Surface Computing: Solve Partial Differential Equations on Surfaces using the Closest Point Method

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Oriel CBL course, Oxford, Aug 2014

Outline of Lectures 1 & 2

Lecture 1

- Applications of Surface PDEs.
- Surface differential operators and examples of surface PDEs.
- Introduction to Closest Point Method (Ruuth–Merriman approach).

Lecture 2

- Matrix formulation of spatial discretizations.
- Octave/MATLAB implementations: diffusion equation on a unit circle/sphere, reaction-diffusion equation on a unit sphere (if time permits).

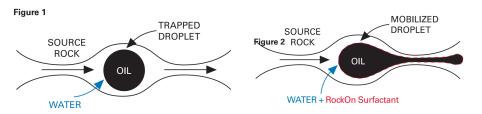
Turing pattern formation on animals¹





 $^{^{1}} http://www.simons foundation.org/quanta/20130325-biologists-home-in-onturing-patterns/\\$

Surfactant diffusing and transported along the interface²



 $^{^2} http://www.halliburton.com/public/multichem/contents/Brochures/web/H010276-RockOn.pdf$

Forest fire front propagation on mountains³





See also level-set simulation on Colin's website: https://people.maths.ox.ac.uk/macdonald/closestpoint/

³http://www.cerfacs.fr/globc/links/presentation/Sieste_delmotte_2011.pdf

Image denoising (Biddle,von Glehn, Macdonald, März, 2013)

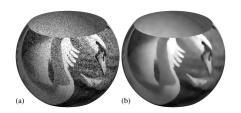
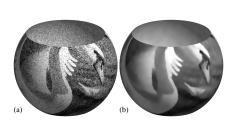
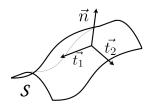


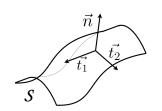
Image denoising (Biddle,von Glehn, Macdonald, März, 2013) Fluid effects (Auer, Macdonald, Treib, Schneider, Westermann 2012)





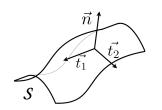






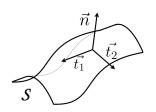
For a scalar function u, there exists a coordinate system (n, t_1, t_2) so that

$$\nabla u = \frac{\partial u}{\partial n}\vec{n} + \frac{\partial u}{\partial t_1}\vec{t_1} + \frac{\partial u}{\partial t_2}\vec{t_2} \quad (1)$$



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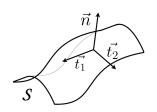
For a vector function $\vec{v} = v_1 \vec{t_1} + v_2 \vec{t_2} + v_3 \vec{n}$:

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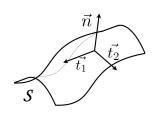
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Laplace-Beltrami Operator:

$$\Delta_{\mathcal{S}} u = \nabla_{\mathcal{S}} \cdot \nabla_{\mathcal{S}} u = \frac{\partial^2 u}{\partial t_1^2} + \frac{\partial^2 u}{\partial t_2^2}$$



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Notice: equation (1) only holds for a special coordinate system (n, t_1, t_2) (see Appendix A). Nevertheless, the spirit is the same for any coordinate system: Surface derivatives are just Cartesian derivatives getting rid of normal components.

Examples of surface PDEs

Turing pattern: reaction-diffusion equation

$$u = \nu_u \Delta_{\mathcal{S}} u + f(u, v)$$

$$v = \nu_v \Delta_{\mathcal{S}} v + g(u, v)$$

Front propagation: level set equation

$$\frac{\partial \phi}{\partial t} + \mathbf{v} \cdot \nabla_{\mathcal{S}} \phi = 0$$

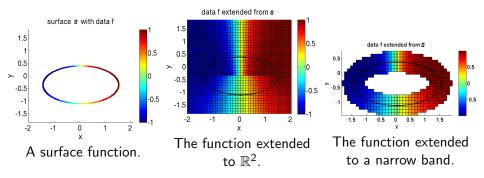
Surfactant: diffusion-advection equation

$$\frac{\partial c}{\partial t} + \mathbf{v} \cdot \nabla c + c \nabla_{\mathcal{S}} \cdot \mathbf{v} - \Delta_{\mathcal{S}} c = 0$$

Image de-noising: anisotropic diffusion

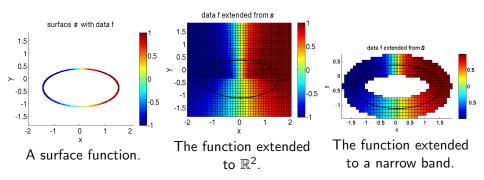
$$\frac{\partial u}{\partial t} = \nabla_{\mathcal{S}} \cdot (g(\|\nabla_{\mathcal{S}} u\|) \nabla_{\mathcal{S}} u)$$

Embedding methods for solving surface PDEs



■ Extend the surface PDE to an equation in the embedding space so that the solution of the embedding equation agree with the solution of the surface PDE.

