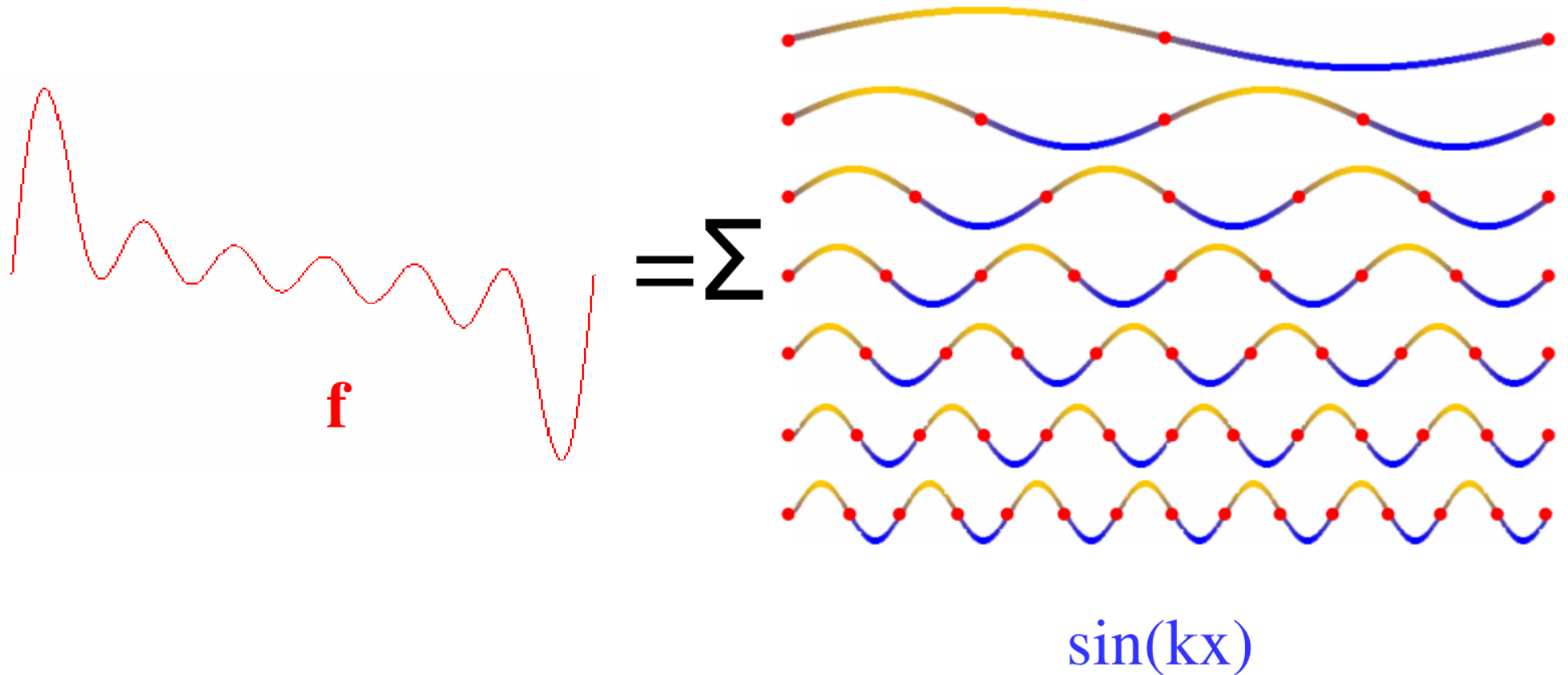
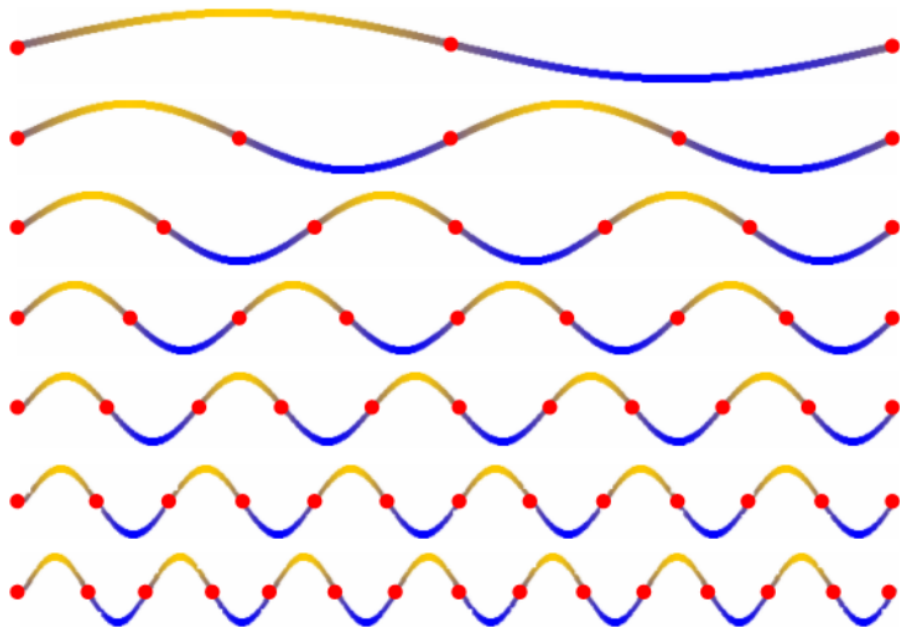


