

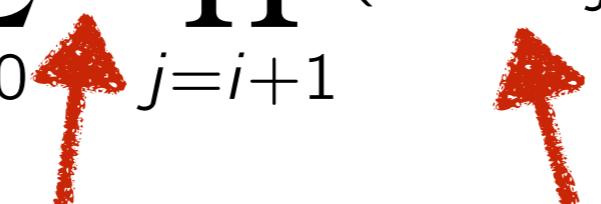
2IMV20

Encoding: spatial data

Recap

Volume rendering equation

- Discretize and simplify

$$I(t) = I_0 e^{-\int_0^t \tau(u) du} + \int_0^t c(s) e^{-\int_s^t \tau(u) du} ds$$
$$I(p) = \sum_{i=0}^{n-1} c_i \prod_{j=i+1}^{n-1} (1 - \tau_j)$$


color **opacity**

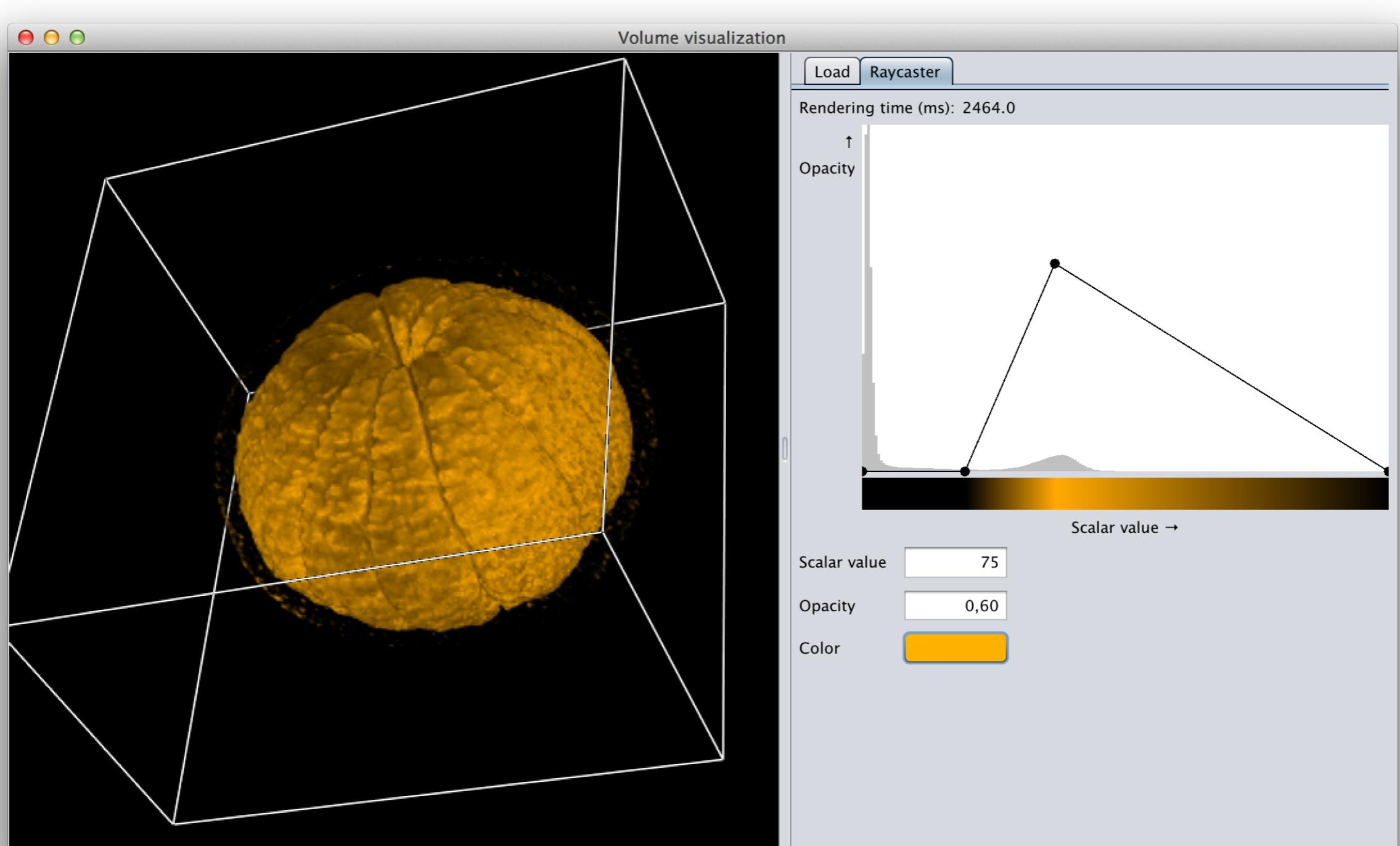
- Compositing order (implementation aspect of above equation)

