

KAUST

CS 247 – Scientific Visualization Lecture 11: Scalar Fields, Pt.7

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Reading Assignment #6 (until Mar 7)



Read (required):

- Real-Time Volume Graphics, Chapter 2 (*GPU Programming*)
- Real-Time Volume Graphics, Chapters 5.5 and 5.6 (you already had to read 5.4) (*Local Volume Illumination*)
- Refresh your memory on eigenvectors and eigenvalues: https://en.wikipedia.org/wiki/Eigenvalues_and_eigenvectors

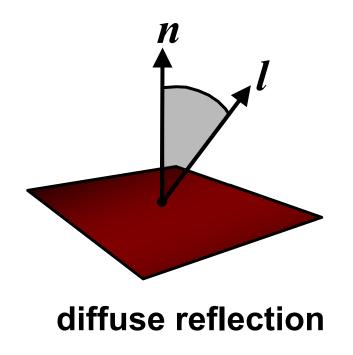
Look at (optional):

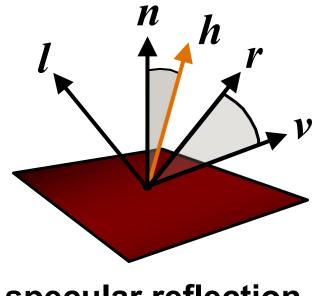
• Riemannian Geometry for Scientific Visualization (notes and videos [part 1]) https://vccvisualization.org/RiemannianGeometryTutorial/

Local Shading Equations



Standard volume shading adapts surface shading Most commonly Blinn/Phong model But what about the "surface" normal vector?





specular reflection

Local Illumination Model: Phong Lighting Model $\mathbf{I}_{\text{Phong}} = \mathbf{I}_{\text{ambient}} + \mathbf{I}_{\text{diffuse}} + \mathbf{I}_{\text{specular}}$ $\mathbf{I}_{\text{diffuse}} = k_d \mathbf{M}_d \mathbf{I}_d \cos \varphi \quad \text{if } \varphi \leq \frac{\pi}{2}$ = $k_d \mathbf{M}_d \mathbf{I}_d \max((\mathbf{n} \cdot \mathbf{l}), 0)$

The Dot Product (Scalar / Inner Product)



Cosine of angle between two vectors times their lengths

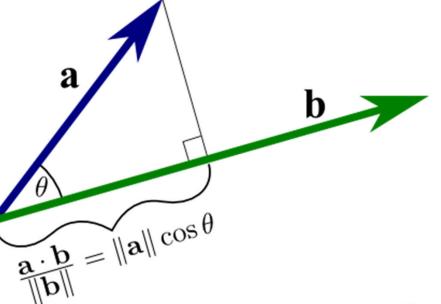
 $\mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^{n} a_i b_i$ $\mathbf{a} \cdot \mathbf{b} = \|\mathbf{a}\| \|\mathbf{b}\| \cos \theta$

(standard inner product in Cartesian coordinates)

Many uses:

. . .

 Project vector onto another vector, project into basis, project into tangent plane,



The Gradient as Normal Vector



Gradient of the scalar field gives direction+magnitude of fastest change

$$\mathbf{g} = \nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}\right)^{\mathrm{T}}$$

(only correct in Cartesian coordinates [see later lectures])

Local approximation to isosurface at any point: tangent plane = plane orthogonal to gradient scalar Normal of this isosurface: normalized gradient vector (negation is common convention) $\mathbf{n} = -\mathbf{g}/|\mathbf{g}|$

values

(Numerical) Gradient Reconstruction

We need to reconstruct the derivatives of a continuous function given as discrete samples

Central differences

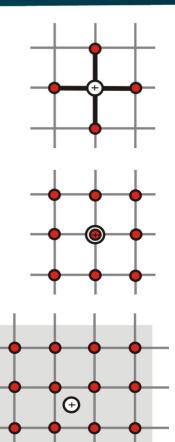
• Cheap and quality often sufficient (2*3 neighbors in 3D)

Discrete convolution filters on grid

• Image processing filters; e.g. Sobel (3³ neighbors in 3D)

Continuous convolution filters

- Derived continuous reconstruction filters
- E.g., the cubic B-spline and its derivatives (4³ neighbors)





Finite Differences



Obtain first derivative from Taylor expansion

$$f(x_0 + h) = f(x_0) + \frac{f'(x_0)}{1!}h + \frac{f''(x_0)}{2!}h^2 + \dots$$
$$= \sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!}h^n.$$

Forward differences / backward differences

$$f(x_0)' = \frac{f(x_0 + h) - f(x_0)}{h} + o(h)$$
$$f(x_0)' = \frac{f(x_0) - f(x_0 - h)}{h} + o(h)$$