Spectral geometry on triangle meshes

Harmonics and spectral filtering



Harmonics and spectral filtering

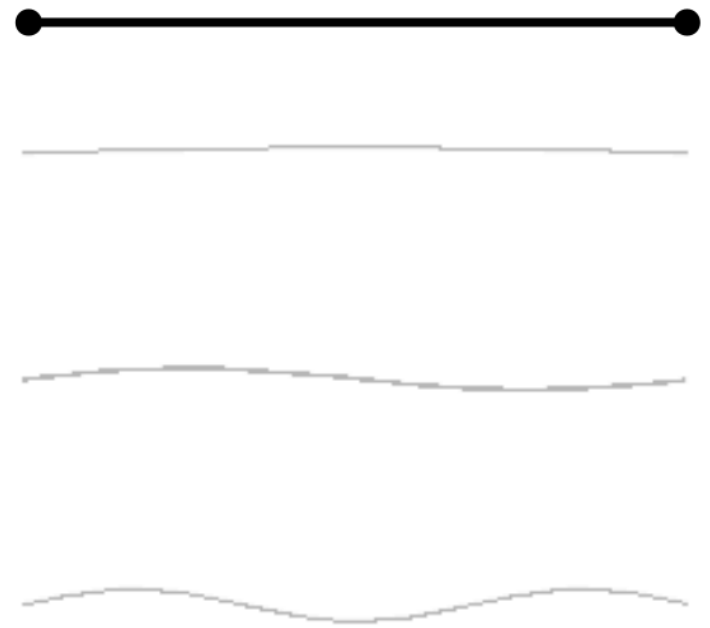
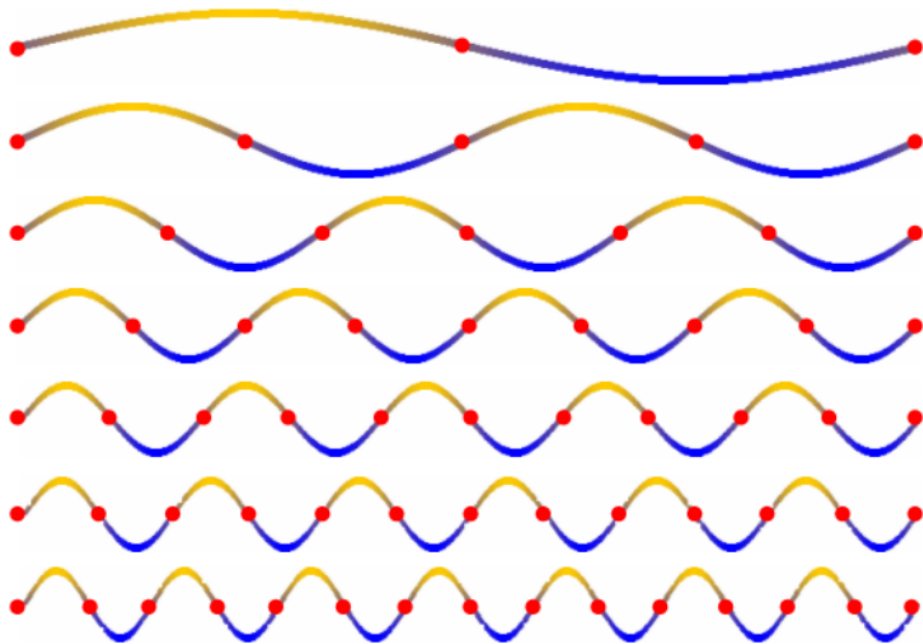


$$\sin(kx)$$

on

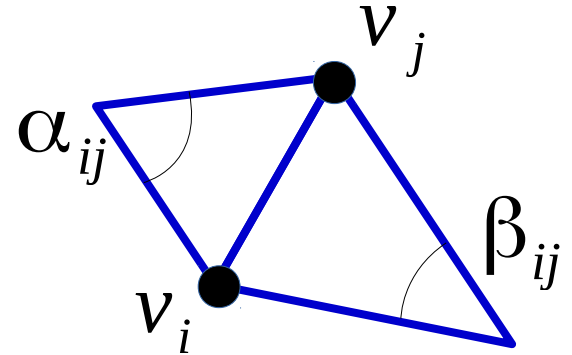
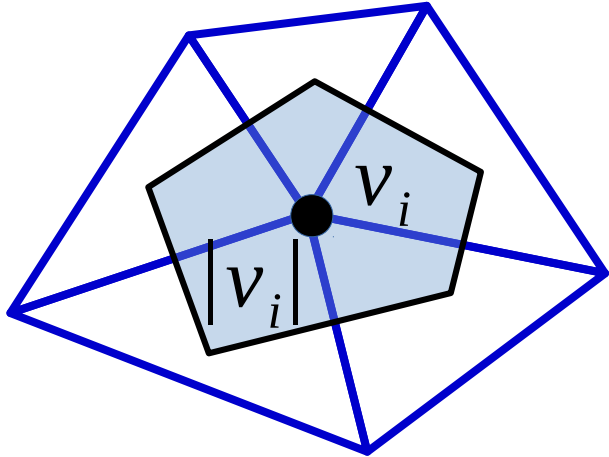


Harmonics and spectral filtering



Strings harmonics = eigenvectors of unidimensional Laplacien

Reminder : Laplacian of scalar functions



$$\nabla^2 f(v_i) = \frac{1}{|v_i|} \sum_{e_{ij}} \frac{\cot(\alpha_{ij}) + \cot(\beta_{ij})}{2} (f(v_j) - f(v_i))$$

Note : You may see the version without $1/|v_i|$ here and there. Once again, the version without is the **integrated** operator (integrated over the area around vertex v_i), and the version with is the point-wise operator.

