

KAUST

CS 247 – Scientific Visualization Lecture 10: Scalar Field Visualization, Pt. 4

Reading Assignment #5 (until Mar 5)



Read (required):

· Gradients of scalar-valued functions

https://en.wikipedia.org/wiki/Gradient

• Critical points

https://en.wikipedia.org/wiki/Critical_point_(mathematics)

• Multivariable derivatives and differentials

https://en.wikipedia.org/wiki/Total_derivative

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https://en.wikipedia.org/wiki/Differential_of_a_function#
Differentials_in_several_variables
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https://en.wikipedia.org/wiki/Hessian_matrix

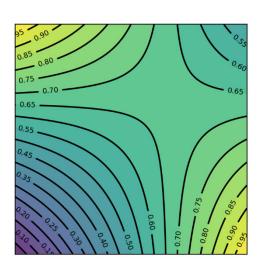
• Dot product, inner product (more general)

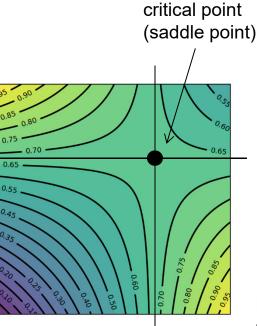
https://en.wikipedia.org/wiki/Dot_product

https://en.wikipedia.org/wiki/Inner_product_space



Critical points are where the gradient vanishes (i.e., is the zero vector)





here, the critical value is 2/3=0.666...

"Asymptotic decider": resolve ambiguous configurations (6 and 9) by comparing specific iso-value with critical value (scalar value at critical point)

Bi-Linear Interpolation



Consider area between 2x2 adjacent samples (e.g., pixel centers):

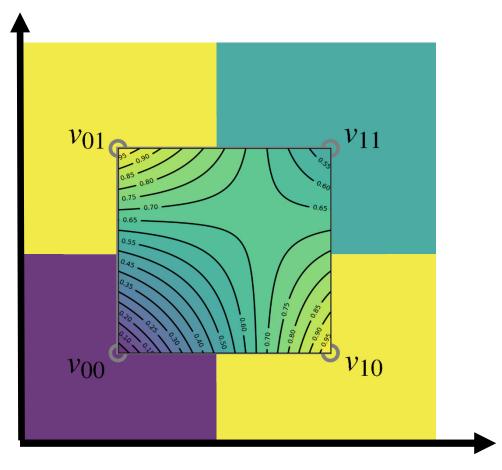
Given any (fractional) position

$\alpha_1 := x_1 - \lfloor x_1 \rfloor$	$\alpha_1 \in [0.0, 1.0)$
$\alpha_2 := x_2 - \lfloor x_2 \rfloor$	$lpha_2 \in [0.0, 1.0)$

and 2x2 sample values

$$\begin{bmatrix} v_{01} & v_{11} \\ v_{00} & v_{10} \end{bmatrix}$$

Compute: $f(\alpha_1, \alpha_2)$



Bi-Linear Interpolation



Interpolate function at (fractional) position (α_1, α_2):

$$f(\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2) = \begin{bmatrix} \boldsymbol{\alpha}_2 & (1 - \boldsymbol{\alpha}_2) \end{bmatrix} \begin{bmatrix} v_{01} & v_{11} \\ v_{00} & v_{10} \end{bmatrix} \begin{bmatrix} (1 - \boldsymbol{\alpha}_1) \\ \boldsymbol{\alpha}_1 \end{bmatrix}$$

$$= (1 - \alpha_1)(1 - \alpha_2)v_{00} + \alpha_1(1 - \alpha_2)v_{10} + (1 - \alpha_1)\alpha_2v_{01} + \alpha_1\alpha_2v_{11}$$

$$= v_{00} + \alpha_1(v_{10} - v_{00}) + \alpha_2(v_{01} - v_{00}) + \alpha_1\alpha_2(v_{00} + v_{11} - v_{10} - v_{01})$$



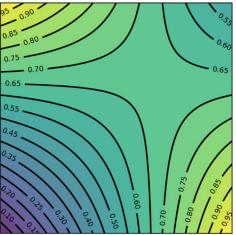
Compute gradient (critical points are where gradient is zero vector):

$$\frac{\partial f(\alpha_1, \alpha_2)}{\partial \alpha_1} = (v_{10} - v_{00}) + \alpha_2(v_{00} + v_{11} - v_{10} - v_{01})$$
$$\frac{\partial f(\alpha_1, \alpha_2)}{\partial \alpha_2} = (v_{01} - v_{00}) + \alpha_1(v_{00} + v_{11} - v_{10} - v_{01})$$