Embedding methods for solving surface PDEs



- Extend the surface PDE to an equation in the embedding space so that the solution of the embedding equation agree with the solution of the surface PDE.
- If we do not extend the surface quantity in a special way, then the Cartesian PDE would be complicated (see Appendix B). We will extend the surface function so that the embedding equation is simple.

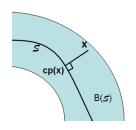
Closest Point Extension and Closest Point Principle

cp : $B(S) \to S$, and cp(x) is a point on the surface that is closest to x.

$$u(\mathbf{y}), \ \mathbf{y} \in \mathcal{S} \stackrel{\text{extend}}{\longrightarrow} v(\mathbf{x}), \ \mathbf{x} \in B(\mathcal{S})$$

$$v(\mathbf{x}) = u(\operatorname{cp}(\mathbf{x})), \quad \mathbf{x} \in B(\mathcal{S}),$$

v is called a closest point extension of u. v is constant along the normals to S. Denote v = Eu.



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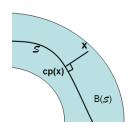
$$u(\mathbf{y}), \ \mathbf{y} \in \mathcal{S} \quad \stackrel{extend}{\longrightarrow} \quad v(\mathbf{x}), \ \mathbf{x} \in \mathcal{B}(\mathcal{S})$$

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Gradient Principle

$$\nabla[(Eu)(y)] = \nabla_S u(y), \ y \in S.$$

Divergence Principle

$$\nabla \cdot [(E\mathbf{A})(y)] = \nabla_S \cdot \mathbf{A}(y), \ y \in S.$$

Laplacian Principle

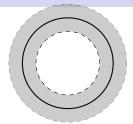
$$\Delta[(Eu)(y)] = \Delta_{\mathcal{S}}u(y), \quad y \in \mathcal{S}.$$

(Ruuth & Merriman 2008, März & Macdonald 2012)

Consider the diffusion equation on a unit circle:

$$\begin{cases} u_t(t,\mathbf{x}) &= & \Delta_{\mathcal{S}}(t,\mathbf{x}), \\ u(0,\mathbf{x}) &= & u_0(\mathbf{x}). \end{cases}$$

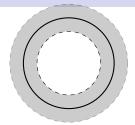
where $\mathbf{x} \in \mathcal{S}$, and $t \in [0, T]$.



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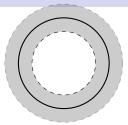
We use forward Euler method for time-stepping, and uniformly divide [0, T] into $t^0 = 0, t^1 = \tau, \cdots, t^N = N\tau = T$. Ideally, we would like:

$$u(t^{n+1},\mathbf{x}) = u(t^n,\mathbf{x}) + \tau \Delta_{\mathcal{S}} u(t^n,\mathbf{x}), \quad n = 0, \dots, N-1$$
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 (2)

Initially, let $v(0, \mathbf{y}) = u_0(\mathsf{cp}(\mathbf{y}))$, for $\mathbf{y} \in B(\mathcal{S})$ (i.e., $v(0, \mathbf{y}) = Eu_0$). Then $\Delta v(0, \mathbf{x}) = \Delta_{\mathcal{S}} u_0(\mathsf{cp}(\mathbf{x}))$ for $\mathbf{x} \in \mathcal{S}$.

If we define:
$$\tilde{v}(\tau, \mathbf{y}) = v(0, \mathbf{y}) + \tau \Delta v(0, \mathbf{y}), \quad \mathbf{y} \in B(S),$$
 (3)

then $\tilde{v}(\tau, \mathbf{x}) = u(\tau, \mathbf{x})$ for $\mathbf{x} \in \mathcal{S}$, where $u(\tau, \mathbf{x}) = u(0, \mathbf{x}) + \tau \Delta_{\mathcal{S}} u(0, \mathbf{x})$ is defined by (2). Question: is $\tilde{v}(\tau, \mathbf{y})$ constant along the normals?