Spectral decomposition

Takes scalars defined on vertices, computes the Laplacian at each vertex

$$L \cdot \begin{bmatrix} f(0) \\ f(1) \\ \cdot \\ \cdot \\ f(|V|-1) \end{bmatrix} = \begin{bmatrix} \nabla^2 f(0) \\ \nabla^2 f(1) \\ \cdot \\ \cdot \\ \nabla^2 f(|V|-1) \end{bmatrix}$$

$\in \mathbb{R}^{|V| \times 1}$ $\in \mathbb{R}^{|V| \times 1}$

$$\begin{cases} L(i, j) = \frac{1}{|v_i|} \frac{\cot(\alpha_{ij}) + \cot(\beta_{ij})}{2} \\ L(i, i) = -\sum_{e_{ij}} L(i, j) \end{cases}$$

Spectral decomposition

Takes scalars defined on vertices, computes the Laplacian at each vertex

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$$\in \mathbb{R}^{|V| \times 1} \quad \in \mathbb{R}^{|V| \times 1}$$

Eigenvectors of Laplacian should be eigenvectors of L

Spectral decomposition

Takes scalars defined on vertices, computes the Laplacian at each vertex

$$L \cdot \begin{bmatrix} f(0) \\ f(1) \\ \cdot \\ \cdot \\ f(|V|-1) \end{bmatrix} = \begin{bmatrix} \nabla^2 f(0) \\ \nabla^2 f(1) \\ \cdot \\ \cdot \\ \nabla^2 f(|V|-1) \end{bmatrix}$$

$$\begin{cases} L(i, j) = \frac{1}{|v_i|} \frac{\cot(\alpha_{ij}) + \cot(\beta_{ij})}{2} \\ L(i, i) = -\sum_{e_{ij}} L(i, j) \end{cases}$$

$$\in \mathbb{R}^{|V| \times 1} \quad \in \mathbb{R}^{|V| \times 1}$$

PROBLEM ! It is not symmetric : $L(i, j) \neq L(j, i)$

→ **Eigenvectors of L are not orthogonal**

Spectral decomposition

$$L = A^{-1} \cdot L_C$$

Point-wise Laplacian

$$\left\{ \begin{array}{l} L(i, j) = \frac{1}{|v_i|} \frac{\cot(\alpha_{ij}) + \cot(\beta_{ij})}{2} \\ L(i, i) = -\sum_{e_{ij}} L(i, j) \end{array} \right.$$

« Integrated » Laplacian :

$$\left\{ \begin{array}{l} L_C(i, j) = \frac{\cot(\alpha_{ij}) + \cot(\beta_{ij})}{2} \\ L_C(i, i) = -\sum_{e_{ij}} L_C(i, j) \end{array} \right.$$

Diagonal mass matrix :

$$A(i, i) = |v_i|$$

Spectral decomposition

« General » eigenvectors of : $-L_C \cdot \psi_i = \lambda_i A \cdot \psi_i$



Pseudo-orthogonality : $\psi_i^T \cdot A \cdot \psi_j = \delta_i^j$ (instead of $\psi_i^T \cdot \psi_j = \delta_i^j$)

C++ : arpack++ (used for the examples made here) , Eigen3
with Spectra

An orthogonal basis

« General » eigenvectors of : $-L_C \cdot \psi_i = \lambda_i A \cdot \psi_i$

Pseudo-orthogonality : $\psi_i^T \cdot A \cdot \psi_j = \delta_i^j$

$$\bar{\psi}_i := \sqrt{A} \cdot \psi_i$$

$$\bar{\psi}_i^T \cdot \bar{\psi}_j = \psi_i^T \cdot \sqrt{A}^T \cdot \sqrt{A} \cdot \psi_j = \psi_i^T \cdot A \cdot \psi_j = \delta_j^i$$

→ $\{\bar{\psi}_i\}_i$ is a good choice for decomposition : It is an orthonormal basis. (choice seen in related works, not the most obvious, see next)

Decomposition

Given a function f on the vertices

$$F_i := \bar{\psi}_i^T \cdot f = \sum_{v_j} \bar{\psi}_i(v_j) f(v_j) \quad \text{is its } i^{\text{th}} \text{ frequency.}$$

f can be recovered from its frequencies (inverse transform) :

$$f = \sum_i F_i \bar{\psi}_i$$

$$\begin{array}{c}
 \left[\begin{array}{c} f \\ f \\ f \end{array} \right] = \underbrace{\left[\begin{array}{c} \bar{\psi}_0 \quad \bar{\psi}_1 \cdots \bar{\psi}_{n-1} \end{array} \right]}_{B^{-1}} \cdot \underbrace{\left[\begin{array}{c} \bar{\psi}_0^T \\ \bar{\psi}_1^T \\ \vdots \\ \bar{\psi}_{n-1}^T \end{array} \right]}_B \cdot \left[\begin{array}{c} f \\ f \\ f \end{array} \right]
 \end{array}$$

Decomposition (probably more correct)

Given a function f on the vertices

$$F_i := \langle \psi_i | f \rangle = \int_x \psi_i(x) f(x) dx = \psi_i^T \cdot A \cdot f \quad \text{is its } i^{\text{th}} \text{ frequency.}$$

f can be recovered from its frequencies (inverse transform) :

$$f = \sum_i F_i \psi_i$$

$$\begin{array}{c}
 \left[\begin{array}{c} f \\ \vdots \\ f \end{array} \right] = \underbrace{\left[\begin{array}{c} \psi_0 \\ \psi_1 \\ \vdots \\ \psi_{n-1} \end{array} \right]}_{\text{Basis } \psi} \cdot \underbrace{\left[\begin{array}{c} \psi_0^T \\ \psi_1^T \\ \vdots \\ \psi_{n-1}^T \end{array} \right]}_{\text{Dot product with Basis } \psi^T \cdot A \cdot f} \cdot \left[\begin{array}{c} f \\ \vdots \\ f \end{array} \right] \cdot A
 \end{array}$$

$$(\psi^T \cdot A \cdot \psi = Id)$$

Filtering

Given a function f on the vertices

$F_i := \bar{\psi}_i^T \cdot f = \sum_{v_j} \bar{\psi}_i(v_j) f(v_j)$ is its i^{th} frequency.