Where are lines of constant value / critical points?

$$\frac{\partial f(\alpha_1, \alpha_2)}{\partial \alpha_1} = 0: \qquad \alpha_2 = \frac{v_{00} - v_{10}}{v_{00} + v_{11} - v_{10} - v_{01}}$$
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if denominator is zero, bi-linear interpolation has degenerated to linear interpolation (or const)! (also means: no isolated critical points!)

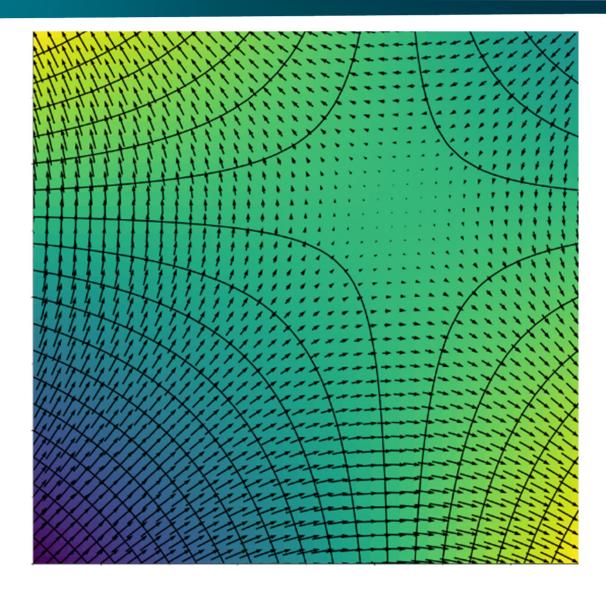


Compute gradient

Note that isolines are farther apart where gradient is smaller

Note the horizontal and vertical lines where gradient becomes vertical/horizontal

Note the critical point



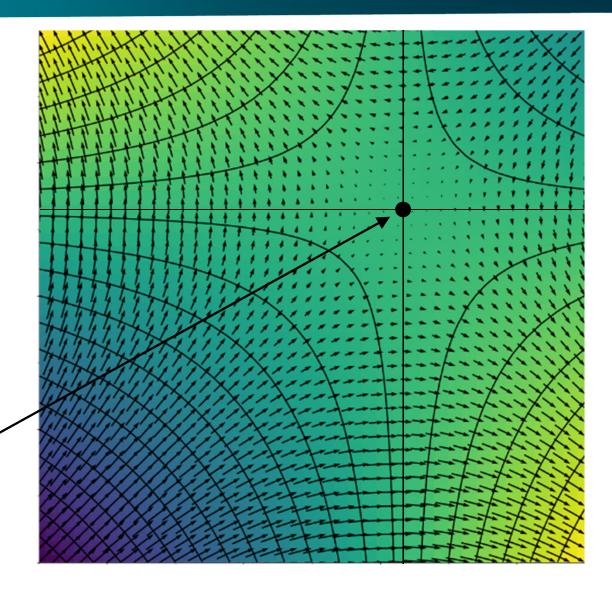


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critical point (saddle point)



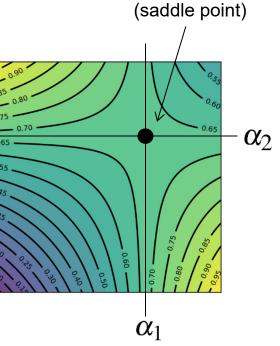
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critical point



Examine Hessian matrix at critical point (non-degenerate critical p.?, ...)