- back-to-front

- $$C_i = \tau_i c_i + (1 - \tau_i) C_{i-1}$$

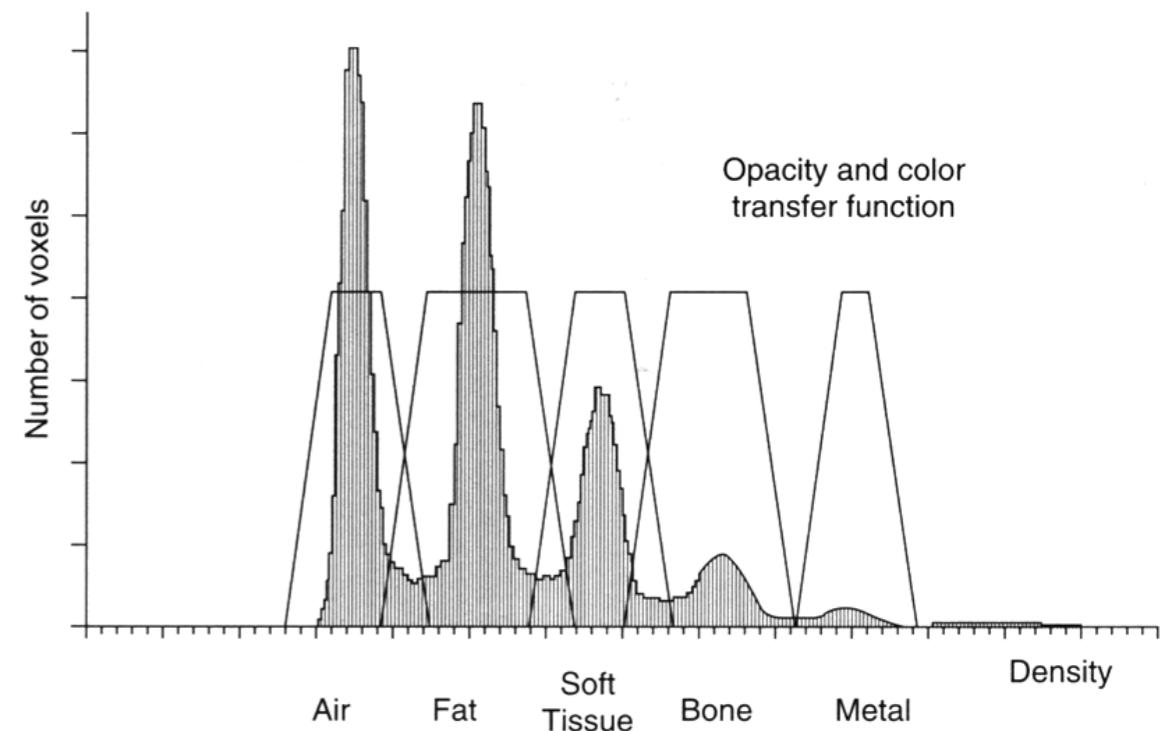
Transfer functions