No, $\tilde{v}(\tau, \mathbf{y})$ is no longer constant along the normals. In order to carry on evolvement with the Cartesian Laplacian Δ , we re-enforce v to be constant along the normals to \mathcal{S} by:

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Suppose we've computed up to $v(t^n,\mathbf{y})$ s.t. $v(t^n,\mathbf{y})$ is constant along the normals to \mathcal{S} , and $v(t^n,\mathbf{x})=u(t^n,\mathbf{x})$ for any $\mathbf{x}\in\mathcal{S}$. Then we can compute $v(t^{n+1},\mathbf{y})$ by alternating the following two steps:

$$\widetilde{v}(t^{n+1}, \mathbf{y}) = v(t^n, \mathbf{y}) + \tau \Delta v(t^n, \mathbf{y})
v(t^{n+1}, \mathbf{y}) = \widetilde{v}(t^{n+1}, \operatorname{cp}(\mathbf{y}))$$

Obviously $v(t^{n+1}, \mathbf{y})$ is still constant along the normals to \mathcal{S} and $v(t^{n+1}, \mathbf{x}) = u(t^{n+1}, \mathbf{x})$ for any $\mathbf{x} \in \mathcal{S}$.

Closest Point Method: Ruuth-Merriman approach 2008

To solve the surface diffusion equation $u_t = \Delta_{\mathcal{S}} u$ on \mathcal{S} , extend the surface function u on \mathcal{S} to function v in $B(\mathcal{S})$: let $v(0,\mathbf{y}) = u_0(\operatorname{cp}(\mathbf{y}))$, $\mathbf{y} \in B(\mathcal{S})$. Then for $n = 0, \dots, N-1$, do: $\tilde{v}(t^{n+1},\mathbf{y}) = v(t^n,\mathbf{y}) + \tau \ \Delta v(t^n,\mathbf{y})$; $v(t^{n+1},\mathbf{y}) = \tilde{v}(t^{n+1},\operatorname{cp}(\mathbf{y}))$.

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$$\tilde{v}(t^{n+1}, \mathbf{y}) = v(t^n, \mathbf{y}) + \tau \Delta v(t^n, \mathbf{y});$$

 $v(t^{n+1}, \mathbf{y}) = \tilde{v}(t^{n+1}, \operatorname{cp}(\mathbf{y})).$

Ruuth-Merriman Closest Point Iteration:

For any closed smooth surface S and corresponding tubular neighborhood B(S), solve a general surface PDE $u_t = f(u, \nabla_S u, \nabla_S \cdot u, \Delta_S u)$:

- (1) Let $v(0, \mathbf{y}) = u_0(\operatorname{cp}(\mathbf{y}))$ for $\mathbf{y} \in B(S)$.
- For $n = 0, \dots, N-1$, do:
- (2) $\tilde{v}(t^{n+1}, \mathbf{y}) = v(t^n, \mathbf{y}) + \tau f(v(t^n, \mathbf{y}), \nabla v(t^n, \mathbf{y}), \nabla \cdot v(t^n, \mathbf{y}), \Delta v(t^n, \mathbf{y}));$
- (3) $v(t^{n+1}, \mathbf{y}) = \tilde{v}(t^{n+1}, \operatorname{cp}(\mathbf{y})).$

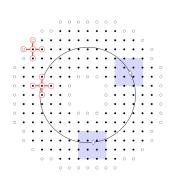
Full discretization: back to diffusion on circle example

$$\tilde{v}(t^{n+1}, \mathbf{y}) = v(t^n, \mathbf{y}) + \tau \Delta v(t^n, \mathbf{y})
v(t^{n+1}, \mathbf{y}) = \tilde{v}(t^{n+1}, \operatorname{cp}(\mathbf{y}))$$