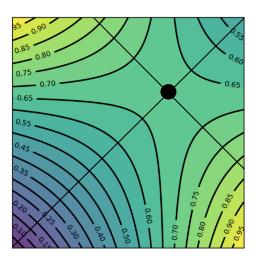
$$\begin{bmatrix} \frac{\partial^2 f}{\partial \alpha_1^2} & \frac{\partial^2 f}{\partial \alpha_1 \partial \alpha_2} \\ \frac{\partial^2 f}{\partial \alpha_2 \partial \alpha_1} & \frac{\partial^2 f}{\partial \alpha_2^2} \end{bmatrix} = \begin{bmatrix} 0 & a \\ a & 0 \end{bmatrix} \qquad a = v_{00} + v_{11} - v_{10} - v_{01}$$

Eigenvalues and eigenvectors (Hessian is symmetric: always real)

$$\lambda_1 = -a \text{ and } \lambda_2 = a$$

 $v_1 = \begin{bmatrix} -1\\ 1 \end{bmatrix}, v_2 = \begin{bmatrix} 1\\ 1 \end{bmatrix}$

(here also: principal curvature magnitudes and directions of this function's graph == surface embedded in 3D)





Examine Hessian matrix at critical point (non-degenerate critical p.?, ...)

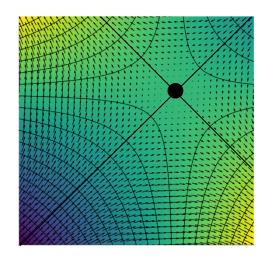
$$\begin{bmatrix} \frac{\partial^2 f}{\partial \alpha_1^2} & \frac{\partial^2 f}{\partial \alpha_1 \partial \alpha_2} \\ \frac{\partial^2 f}{\partial \alpha_2 \partial \alpha_1} & \frac{\partial^2 f}{\partial \alpha_2^2} \end{bmatrix} = \begin{bmatrix} 0 & a \\ a & 0 \end{bmatrix} \qquad a = v_{00} + v_{11} - v_{10} - v_{01}$$

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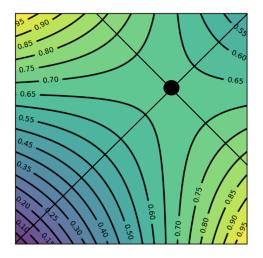
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 and $\lambda_2 = a$

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degenerate means determinant = 0 (at least one eigenvalue = 0); bi-linear is simple: a = 0 means degenerated to linear anyway: no critical point at all! (except constant function) (but with more than one cell: can have max or min at vertices)



Interlude: Implicit Function Theorem



When can I write an implicit function in \mathbb{R}^{n+m} such that it is the graph of a function $f: \mathbb{R}^n \to \mathbb{R}^m$ at least locally?

That is: is this implicitly described function an *n*-manifold embedded in \mathbb{R}^{n+m} ? (with local coordinates in \mathbb{R}^n)

$$G(f) := \{ (x, f(x)) | x \in \mathbb{R}^n \} \subset \mathbb{R}^n \times \mathbb{R}^m \simeq \mathbb{R}^{n+m}$$

Theorem: if $m \ge m$ Jacobian matrix is invertible (easier for scalar field: check if gradient of f is non-zero)

See https://en.wikipedia.org/wiki/Implicit_function_theorem General result: constant rank theorem

From 2D to 3D (Domain)



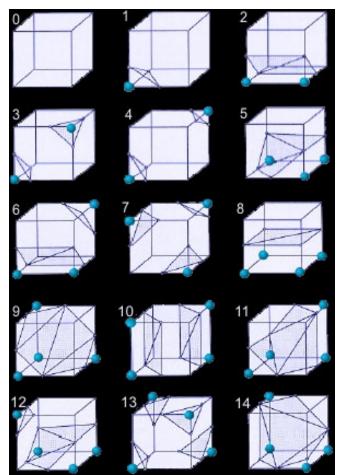
2D - Marching Squares Algorithm:

- 1. Locate the contour corresponding to a user-specified iso value
- 2. Create lines

- 3D Marching Cubes Algorithm:
 - 1. Locate the surface corresponding to a user-specified iso value
 - 2. Create triangles
 - 3. Calculate normals to the surface at each vertex
 - 4. Draw shaded triangles

Marching Cubes





- For each cell, we have 8 vertices with 2 possible states each (inside or outside).
- This gives us 2⁸ possible patterns = 256 cases.
- Enumerate cases to create a LUT
- Use symmetries to reduce problem from 256 to 15 cases.

Explanations

- Data Visualization book, 5.3.2
- Marching Cubes: A high resolution 3D surface construction algorithm, Lorensen & Cline, ACM SIGGRAPH 1987

Contours of 3D scalar fields are known as isosurfaces. Before 1987, isosurfaces were computed as

- contours on planar slices, followed by
- "contour stitching".

