Written Assignment 5

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Exercise 1

Details in papers [1] [2] [3] by Crane et al.

In contrast to algorithms that compute shortest paths along a graph (like Dijkstra, A^*), the *heat method* computes the distance to points on a continuous, curved domain. Typically distance computation for some distance function ϕ is formulated using the *Eikonal equation*:

$$|\nabla \phi| = 1$$
 (distance changes by 1 meter per meter)

However, this results in a system of non-linear hyperbolic equations which is expensive to solve.

The heat method takes inspiration from a result by S. R. Srinivasa Varadhan which says that distance between a source point x and destination y on a curved domain can be recovered via a simple pointwise transformation of the heat kernel $k_{t,x}$:

$$\phi(x,y) = \lim_{t \to 0} \sqrt{-4t \log k_{t,x}(y)}$$

However, reconstructing the heat kernel is prohibitive in practice, and this formula lacks robustness to numerical error. The geodesic distance varies a lot with tiny errors in reconstruction.

The heat method works on arbitrary domains: smooth manifolds, triangle meshes, polygon meshes, point clouds, etc. All we need to define is the gradient, divergence and Laplacian. The algorithm works as follows:

- Integrate the heat flow $\dot{u} = \nabla u$ for some fixed time t.
- Evaluate the vector field $X = -\frac{\nabla u_t}{|\nabla u_t|}$.
- Solve the Poisson equation $\Delta \phi = \nabla \cdot X$.

By approximating Step 1 using backward Euler integration (id $-t\Delta$) $u_t = \delta_x$ we effectively convert the problem into a linear elliptic equation. For triangle meshes, the authors provide performance and convergence guarantees given some requirements are met – related to mesh resolution and triangulation quality.

Exercise 2

We make use of the composition theorem from Convex Optimization - Boyd and Vandenberghe.

A nondecreasing convex function of a convex function is convex.

Suppose we have f(x) = ||x|| and $g(x) = x^2$. Because f and g are convex, we now have $g \circ f(x) = ||x||^2$ is convex. We can plug differential functions ϕ_1, ϕ_2 into a convex combination:

$$|\eta| |\nabla \phi_1 - X||^2 + (1 - \eta) ||\nabla \phi_2 - X||^2 \ge ||\eta(\nabla \phi_1 - X) + (1 - \eta)(\nabla \phi_2 - X)||^2$$
$$= ||\eta \nabla \phi_1 + (1 - \eta)\nabla \phi_2 - X||^2$$

We can make the above claim By integrating on the manifold M:

$$\eta \int_{M} ||\nabla \phi_{1} - X||^{2} dA + (1 - \eta) \int_{M} ||\nabla \phi_{2} - X||^{2} dA \ge \int_{M} ||\eta \nabla \phi_{1} + (1 - \eta) \nabla \phi_{2} - X||^{2} dA$$
$$\eta E(\phi_{1}) + (1 - \eta) E(\phi_{2}) \ge E(\eta \phi_{1} + (1 - \eta) \phi_{2})$$

 $\therefore E$ is convex.

Exercise 3

Restating Green's first identity, with the assumption that $\nabla f \cdot n = 0$:

$$\langle \Delta f, g \rangle = -\langle \nabla f, \nabla g \rangle + \langle \nabla f, \eta, g \rangle_{\partial}^{0}$$

$$\implies \langle \nabla f, \nabla g \rangle = -\langle \Delta f, g \rangle \tag{1}$$

The energy functional E can be expressed as:

$$\begin{split} E(\phi) &:= \int_{M} ||\nabla \phi - X||^2 dA \\ &= \int_{M} \langle \langle \nabla \phi - X, \nabla \phi - X \rangle \rangle dA \\ &= \int_{M} \underbrace{(\langle \langle \nabla \phi, \nabla \phi \rangle \rangle - 2 \langle \langle \nabla \phi, X \rangle \rangle dA + \langle \langle X, X \rangle \rangle)}_{u} \ d\underbrace{A}_{v} \end{split}$$

A corollary of the divergence theorem:

$$\langle \langle \nabla \phi, X \rangle \rangle = \langle \langle \phi, -\nabla \cdot X \rangle \rangle \tag{2}$$