Finite Differences



Central differences

$$f(x_0 + h) = f(x_0) + \frac{f'(x_0)}{1!}h + \frac{f''(x_0)}{2!}h^2 + o(h^3)$$

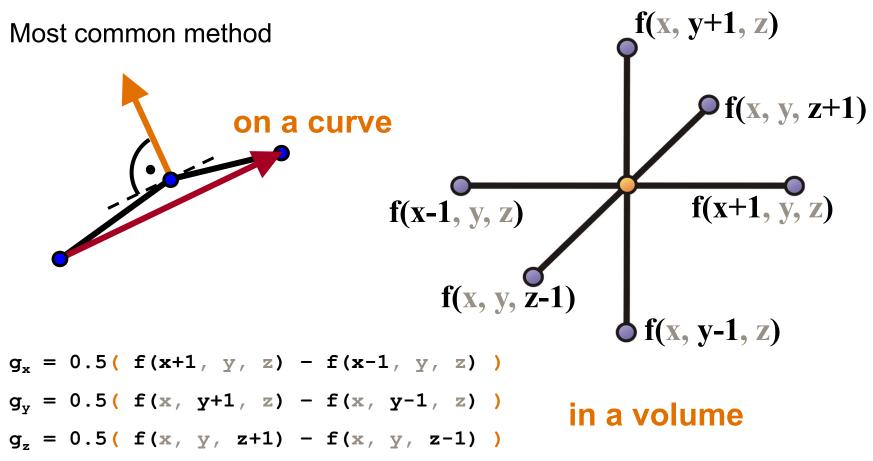
$$f(x_0 - h) = f(x_0) - \frac{f'(x_0)}{1!}h + \frac{f''(x_0)}{2!}h^2 + o(h^3)$$

$$f'(x_0) = \frac{f(x_0 + h) - f(x_0 - h)}{2h} + o(h^2)$$

Central Differences



Need only two neighboring voxels per derivative



Gradient and Directional Derivative



Gradient $\nabla f(x, y, z)$ of scalar function f(x, y, z):

(in Cartesian coordinates)

$$\nabla f(x, y, z) = \left(\frac{\partial f(x, y, z)}{\partial x}, \frac{\partial f(x, y, z)}{\partial y}, \frac{\partial f(x, y, z)}{\partial z}\right)^T$$

Directional derivative in direction ${f u}$:

$$D_{\mathbf{u}}f(x,y,z) = \nabla f(x,y,z) \cdot \mathbf{u}$$

And therefore also:

$$D_{\mathbf{u}}f(x, y, z) = ||\nabla f|| ||\mathbf{u}|| \cos \theta$$

Gradient and Directional Derivative



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(in Cartesian coordinates)

$$\nabla f(x, y, z) = \left(\frac{\partial f(x, y, z)}{\partial x}, \frac{\partial f(x, y, z)}{\partial y}, \frac{\partial f(x, y, z)}{\partial z}\right)^T$$

(Cartesian vector components; basis vectors not shown)

But: always need **basis vectors**! With Cartesian basis:

$$\nabla f(x, y, z) = \frac{\partial f(x, y, z)}{\partial x} \mathbf{i} + \frac{\partial f(x, y, z)}{\partial y} \mathbf{j} + \frac{\partial f(x, y, z)}{\partial z} \mathbf{k}$$

What about the Basis?

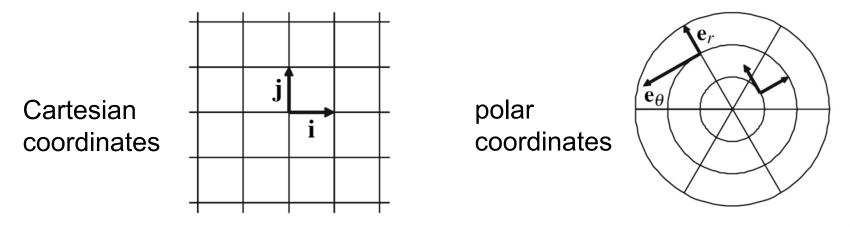


On the previous slide, this actually meant

$$\nabla f(x, y, z) = \frac{\partial f(x, y, z)}{\partial x} \mathbf{i}(x, y, z) + \frac{\partial f(x, y, z)}{\partial y} \mathbf{j}(x, y, z) + \frac{\partial f(x, y, z)}{\partial z} \mathbf{k}(x, y, z)$$

It's just that the Cartesian basis vectors are the same everywhere...

But this is not true for many other coordinate systems:



What about the Basis?