The marching cubes algorithm computes contours directly in 3D.

- Pieces of the isosurfaces are generated on a cell-by-cell basis.
- Similar to marching squares, a 8-bit number is computed from the 8 signs of $\tilde{f}(x_i)$ on the corners of a hexahedral cell.
- The isosurface piece is looked up in a table with 256 entries.

How to build up the table of 256 cases?

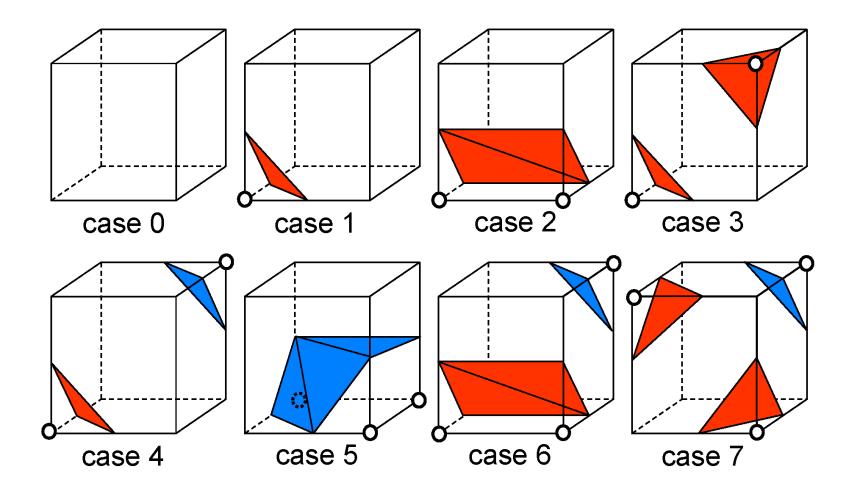
Lorensen and Cline (1987) exploited 3 types of symmetries:

- rotational symmetries of the cube
- reflective symmetries of the cube
- sign changes of $\tilde{f}(x_i)$

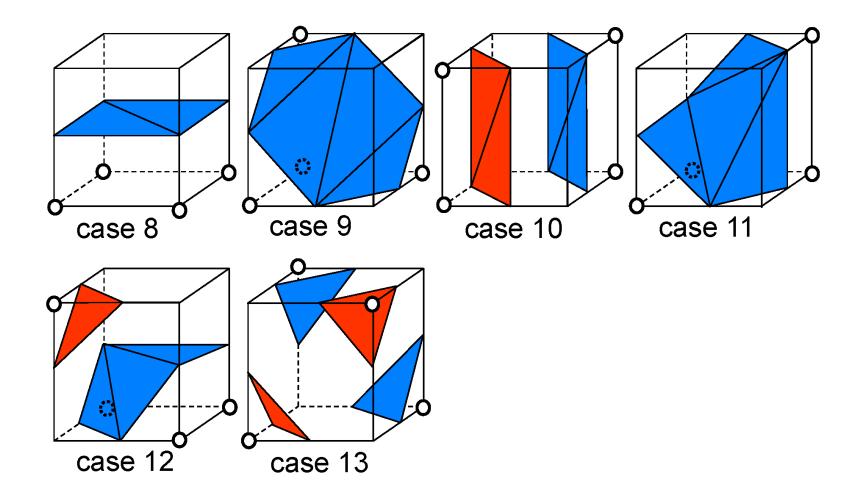
They published a reduced set of 14^{*)} cases shown on the next slides where

- white circles indicate positive signs of $\tilde{f}(x_i)$
- the positive side of the isosurface is drawn in red, the negative side in blue.
- *) plus an unnecessary "case 14" which is a symmetric image of case 11.

Ronald Peikert



SciVis 2009 - Contouring and Isosurfaces



Ronald Peikert

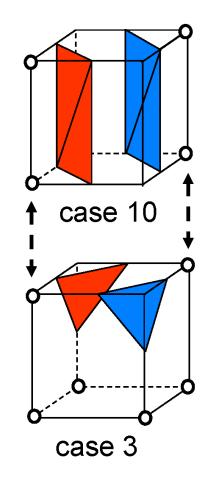
SciVis 2009 - Contouring and Isosurfaces