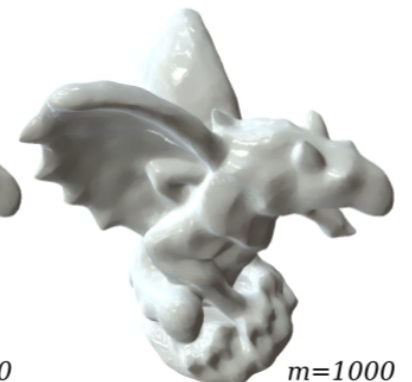
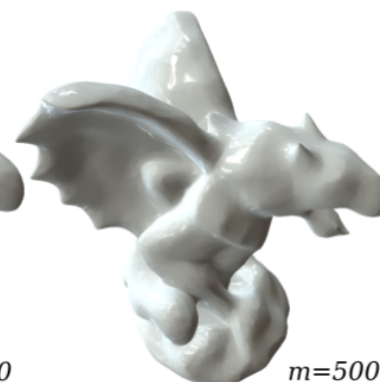
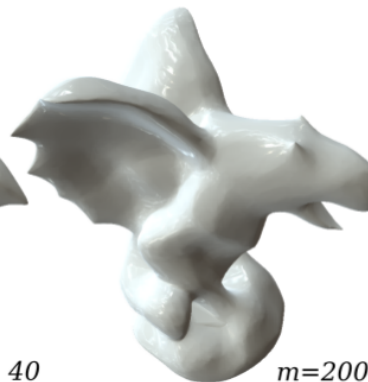
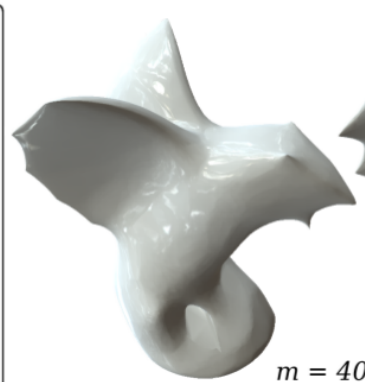
Filter h can be applied on the frequencies: $h \circ f = \sum_i h(F_i) \bar{\psi}_i$

Filtering

Given a function f on the vertices

$$F_i := \bar{\psi}_i^T \cdot f = \sum_{v_j} \bar{\psi}_i(v_j) f(v_j) \quad \text{is its } i^{\text{th}} \text{ frequency.}$$

Filter h can be applied on the frequencies: $h \circ f = \sum_i h(F_i) \bar{\psi}_i$

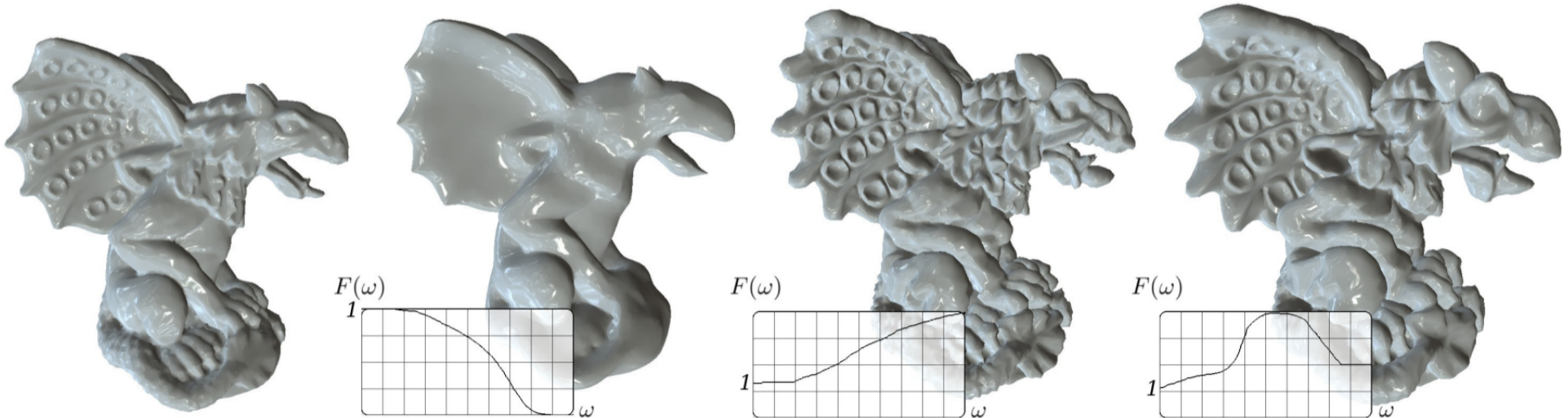


Filtering

Given a function f on the vertices

$$F_i := \bar{\psi}_i^T \cdot f = \sum_{v_j} \bar{\psi}_i(v_j) f(v_j) \quad \text{is its } i^{\text{th}} \text{ frequency.}$$

Filter h can be applied on the frequencies: $h \circ f = \sum_i h(F_i) \bar{\psi}_i$

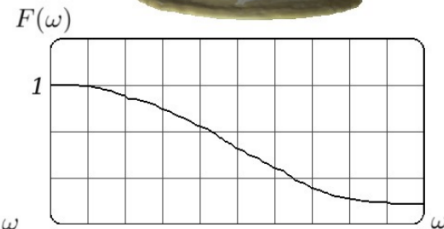
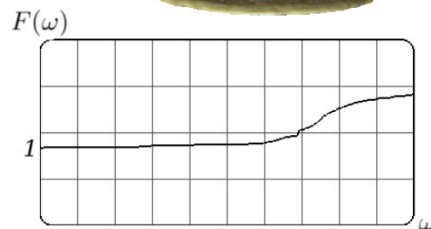