- Map data values to color c_i and opacity τ_i

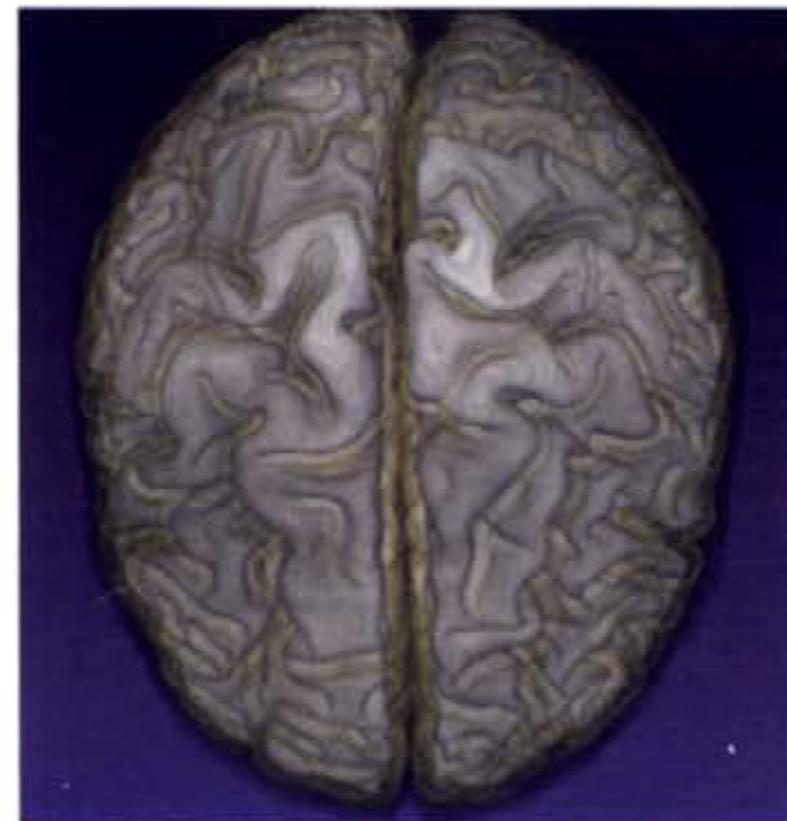
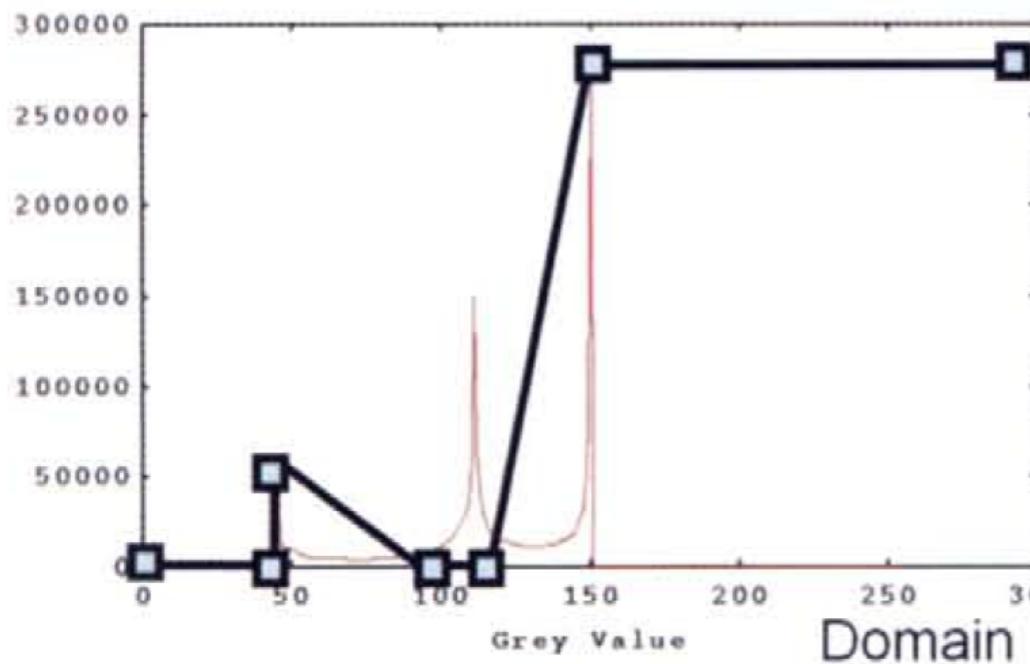


