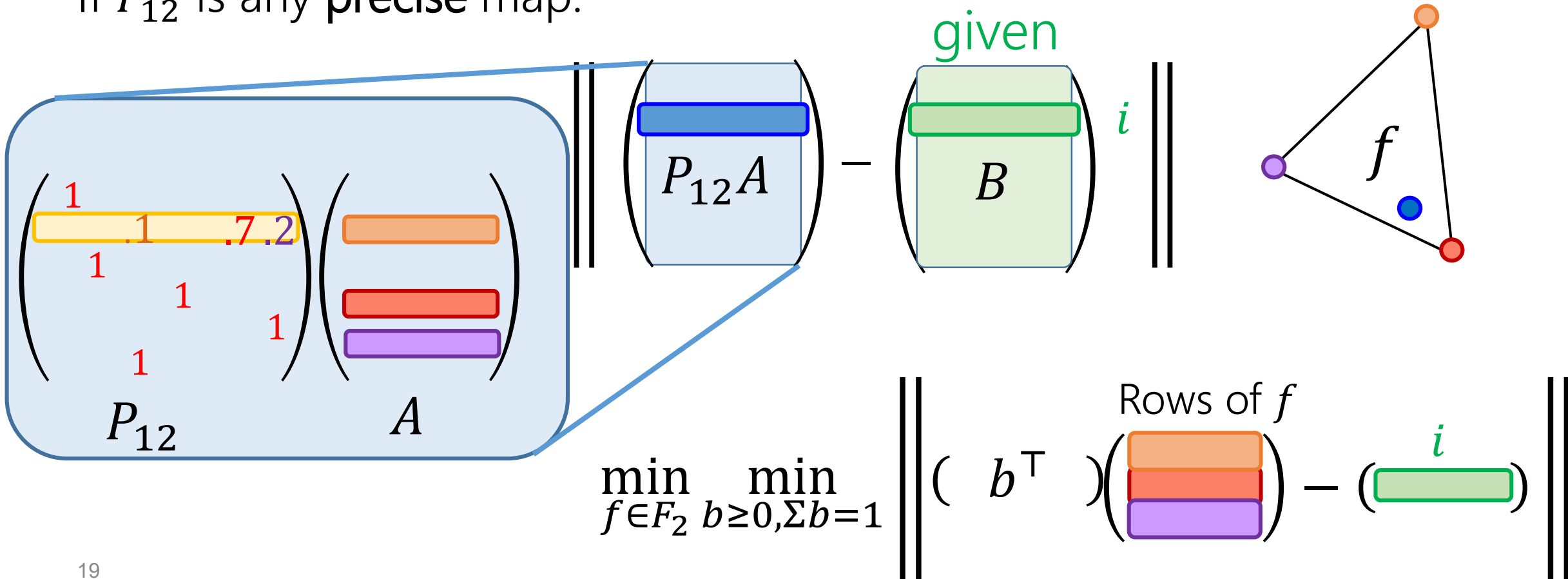
P_{12} is a binary stochastic matrix



Optimization

$$P_{12}^* = \arg \min_{P_{12} \in S} \|P_{12}A - B\|_{M_1}^2$$

If P_{12} is any **precise** map:



Optimization

$$P_{12}^* = \arg \min_{P_{12} \in S} \|P_{12}A - B\|_{M_1}^2$$

If P_{12} is any **precise** map:

$$\min_{f \in F_2} \min_{b \geq 0, \sum b = 1} \left\| \begin{pmatrix} b^T \end{pmatrix} \begin{pmatrix} \text{Rows of } f \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix} - \begin{pmatrix} i \end{pmatrix} \right\|$$

Seems expensive

- Optimize barycentric coordinates by projecting the i_{th} row to a triangle in \mathbb{R}^{k_2} (geometric algorithm)
- Parallelizable!