Filtering

Given a function f on the vertices

$$F_i := \bar{\psi}_i^T \cdot f = \sum_{v_j} \bar{\psi}_i(v_j) f(v_j) \quad \text{is its } i^{\text{th}} \text{ frequency.}$$

Filter h can be applied on the frequencies: $h \circ f = \sum_i h(F_i) \bar{\psi}_i$

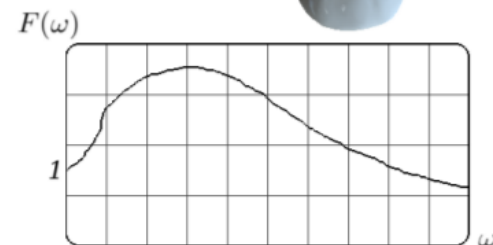
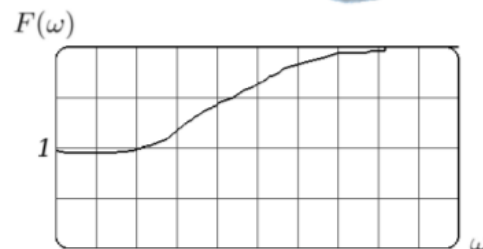


Filtering

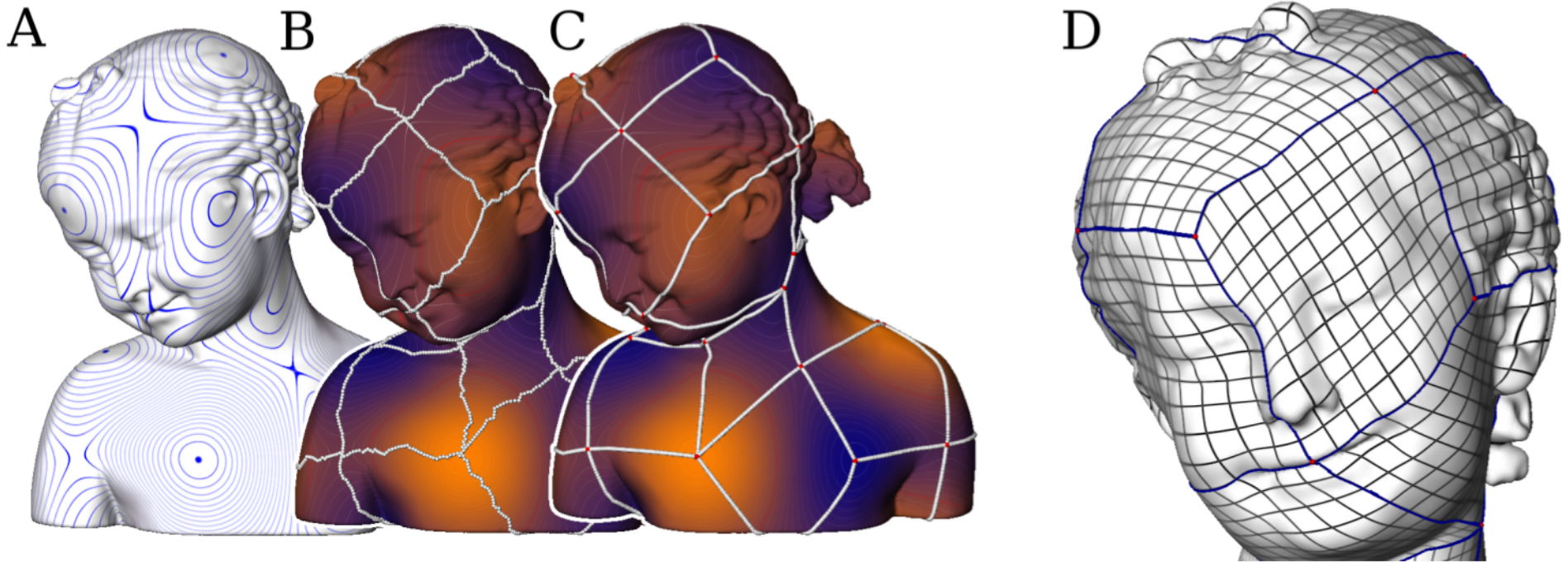
Given a function f on the vertices

$$F_i := \bar{\psi}_i^T \cdot f = \sum_{v_j} \bar{\psi}_i(v_j) f(v_j) \quad \text{is its } i^{\text{th}} \text{ frequency.}$$

Filter h can be applied on the frequencies: $h \circ f = \sum_i h(F_i) \bar{\psi}_i$



Quad meshing



Shape retrieval



Heat diffusion

$\{\psi_i\}_i$ is a good basis for heat diffusion :

$$\begin{cases} \partial_t u(x, t) = \nabla_x^2 u(x, t) \\ u(x, 0) = u_0(x) \end{cases}$$

$$u(x, t) = \sum_i \alpha_i(t) \psi_i(x) \quad (\text{decompose solution on basis})$$

$$\partial_t u(x, t) = \nabla_x^2 u(x, t) \longrightarrow \sum_i \dot{\alpha}_i(t) \psi_i = \sum_i -\lambda_i \alpha_i(t) \psi_i$$

$$\dot{\alpha}_i(t) + \lambda_i \alpha_i(t) = 0 \longrightarrow \alpha_i(t) = \alpha_i(0) \exp(-\lambda_i t)$$

$$\text{and } \alpha_i(0) = \int_x \psi_i(x) u_0(x) dx$$

$$\longrightarrow u(k, t) = \int_x \sum_i \psi_i(x) \psi_i(k) \exp(-\lambda_i t) u_0(x) \quad (\text{in the continuous setting})$$