Transfer function design strategy

- Trial-and-error: repeat until satisfied
- Make use of density histogram
- Try to emphasize boundaries



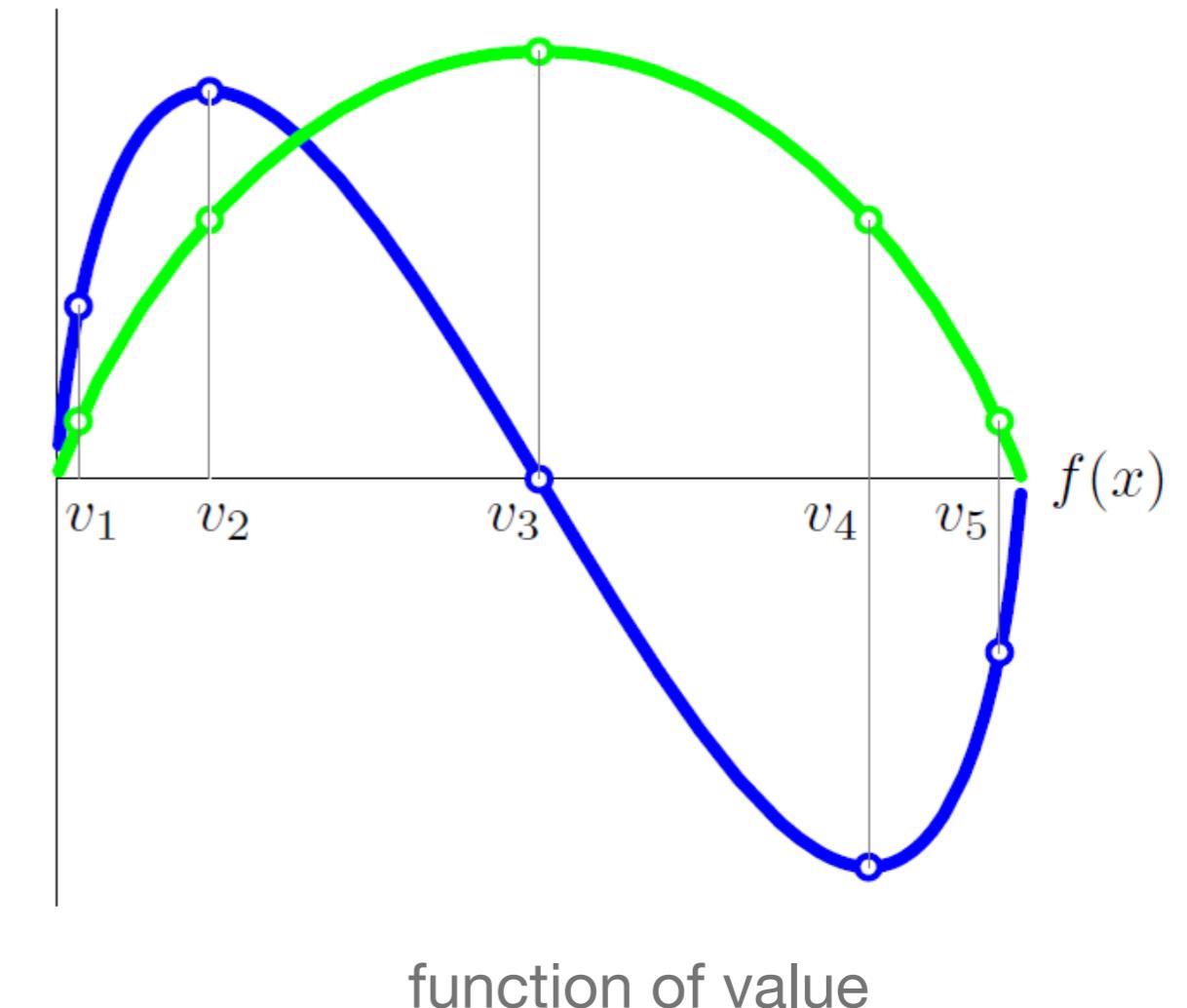
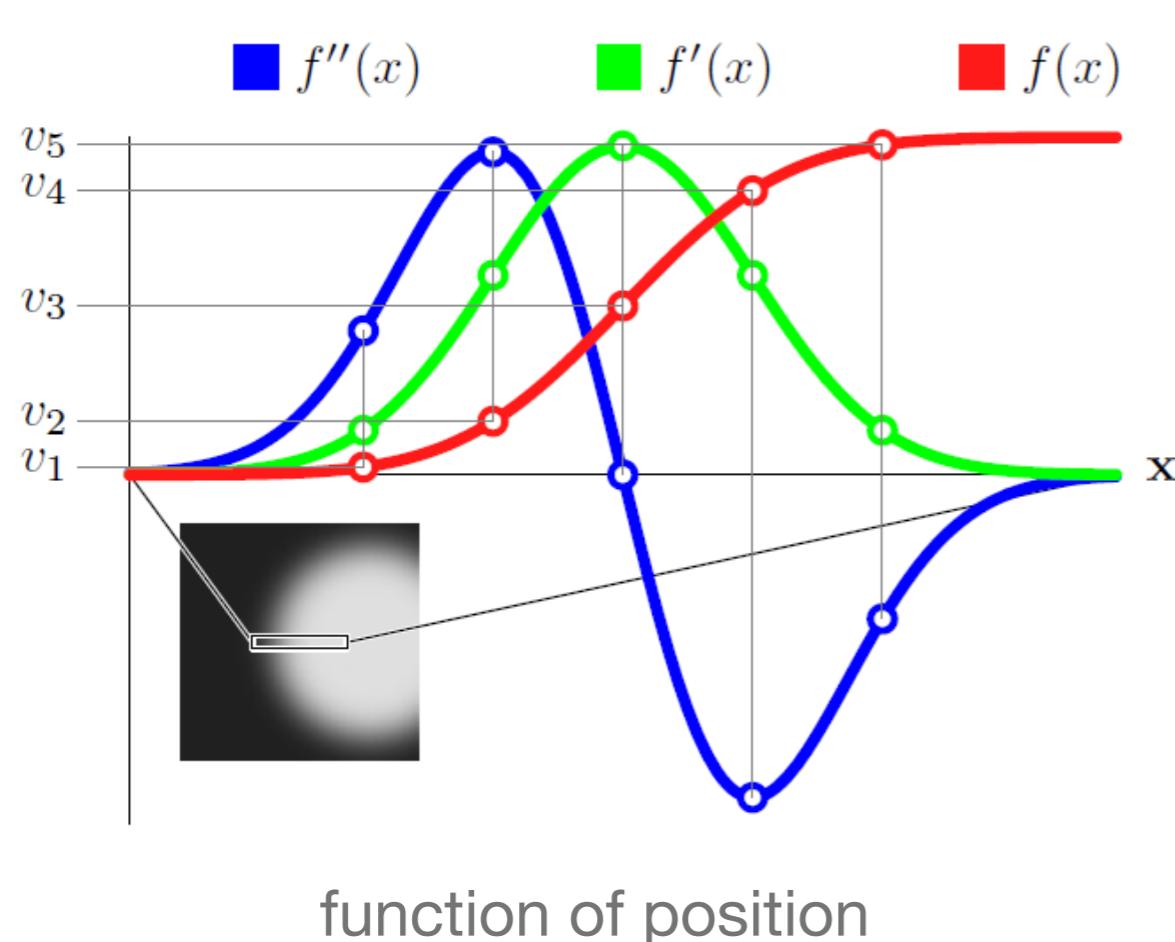
Frequency/Range