Optimization

Our energies are not of this form exactly:

$$E_D(P_{12}) = \text{Tr}((P_{12}X_2)^\top W_1 P_{12} X_2)$$

$$E_R(P_{12}, P_{21}) = \|P_{21} \underbrace{P_{12}} X_2 - X_2\|_{M_2}^2 + \|P_{12} \underbrace{P_{21}} X_1 - X_1\|_{M_1}^2$$

Should not depend on P_{12}

We use "half quadratic splitting" such that our energy is of the desired form

Optimization

Introduce new variables

- X_{12} should approximate $P_{12}X_2$, so we add a term $\|P_{12}X_2 - X_{12}\|^2$
- X_{21} should approximate $P_{21}X_1$, so we add a term $\|P_{21}X_1 - X_{21}\|^2$

We replace $P_{12}X_2$ by X_{12} wherever it bothers our optimization

Optimization

We rewrite our energies with the new variables:

$$E_D(X_{12}) = \text{Tr}(X_{12}^\top W_1 X_{12})$$

$$E_R(X_{12}, X_{21}, P_{12}, P_{21}) = \|P_{21}X_{12} - X_2\|_{M_2}^2 + \|P_{12}X_{21} - X_1\|_{M_1}^2$$

$$E_Q(X_{12}, P_{12}) = \|P_{12}X_2 - X_{12}\|_{M_1}^2$$

Optimization

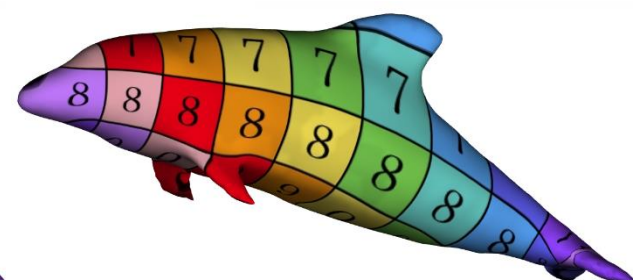
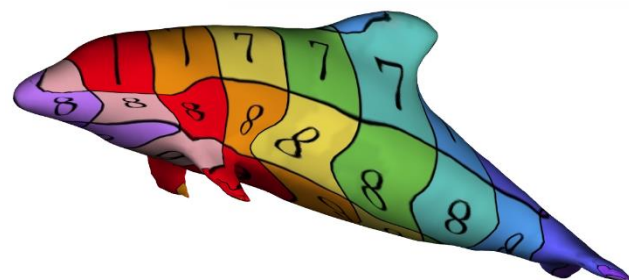
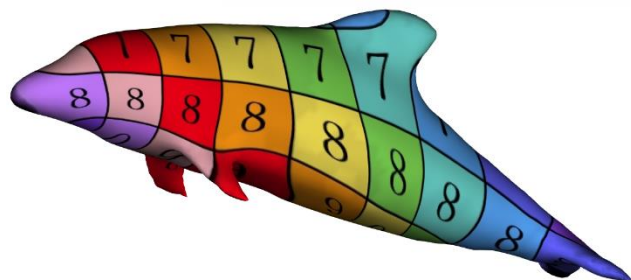
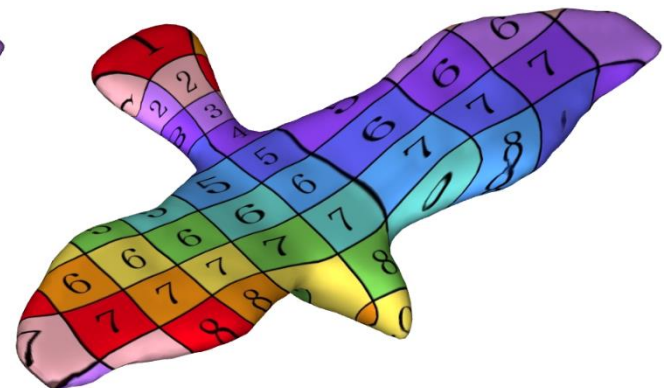
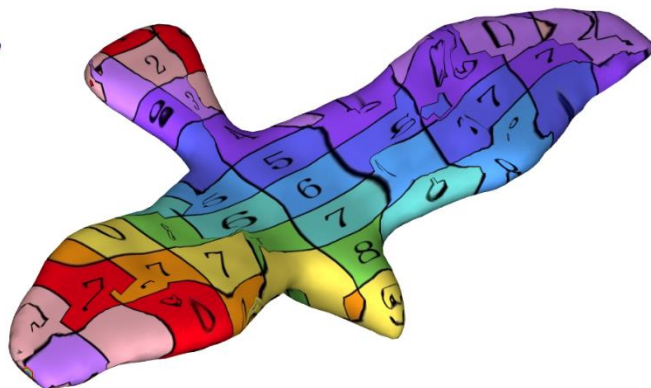
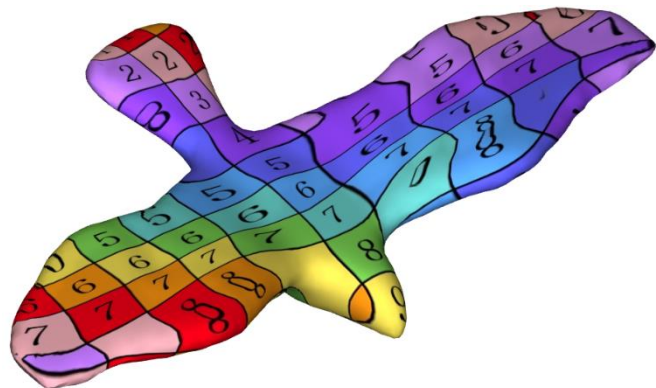
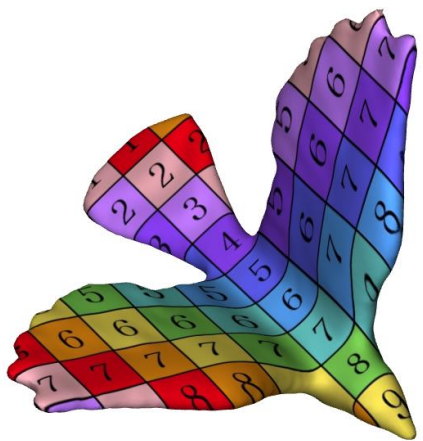
We optimize the energy:

$$\begin{aligned} E(X_{12}, X_{21}, P_{12}, P_{21}) = & \alpha E_D(X_{12}) + \alpha E_D(X_{21}) + && \text{Dirichlet} \\ & + (1 - \alpha) E_R(X_{12}, X_{21}, P_{12}, P_{21}) + && \text{Reversibility} \\ & + \beta E_Q(X_{12}, P_{12}) + \beta E_Q(X_{21}, P_{21}) && \text{Penalty} \end{aligned}$$

by alternately optimizing for each variable

- Optimize P_{12} or P_{21} using projection
- Optimize X_{12} or X_{21} by solving a linear system

Results – SHREC'07



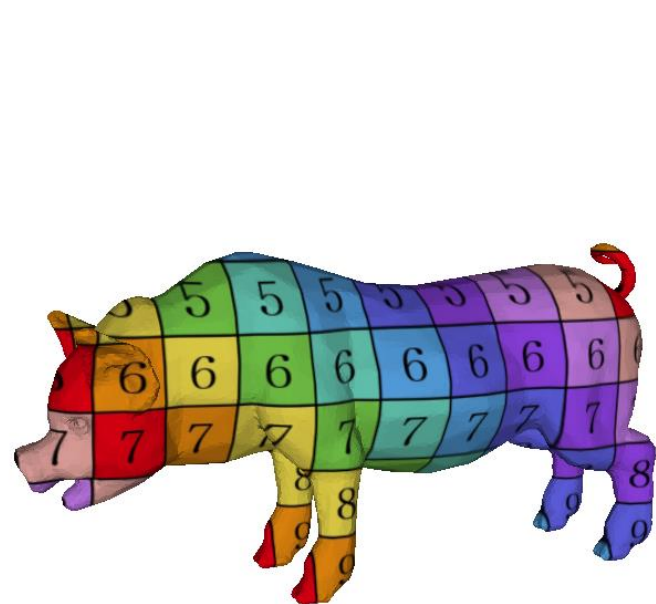
Target

Hyperbolic
Orbifolds

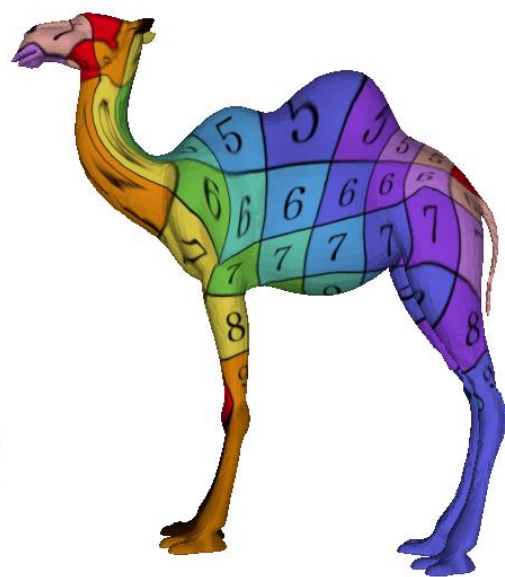
Weighted
Averages

Ours

Results – SHREC'07



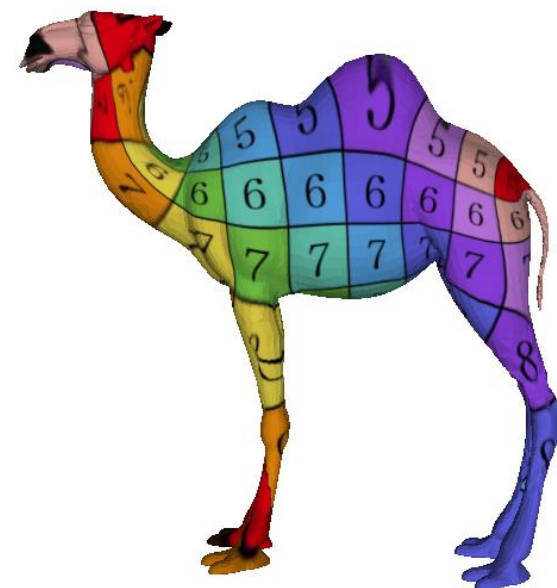
Target



Hyperbolic
Orbifolds



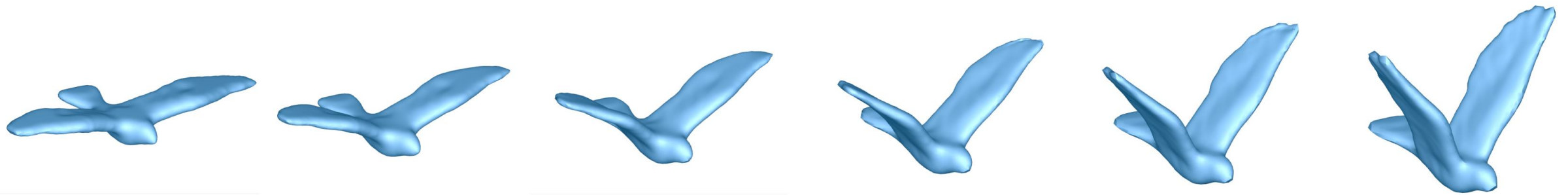
Weighted
Averages



Ours

Results

Interpolation methods require the source and target shape to have a matching triangulation, that can be computed by our method



Heeren, Behrend, Martin Rumpf, Peter Schröder, Max Wardetzky and Benedikt Wirth, "Exploring the Geometry of the Space of Shells", 2014