Closed-form
solution

Heat diffusion

$$h_t(j, k) = \sum_i \psi_i(j) \psi_i(k) \exp(-\lambda_i t) : \text{heat kernel at } (j, k)$$

$\{h_t(j, j)\}_t$: multi-scale signature of vertex j



t = 1

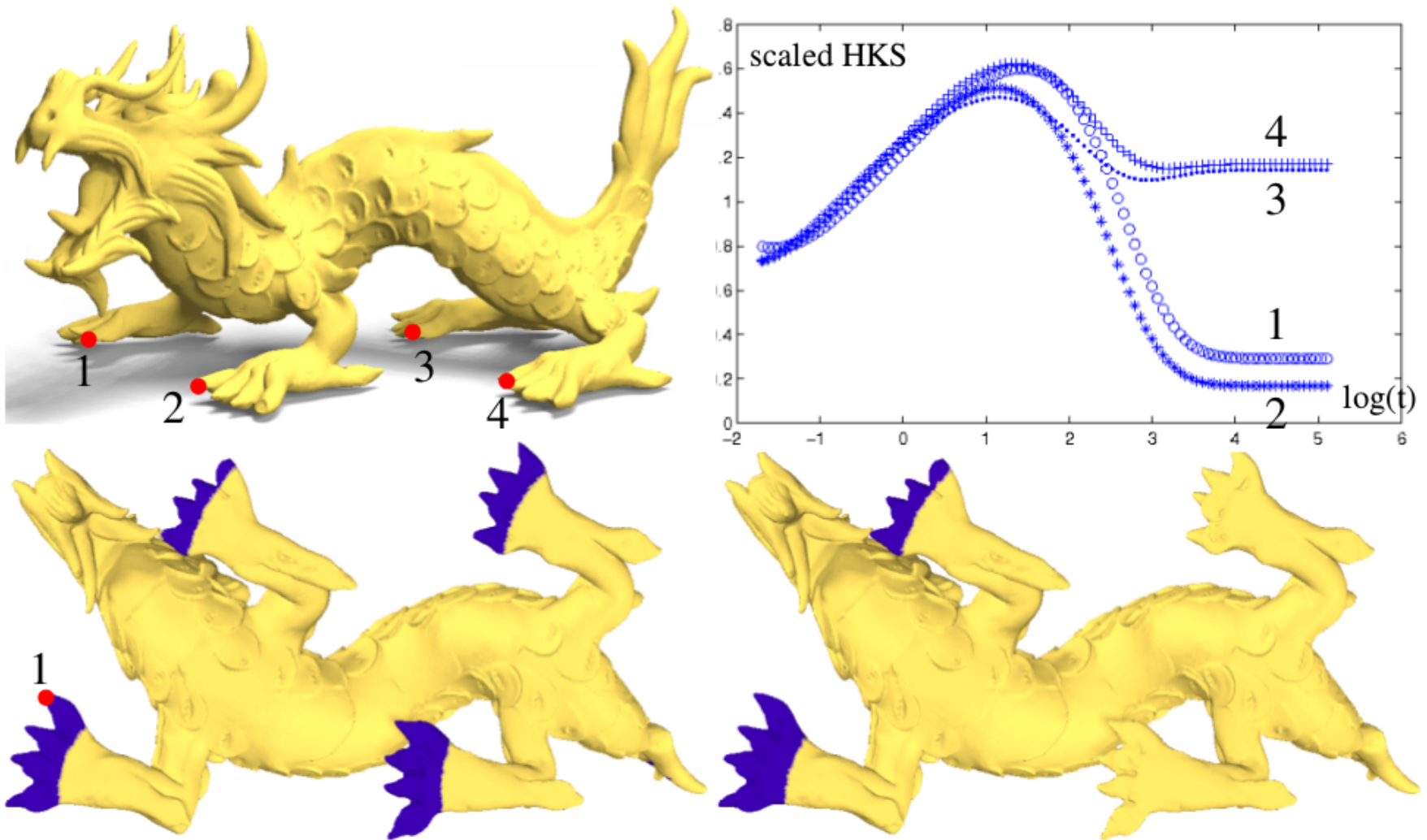


t = 100



t = 10 000

Heat kernel signature

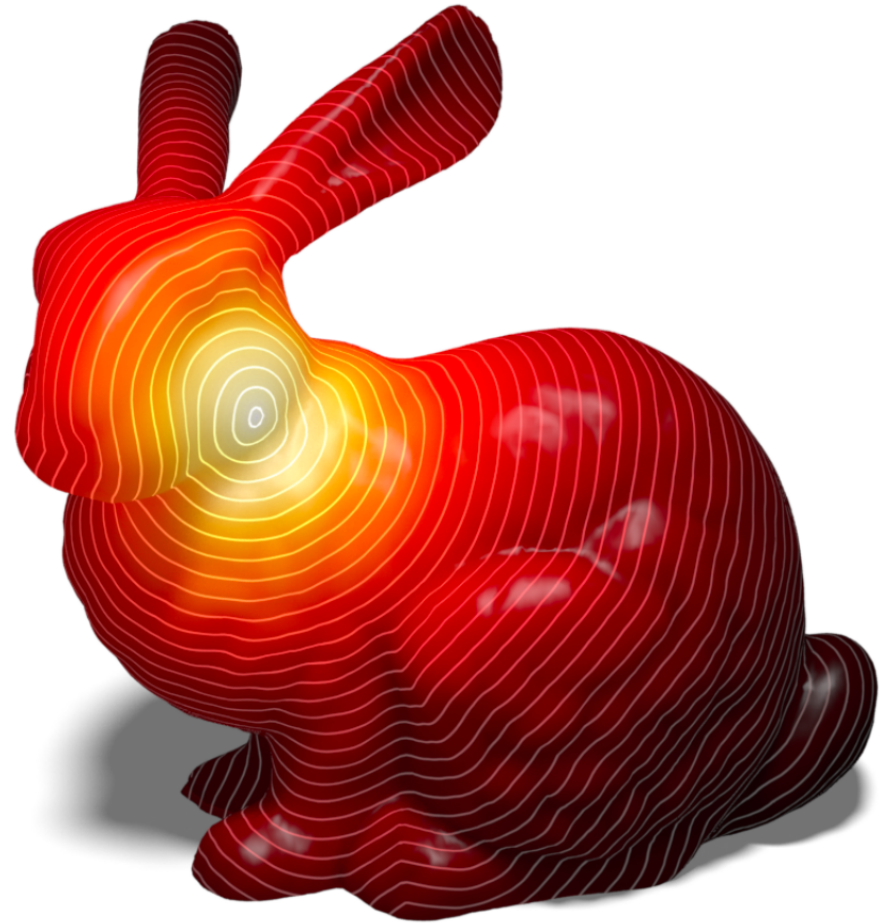


Geodesics in Heat

Link with :

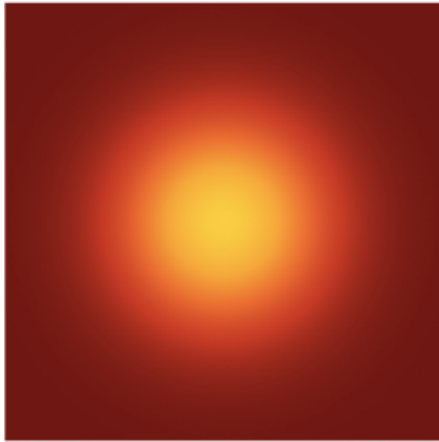
- Spectral properties
- Physics (heat)

Different from front-propagation approaches



[Crane et al. 2008] Geodesics in Heat: A New Approach to Computing Distance Based on Heat Flow

Geodesics in Heat



u

$$\partial_t u = \nabla^2 u$$