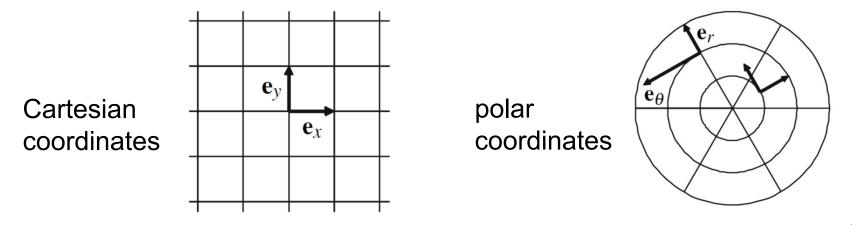


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But this is not true for many other coordinate systems:



The Gradient as a Differential Form



The gradient as a *differential* (differential 1-form) is the "primary" concept (also "total differential" or "total derivative")

$$df = \frac{\partial f}{\partial x} \, dx + \frac{\partial f}{\partial y} \, dy + \frac{\partial f}{\partial z} \, dz$$

A differential 1-form is a scalar-valued linear function that takes a (direction) vector as input, and gives a scalar as output

Each of the 1-forms df, dx, dy, dz takes direction vector as input, gives scalar output

In the expression of the gradient df above, all 1-forms on the right-hand side get the same vector as input

df is simply a linear combination of the coordinate differentials dx, dy, dz

The Gradient as a Differential Form



The gradient as a *differential* (differential 1-form) is the "primary" concept (also "total differential" or "total derivative")

$$df = \frac{\partial f}{\partial x} \, dx + \frac{\partial f}{\partial y} \, dy + \frac{\partial f}{\partial z} \, dz$$

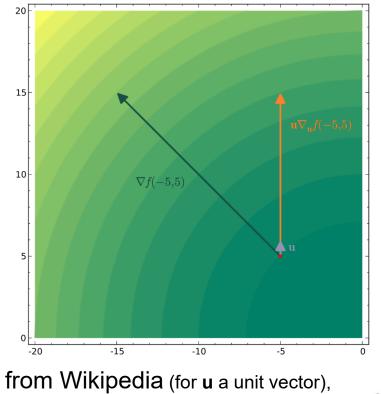
The directional derivative and the gradient vector

$$D_{\mathbf{u}}f = df(\mathbf{u})$$
$$df(\mathbf{u}) = \nabla f \cdot \mathbf{u}$$

The gradient vector is then *defined*, such that:

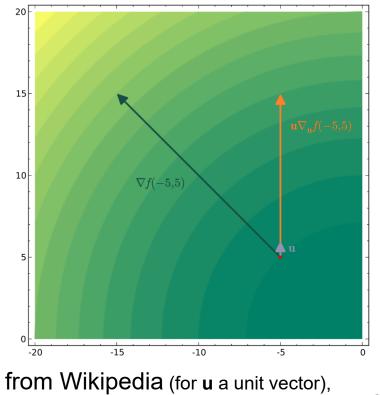
$$\nabla f \cdot \mathbf{u} := df(\mathbf{u})$$





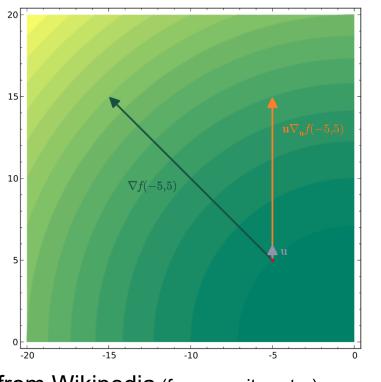
the function here is $f(x,y) = x^2 + y^2$ $\nabla f(x,y) = 2x\mathbf{i} + 2y\mathbf{j}$



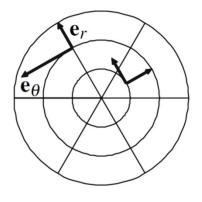


the function here is $f(x,y) = x^2 + y^2$ $\nabla f(x,y) = 2x \mathbf{e}_x + 2y \mathbf{e}_y$ df(x,y) = 2x dx + 2y dy





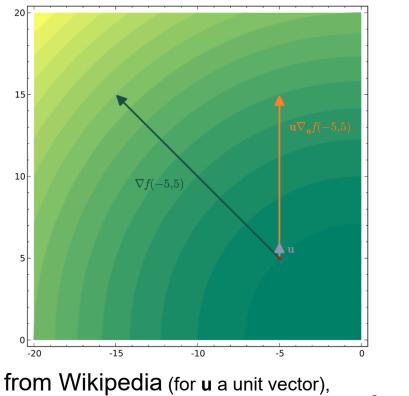
how about in polar coordinates?



from Wikipedia (for **u** a unit vector), the function here is $f(r, \theta) = r^2$