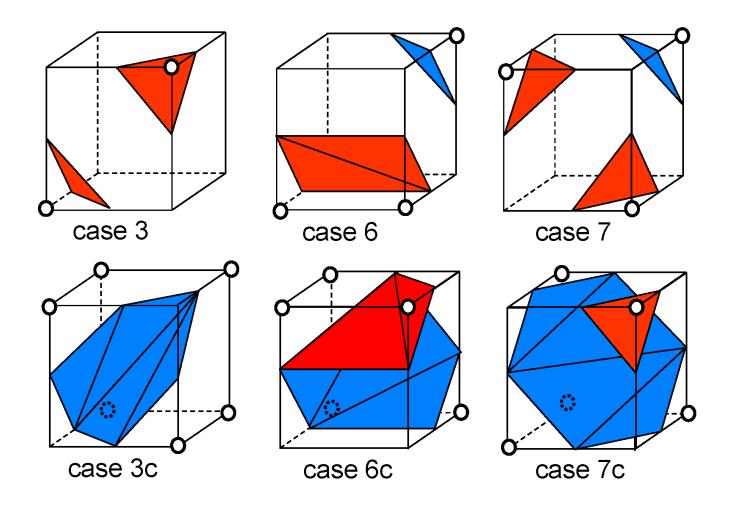
Do the pieces fit together?

- The correct isosurfaces of the trilinear interpolant would fit (trilinear reduces to bilinear on the cell interfaces)
- but the marching cubes polygons don't necessarily fit.

Example

- case 10, on top of
- case 3 (rotated, signs changed)
 have matching signs at nodes but polygons don't fit.





SciVis 2009 - Contouring and Isosurfaces

Summary of marching cubes algorithm:

Pre-processing steps:

- build a table of the 28 cases
- derive a table of the 256 cases, containing info on
 - intersected cell edges, e.g. for case 3/256 (see case 2/28):
 (0,2), (0,4), (1,3), (1,5)
 - triangles based on these points, e.g. for case 3/256:
 (0,2,1), (1,3,2).

Loop over cells:

- find sign of $\tilde{f}(x_i)$ for the 8 corner nodes, giving 8-bit integer
- use as index into (256 case) table
- find intersection points on edges listed in table, using linear interpolation
- generate triangles according to table

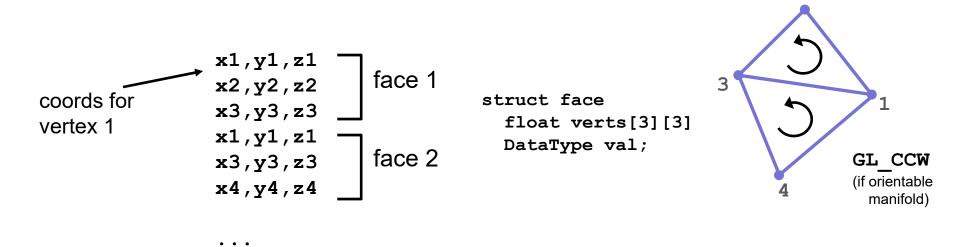
Post-processing steps:

- connect triangles (share vertices)
- compute normal vectors
 - by averaging triangle normals (problem: thin triangles!)
 - by estimating the gradient of the field $f(x_i)$ (better)

Triangle Mesh Data Structure (1)



Store list of vertices; vertices shared by triangles are replicated Render, e.g., with OpenGL immediate mode, ...



Redundant, large storage size, cannot modify shared vertices easily Store data values per face, or separately

Triangle Mesh Data Structure (2)



Indexed face set: store list of vertices; store triangles as indexes

Render using separate vertex and index arrays / buffers



Less redundancy, more efficient in terms of memory

Easy to change vertex positions; still have to do (global) search for shared edges (local information)

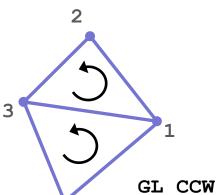
Orientability (2-manifold embedded in 3D)

Orientability of 2-manifold:

Possible to assign consistent normal vector orientation

Triangle meshes

- Edges
 - Consistent ordering of vertices: CCW (counter-clockwise) or CW (clockwise) (e.g., (3,1,2) on one side of edge, (1,3,4) on the other side)
- Triangles
 - Consistent front side vs. back side
 - Normal vector; or ordering of vertices (CCW/CW)
 - See also: "right-hand rule"





Moebius strip (only one side!)



not orientable

Thank you.

Thanks for material

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