Full discretization: back to diffusion on circle example

$$\begin{split} \tilde{v}(t^{n+1},\mathbf{y}) &= v(t^n,\mathbf{y}) + \tau \Delta v(t^n,\mathbf{y}) \\ v(t^{n+1},\mathbf{y}) &= \tilde{v}(t^{n+1},\mathsf{cp}(\mathbf{y})) \\ \text{Let } v(t^n,x_j,y_k) &\approx v_{j,k}^n \\ \tilde{v}_{j,k}^{n+1} &= v_{j,k}^n + \tau \frac{v_{j-1,k}^n + v_{j+1,k}^n + v_{j,k-1}^n + v_{j,k+1}^n - 4v_{j,k}^n}{h^2} \\ \text{We hope } v_{j,k}^{n+1} &= \tilde{v}^{n+1}(\mathsf{cp}(x_j,y_k)), \\ \text{but } \mathsf{cp}(x_j,y_k) \text{ is not a grid point. We approximate } \tilde{v}^{n+1}(\mathsf{cp}(x_j,y_k)) \text{ through } \\ \text{Lagrange polynomial interpolation:} \\ \sum_{(x_l,y_m) \in \mathsf{Interp}(\mathsf{cp}(x_j,y_k))} \omega_{l,m} \tilde{v}_{l,m}^{n+1} \\ \text{(More details to derive on board..)} \end{split}$$

Macdonald & Ruuth, 2009



Laplacian stencil $\mathsf{Lap}\Big((x_j,y_k)\Big)$ Interpolation stencil $\mathsf{Interp}\Big(\mathsf{cp}(x_j,y_k)\Big)$

How do we choose the computational band?

$$band(E) = \bigcup_{\mathbf{x} \in \mathcal{S}} \{Interp(\mathbf{x})\}\$$

$$band(L) = \bigcup_{\mathbf{x}_i \in band(E)} \{ Lap(\mathbf{x}_i) \}$$

$$band(E) \subset band(L)$$

In practice, choose a band B so that $B \supset band(L)$.

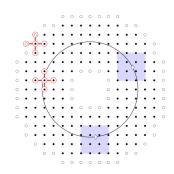
An empirical formula (Ruuth–Merriman, 2008) is:

$$B = \{\mathbf{x}_i : \|\mathbf{x}_i - \operatorname{cp}(\mathbf{x}_i)\|_2 \le C\Delta x\},\$$

where

$$C = \sqrt{(d-1)(\frac{p+1}{2})^2 + (order/2 + \frac{p+1}{2})^2}.$$

Macdonald & Ruuth, 2009



Laplacian stencil $Lap(x_i)$ Interpolation stencil Interp(x)

$$\tau = O(h^2)$$

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One intuition: the continuous heat equation satisfies maximum principle.

$$\max_{\mathbf{x}} u(t_1, \mathbf{x}) \geq \max_{\mathbf{x}} u(t_2, \mathbf{x}), \quad t_1 \leq t_2.$$

Therefore we hope our numerical solution also satisfies this principle. If we forget about the surface, just consider the heat equation in 2D:

$$\begin{array}{rcl} v_{j,k}^{n+1} & = & v_{j,k}^{n} + \frac{\tau}{h^{2}} (v_{j-1,k}^{n} + v_{j+1,k}^{n} + v_{j,k-1}^{n} + v_{j,k+1}^{n} - 4v_{j,k}^{n}) \\ & = & (1 - 4\frac{\tau}{h^{2}})v_{j,k}^{n} + \frac{\tau}{h^{2}}v_{j-1,k}^{n} + \frac{\tau}{h^{2}}v_{j+1,k}^{n} + \frac{\tau}{h^{2}}v_{j,k-1}^{n} + \frac{\tau}{h^{2}}v_{j,k+1}^{n} \end{array}$$

Sufficient condition for discrete maximum principle $\max_{j,k} v^{n+1} \leq \max_{j,k} v^n$ to hold is that all the coefficients are non-negative. We need $1-4\frac{\tau}{h^2} \geq 0$. Therefore $\tau \leq \frac{1}{4}h^2$.

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$$= (1 - 4\frac{\tau}{h^{2}}) v_{j,k}^{n} + \frac{\tau}{h^{2}} v_{j-1,k}^{n} + \frac{\tau}{h^{2}} v_{j+1,k}^{n} + \frac{\tau}{h^{2}} v_{j,k-1}^{n} + \frac{\tau}{h^{2}} v_{j,k+1}^{n}$$

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Rigorously speaking, discrete maximum principle does not hold in the Ruuth–Merriman algorithm. However for numerical stability, $\tau = O(h^2)$ is required.