$$(u_t - u_0)/t = \nabla^2 u_t$$

$$u_t - t \nabla^2 u_t = u_0$$

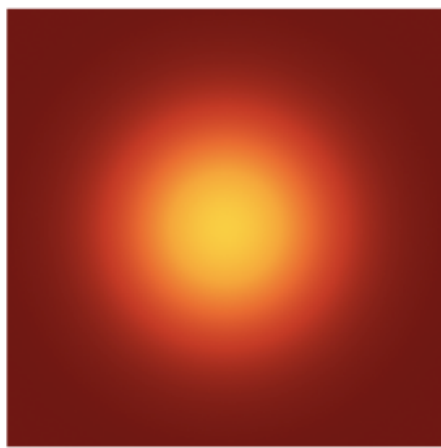
$$(id - t \nabla^2) u_t = u_0$$

Linear
system

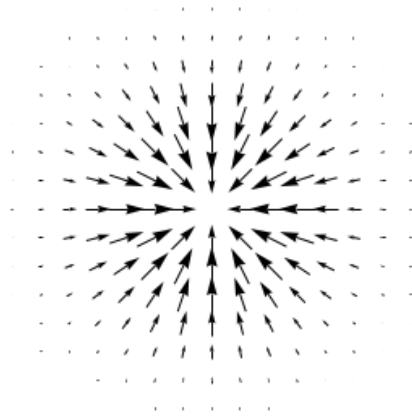
Algorithm 1 The Heat Method

- I. Integrate the heat flow $\dot{u} = \Delta u$ for some fixed time t .

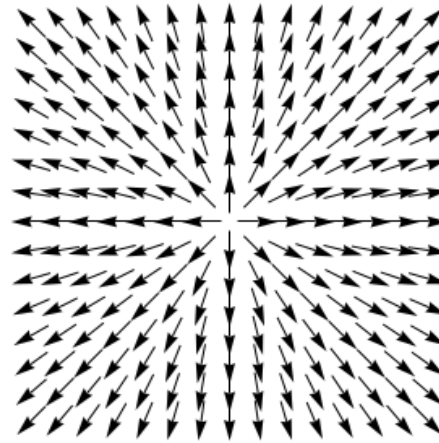
Geodesics in Heat



u



∇u

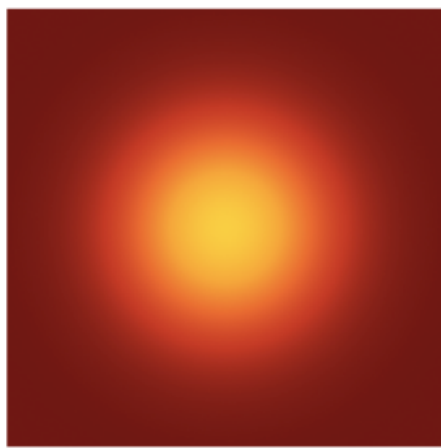


X

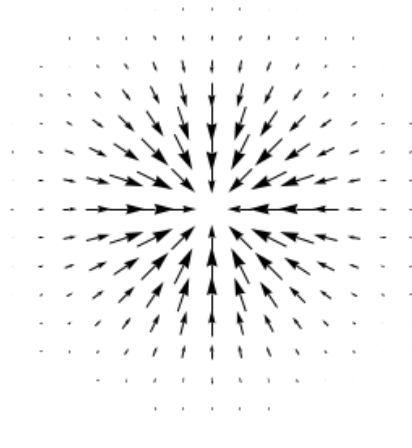
Algorithm 1 The Heat Method

- I. Integrate the heat flow $\dot{u} = \Delta u$ for some fixed time t .
- II. Evaluate the vector field $X = -\nabla u / |\nabla u|$.