Using integration by parts $\int u dv = uv - \int v du$ along with du = 0:

$$\frac{E(\phi)}{A} = -\langle\langle \Delta f, g \rangle\rangle - 2\langle\langle \nabla \phi, X \rangle\rangle + ||X||^2$$
 from (1)

$$= -\langle \langle \Delta f, g \rangle \rangle + 2\langle \langle \phi, \nabla \cdot X \rangle \rangle + ||X||^2 \qquad \text{from (2)}$$

Exercise 4

$$\begin{split} E(\phi + \epsilon \psi) &= -\langle \langle \Delta(\phi + \epsilon \psi), \phi + \epsilon \psi \rangle \rangle + 2 \langle \langle \phi + \epsilon \psi, \nabla \cdot X \rangle \rangle + ||X||^2 \\ &= -\langle \langle \Delta \phi + \epsilon \Delta \psi, \phi + \epsilon \psi \rangle \rangle + 2 \langle \langle \phi + \epsilon \psi, \nabla \cdot X \rangle \rangle + ||X||^2 \\ &= -\langle \langle \Delta \phi, \phi \rangle \rangle - \epsilon \langle \langle \Delta \phi, \psi \rangle \rangle - \epsilon \langle \langle \Delta \psi, \phi \rangle \rangle - \epsilon^2 \langle \langle \Delta \psi, \psi \rangle \rangle + 2 \langle \langle \phi, \nabla \cdot X \rangle \rangle + 2 \epsilon \langle \langle \psi, \nabla \cdot X \rangle \rangle + ||X||^2 \\ &= E(\phi) - \epsilon \langle \langle \Delta \phi, \psi \rangle \rangle - \epsilon \langle \langle \Delta \psi, \phi \rangle \rangle - \epsilon^2 \langle \langle \Delta \psi, \psi \rangle \rangle + 2 \epsilon \langle \langle \psi, \nabla \cdot X \rangle \rangle \end{split}$$

Taking the limit $\epsilon \to 0$ and dropping the term quadratic in ϵ :

$$D_{\psi}E(\phi) = \lim_{\epsilon \to 0} \frac{E(\phi + \epsilon \psi) - E(\phi)}{\epsilon}$$

$$= -\langle\langle \Delta \phi, \psi \rangle\rangle - \langle\langle \Delta \psi, \phi \rangle\rangle + 2\langle\langle \psi, \nabla \cdot X \rangle\rangle$$

$$= -2\langle\langle \Delta \phi, \psi \rangle\rangle + 2\langle\langle \psi, \nabla \cdot X \rangle\rangle$$

$$= 2\langle\langle \psi, \nabla \cdot X - \Delta \phi \rangle\rangle$$

Exercise 5

From our previous result, we have:

$$D_{\psi}E(\phi) = 2\langle\langle\nabla\cdot X - \Delta\phi, \psi\rangle\rangle = \nabla E(\phi), \psi\rangle\rangle$$

$$\implies \nabla\cdot X - \Delta\phi = \nabla E(\phi)$$

 $\therefore \nabla E(\phi) = 0 \text{ if and only if } \Delta \phi = \nabla \cdot X.$

Exercise 6

Stokes'/divergence theorem allows us to convert the integral of divergence of X over the domain M into a boundary integral over ∂M .

$$\begin{split} \int_{M} \nabla \cdot X \ dA &= \int_{\partial M} n \cdot X \ dl \\ &= \sum_{j} \left(\frac{e_1}{|e_1|} \cdot X_j \right) l_1 + \left(\frac{e_2}{|e_2|} \cdot X_j \right) l_2 \\ &= \sum_{j} \frac{l_1}{|e_1|} e_1 \cdot X_j + \frac{l_2}{|e_2|} e_2 \cdot X_j \\ &= \sum_{j} \frac{1}{2} \cot \theta_1 (e_1 \cdot X_j) + \frac{1}{2} \cot \theta_2 (e_2 \cdot X_j) \\ &= \frac{1}{2} \sum_{j} \cot \theta_1 (e_1 \cdot X_j) + \cot \theta_2 (e_2 \cdot X_j) \end{split}$$

Exercise 7, 8, 9

TODO