Matrix formulation

$$\begin{split} \tilde{\mathbf{v}}^{n+1} &= \mathbf{v}^n + \tau \Delta \mathbf{v}^n \\ \tilde{\mathbf{v}}^{n+1}_{j,k} &= \mathbf{v}^n_{j,k} + \tau \frac{\mathbf{v}^n_{j-1,k} + \mathbf{v}^n_{j+1,k} + \mathbf{v}^n_{j,k-1} + \mathbf{v}^n_{j,k+1} - 4\mathbf{v}^n_{j,k}}{h^2} \\ \iff \tilde{\mathbf{v}}^{n+1}_h &= \mathbf{v}^n_h + \tau \mathbf{L}_h \mathbf{v}^n_h \end{split}$$

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Benefits of matrix formulation:

- Vectorized implementations.
- Eigenvalue analysis for numerical stability.

Appendix A: Orthogonal curvilinear coordinate systems⁴

Orthogonal coordinate system (u, v, w), unit vectors $(\hat{\mathbf{u}}, \hat{\mathbf{v}}, \hat{\mathbf{w}})$. Suppose the coordinates change by infinitesimal amount $(u, v, w) \rightarrow (u + du, v + dv, w + dw)$, then the length vector \mathbf{s} changes by

$$d\mathbf{s} = \frac{\partial \mathbf{s}}{\partial u} du + \frac{\partial \mathbf{s}}{\partial v} dv + \frac{\partial \mathbf{s}}{\partial w} dw = f du \hat{\mathbf{u}} + g dv \hat{\mathbf{v}} + h dw \hat{\mathbf{w}},$$

where $f = \|\frac{\partial s}{\partial u}\|$, $g = \|\frac{\partial s}{\partial v}\|$, $h = \|\frac{\partial s}{\partial w}\|$.

Cartesian
$$(x, y, z)$$
, $(\hat{\mathbf{x}}, \hat{\mathbf{y}}, \hat{\mathbf{z}})$
 $d\mathbf{s} = dx\hat{\mathbf{x}} + dy\hat{\mathbf{y}} + dz\hat{\mathbf{z}}$,
 $(f = 1, g = 1, h = 1)$

Spherical
$$(r, \theta, \phi)$$
, $(\hat{\mathbf{r}}, \hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\phi}})$
 $d\mathbf{s} = dr\hat{\mathbf{r}} + rd\theta\hat{\boldsymbol{\theta}} + r\sin(\theta)d\phi\hat{\boldsymbol{\phi}}$,
 $(f = 1, g = r, h = r\sin(\theta))$

 $x(r,\theta,\varphi)$

⁴http://www.theory.caltech.edu/classes/ph125a/VCCC.pdf

Calculus in orthogonal curvilinear coordinate systems

Gradient: For a scalar function F(u, v, w), we would like to calculate

$$\nabla F = (\nabla F)_u \hat{\mathbf{u}} + (\nabla F)_v \hat{\mathbf{v}} + (\nabla F)_w \hat{\mathbf{w}}.$$

If the coordinates change by $(u, v, w) \rightarrow (u + du, v + dv, w + dw)$ then scalar function F changes by

$$dF = \frac{\partial F}{\partial u}du + \frac{\partial F}{\partial v}dv + \frac{\partial F}{\partial w}dw \tag{4}$$

Also we have

$$dF = \nabla F \cdot d\mathbf{s} = (\nabla F)_u f du + (\nabla F)_v f dv + (\nabla F)_w f dw$$
 (5)

Comparing (4) and (5) we have $(\nabla F)_u = \frac{1}{f} \frac{\partial F}{\partial u}$, $(\nabla F)_v = \frac{1}{g} \frac{\partial F}{\partial v}$, and $(\nabla F)_w = \frac{1}{h} \frac{\partial F}{\partial w}$. Therefore

$$\nabla F = \frac{1}{f} \frac{\partial F}{\partial u} \hat{\mathbf{u}} + \frac{1}{g} \frac{\partial F}{\partial v} \hat{\mathbf{v}} + \frac{1}{h} \frac{\partial F}{\partial w} \hat{\mathbf{w}}.$$

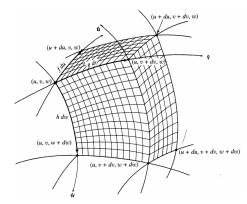
Calculus in orthogonal curvilinear coordinate systems