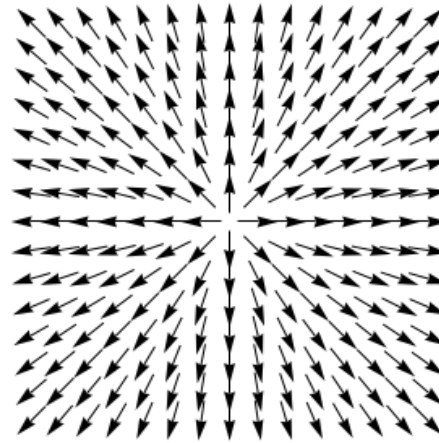
Geodesics in Heat



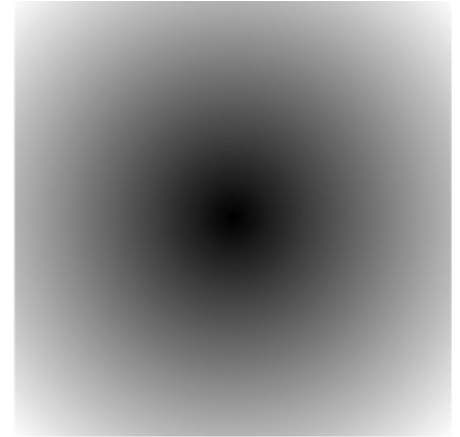
u



∇u



X



ϕ

Algorithm 1 The Heat Method

- I. Integrate the heat flow $\dot{u} = \Delta u$ for some fixed time t .
 - II. Evaluate the vector field $X = -\nabla u / |\nabla u|$. **Linear**
 - III. Solve the Poisson equation $\Delta \phi = \nabla \cdot X$. **system**
-

Geodesics in Heat

Step I $(id - t \nabla^2) u_t = u_0$

Linear system :
can be prefactored indep of u_0

Step II $\vec{X} = -\nabla u_t / \|\nabla u_t\|$

straightforward

Step III $\nabla^2 \phi = \nabla \cdot \vec{X}$

Linear system :
can be prefactored indep of u_0

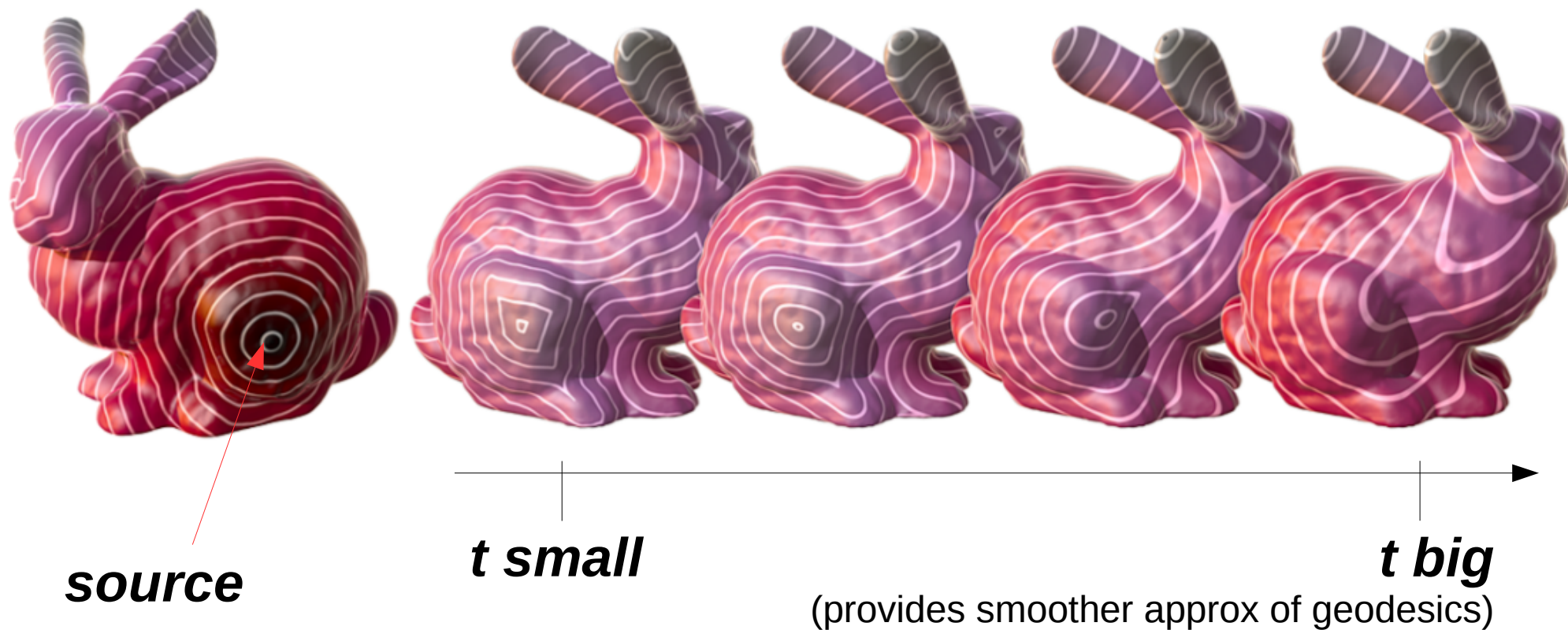
Geodesics in Heat

Laplacian operators have been studied for general polygonal meshes and pointsets :



[Crane et al. 2008] Geodesics in Heat: A New Approach to Computing Distance Based on Heat Flow

Geodesics in Heat : value of t ?



[Crane et al. 2008] Geodesics in Heat: A New Approach to Computing Distance Based on Heat Flow