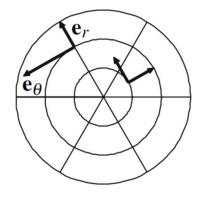
 $\nabla f(r,\theta) = 2r\mathbf{e}_r + 0\frac{1}{r^2}\mathbf{e}_\theta = 2r\mathbf{e}_r$ $df(r,\theta) = 2rdr + 0d\theta = 2rdr$



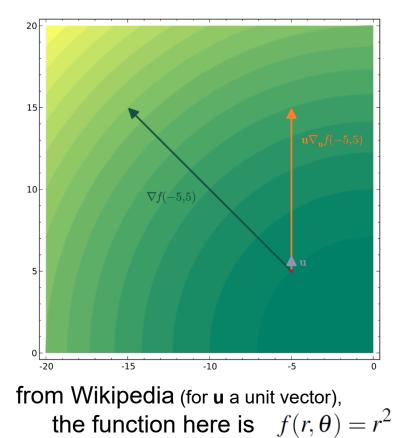


the function here is $f(r, \theta) = r^2$ $\nabla f(r, \theta) = 2r \mathbf{e}_r + 0 \frac{1}{r^2} \mathbf{e}_{\theta} = 2r \mathbf{e}_r$ $df(r, \theta) = 2r dr + 0 d\theta = 2r dr$

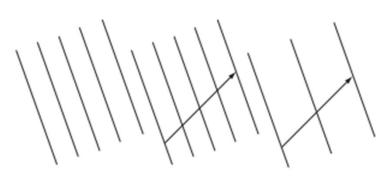
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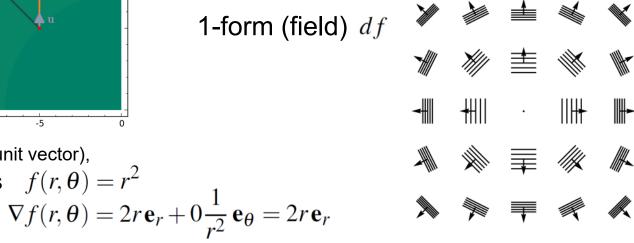






different 1-forms evaluated in some direction





 $df(r,\theta) = 2rdr + 0d\theta = 2rdr$

Inner Products and Metric Tensor (Field)



Symmetric, covariant second-order tensor field: *defines* inner product on manifold (in each tangent space)

 $\langle \mathbf{v}, \mathbf{w} \rangle := \mathbf{g}(\mathbf{v}, \mathbf{w}) = \|\mathbf{v}\| \|\mathbf{w}\| \cos \theta$

Inner Products and Metric Tensor (Field)



Symmetric, covariant second-order tensor field: *defines* inner product on manifold (in each tangent space)

$$\langle \mathbf{v}, \mathbf{w} \rangle := \mathbf{g}(\mathbf{v}, \mathbf{w}) = \|\mathbf{v}\| \|\mathbf{w}\| \cos \theta$$

$$g_{ij} = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} v^1 \\ v^2 \end{bmatrix}$$

$$\|\mathbf{v}\|^2 = \begin{bmatrix} v^1 & v^2 \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \begin{bmatrix} v^1 \\ v^2 \end{bmatrix}$$

$$= \mathbf{g}(\mathbf{v}, \mathbf{v})$$

$$= g_{ij}v^iv^j$$

$$= \mathbf{v}^T \mathbf{g} \mathbf{v}$$

$$\|\mathbf{v}\|^2 = \begin{bmatrix} v^1 & v^2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

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$$\|\mathbf{v}\|^2 = \begin{bmatrix} v^1 & v^2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v^1 \\ v^2 \end{bmatrix} = \mathbf{v}^T \mathbf{v}$$

Inner Products and Metric Tensor (Field)



Components of metric referred to coordinates

$$g_{ij} := \langle \mathbf{e}_i, \mathbf{e}_j \rangle$$

A second-order tensor field is bi-linear, i.e., linear in each (vector/covector) argument separately

From bi-linearity we immediately get:

$$\langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{g} \left(v^i \mathbf{e}_i, w^j \mathbf{e}_j \right)$$

= $v^i w^j \langle \mathbf{e}_i, \mathbf{e}_j \rangle$
= $g_{ij} v^i w^j$

Tensor Calculus

Highly recommended:

Very nice book,

complete lecture on Youtube!

Pavel Grinfeld

Introduction to Tensor Analysis and the Calculus of Moving Surfaces

D Springer



Thank you.

Thanks for material

- Helwig Hauser
- Eduard Gröller
- Daniel Weiskopf
- Torsten Möller
- Ronny Peikert
- Philipp Muigg
- Christof Rezk-Salama