Divergence: Vector function
$$\mathbf{A}(u, v, w) = \mathbf{A}_u \hat{\mathbf{u}} + \mathbf{A}_v \hat{\mathbf{v}} + \mathbf{A}_w \hat{\mathbf{w}}.$$

$$\int_{\mathbf{S}} \mathbf{A} \cdot d\mathbf{S} = (\nabla \cdot \mathbf{A}) dV$$

$$\begin{split} \int_{\mathbf{S}(\text{front+back})} \mathbf{A} \cdot d\mathbf{S} \\ &= -(gh\mathbf{A}_u)dvdw|_{(u,v,w)} + \\ &(gh\mathbf{A}_u)dvdw|_{(u+du,v,w)} \\ &= \frac{\partial}{\partial u}(gh\mathbf{A}_u)dudvdw \\ \text{Left+Right} &= \frac{\partial}{\partial v}(fh\mathbf{A}_v)dudvdw \\ \text{Top+Bottom} &= \frac{\partial}{\partial w}(fg\mathbf{A}_w)dudvdw \end{split}$$

Using dV = (fgh)dudvdw, we have:



Infinitesimal volume

$$abla \cdot \mathbf{A} = rac{1}{fgh} \Big(rac{\partial}{\partial u} (gh\mathbf{A}_u) + rac{\partial}{\partial v} (fh\mathbf{A}_v) + rac{\partial}{\partial w} (fg\mathbf{A}_w) \Big)$$

Gradient:
$$\nabla F = \frac{1}{f} \frac{\partial F}{\partial u} \hat{\mathbf{u}} + \frac{1}{g} \frac{\partial F}{\partial v} \hat{\mathbf{v}} + \frac{1}{h} \frac{\partial F}{\partial w} \hat{\mathbf{w}}.$$

Divergence:
$$\nabla \cdot \mathbf{A} = \frac{1}{fgh} \left(\frac{\partial}{\partial u} (gh\mathbf{A}_u) + \frac{\partial}{\partial v} (fh\mathbf{A}_v) + \frac{\partial}{\partial w} (fg\mathbf{A}_w) \right)$$
.

Laplacian:
$$\Delta F = \nabla \cdot \nabla F = \frac{1}{fgh} \left(\frac{\partial}{\partial u} \left(\frac{gh}{f} \frac{\partial F}{\partial u} \right) + \frac{\partial}{\partial v} \left(\frac{fh}{g} \frac{\partial F}{\partial v} \right) + \frac{\partial}{\partial w} \left(\frac{fg}{h} \frac{\partial F}{\partial w} \right) \right).$$

Exercise: gradient, divergence, and Laplacian in spherical coordinates.

Gradient: $\nabla F = \frac{1}{f} \frac{\partial F}{\partial u} \hat{\mathbf{u}} + \frac{1}{g} \frac{\partial F}{\partial v} \hat{\mathbf{v}} + \frac{1}{h} \frac{\partial F}{\partial w} \hat{\mathbf{w}}.$

Divergence: $\nabla \cdot \mathbf{A} = \frac{1}{fgh} \left(\frac{\partial}{\partial u} (gh\mathbf{A}_u) + \frac{\partial}{\partial v} (fh\mathbf{A}_v) + \frac{\partial}{\partial w} (fg\mathbf{A}_w) \right)$.

Laplacian: $\Delta F = \nabla \cdot \nabla F = \frac{1}{fgh} \left(\frac{\partial}{\partial u} \left(\frac{gh}{f} \frac{\partial F}{\partial u} \right) + \frac{\partial}{\partial v} \left(\frac{fh}{g} \frac{\partial F}{\partial v} \right) + \frac{\partial}{\partial w} \left(\frac{fg}{h} \frac{\partial F}{\partial w} \right) \right).$

Exercise: gradient, divergence, and Laplacian in spherical coordinates.

For a smooth surface, consider (n, t_1, t_2) , with unit vectors $(\hat{\mathbf{n}}, \hat{\mathbf{t_1}}, \hat{\mathbf{t_2}})$, where $\hat{\mathbf{n}}$ is the unit normal field, $\hat{\mathbf{t_1}}$, and $\hat{\mathbf{t_2}}$ are unit tangential fields. Surface Gradient: $\nabla_{\mathcal{S}} F = \frac{1}{\sigma} \frac{\partial F}{\partial t_1} \hat{\mathbf{t_1}} + \frac{1}{h} \frac{\partial F}{\partial t_1} \hat{\mathbf{t_2}}$.

Surface Divergence: $\nabla_{\mathcal{S}} \cdot \mathbf{A} = \frac{1}{fgh} \left(\frac{\partial}{\partial t_1} (fh \mathbf{A}_{t_1}) + \frac{\partial}{\partial t_2} (fg \mathbf{A}_{t_2}) \right)$

Surface Laplacian (Laplace-Beltrami):

$$\Delta_{\mathcal{S}}F = \nabla_{\mathcal{S}} \cdot \nabla_{\mathcal{S}}F = \frac{1}{fgh} \left(\frac{\partial}{\partial t_{1}} \left(\frac{fh}{g} \frac{\partial F}{\partial t_{1}} \right) + \frac{\partial}{\partial t_{2}} \left(\frac{fg}{h} \frac{\partial F}{\partial t_{2}} \right) \right)$$

Appendix B: Surface Differential Operators in Cartesian Space

Let u be a scalar function defined on a dimension-(n-1) \mathcal{S} embedded in \mathbb{R}^n , v defined in \mathbb{R}^n be an extension of u: $v|_{\mathcal{S}} = u$, and $\hat{\mathbf{n}}$ be the unit normal vector of \mathcal{S} .

$$\nabla_{\mathcal{S}} u = \nabla_{\mathcal{S}} v = \nabla v - (\nabla v \cdot \hat{\mathbf{n}}) \hat{\mathbf{n}} = \nabla v - \hat{\mathbf{n}} (\hat{\mathbf{n}}^T \nabla v) = \nabla v - (\hat{\mathbf{n}} \mathbf{n}^T) \nabla v = (\mathbf{I} - \hat{\mathbf{n}} \hat{\mathbf{n}}^T) \nabla v = \mathbf{P} \nabla v,$$

where $\mathbf{P} = \mathbf{I} - \hat{\mathbf{n}}\hat{\mathbf{n}}^T$ is the projection operator (matrix).

Appendix B: Surface Differential Operators in Cartesian Space

Let u be a scalar function defined on a dimension-(n-1) S embedded in \mathbb{R}^n , v defined in \mathbb{R}^n be an extension of u: $v|_{S} = u$, and $\hat{\mathbf{n}}$ be the unit normal vector of S.

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where $\mathbf{P} = \mathbf{I} - \hat{\mathbf{n}} \hat{\mathbf{n}}^T$ is the projection operator (matrix).

Let **A** be a vector function on S, **B** in \mathbb{R}^n be an extension of **A**:

$$\begin{split} \nabla_{\mathcal{S}} \cdot \mathbf{A} &= \nabla_{\mathcal{S}} \cdot \mathbf{B} = \mathbf{P} \nabla \cdot \mathbf{B} \\ &= (\mathbf{I} - \hat{\mathbf{n}} \hat{\mathbf{n}}^T) \nabla \cdot \mathbf{B} = \nabla \cdot \mathbf{B} - \hat{\mathbf{n}}^T (\nabla \mathbf{B}) \hat{\mathbf{n}}, \end{split}$$

where $\nabla \mathbf{B}$ is the Jacobian matrix of \mathbf{B} .

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Let **A** be a vector function on S, **B** in \mathbb{R}^n be an extension of **A**:

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where $\nabla \mathbf{B}$ is the Jacobian matrix of \mathbf{B} .

$$\Delta_{\mathcal{S}} u = \Delta_{\mathcal{S}} v = \nabla_{\mathcal{S}} \cdot \nabla_{\mathcal{S}} v = \mathbf{P} \nabla \cdot \mathbf{P} \nabla v$$
(optional exercise) = $\nabla \cdot \nabla v - \kappa \frac{\partial v}{\partial \hat{\mathbf{n}}} - \hat{\mathbf{n}}^T \mathsf{Hess}(v) \hat{\mathbf{n}}$,

where $\kappa = \nabla \cdot \hat{\mathbf{n}}$, $\frac{\partial v}{\partial \hat{\mathbf{n}}} = \nabla v \cdot \hat{\mathbf{n}}$, Hess(v) be the Hessian of v.