Transfer functions continued

Data-driven transfer function design

- Boundary exists where
 - maximum in first-order derivative
 - zero crossing in second-order derivative



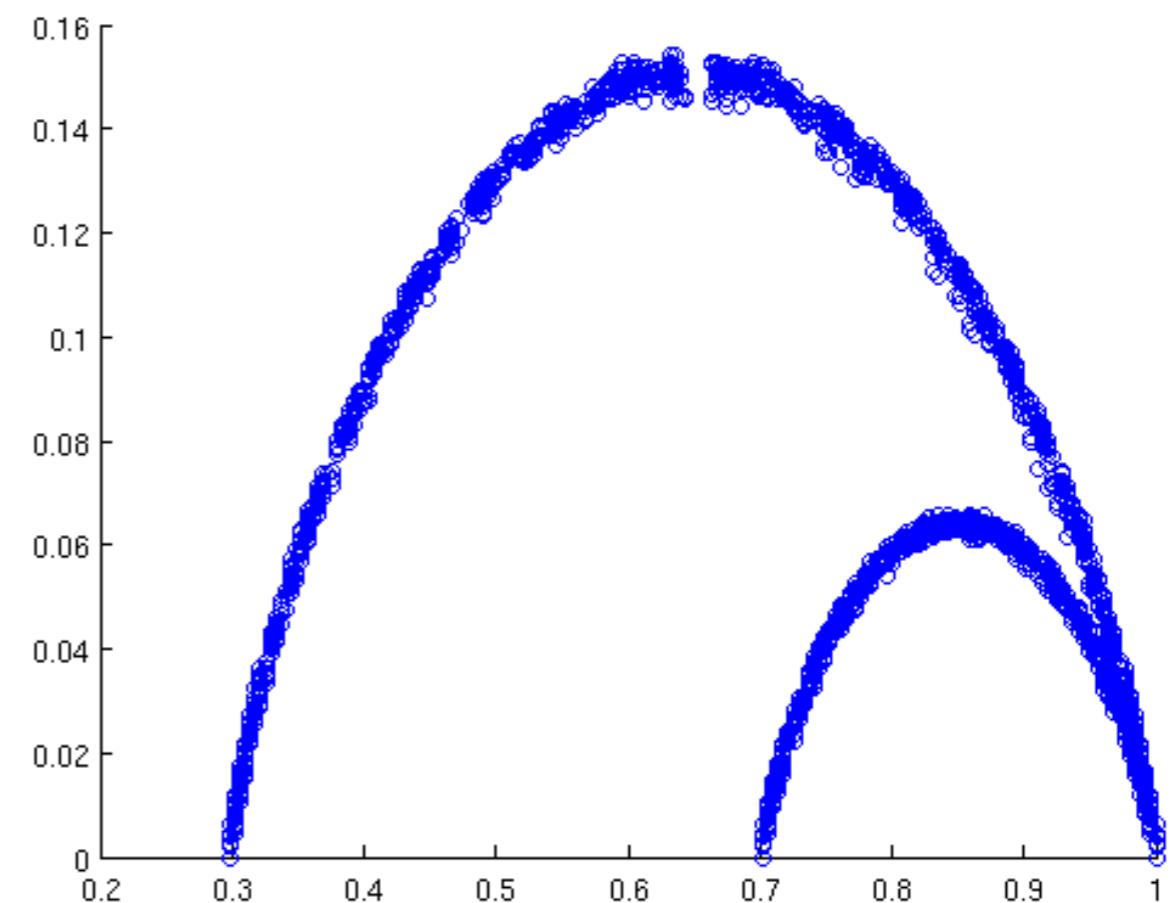
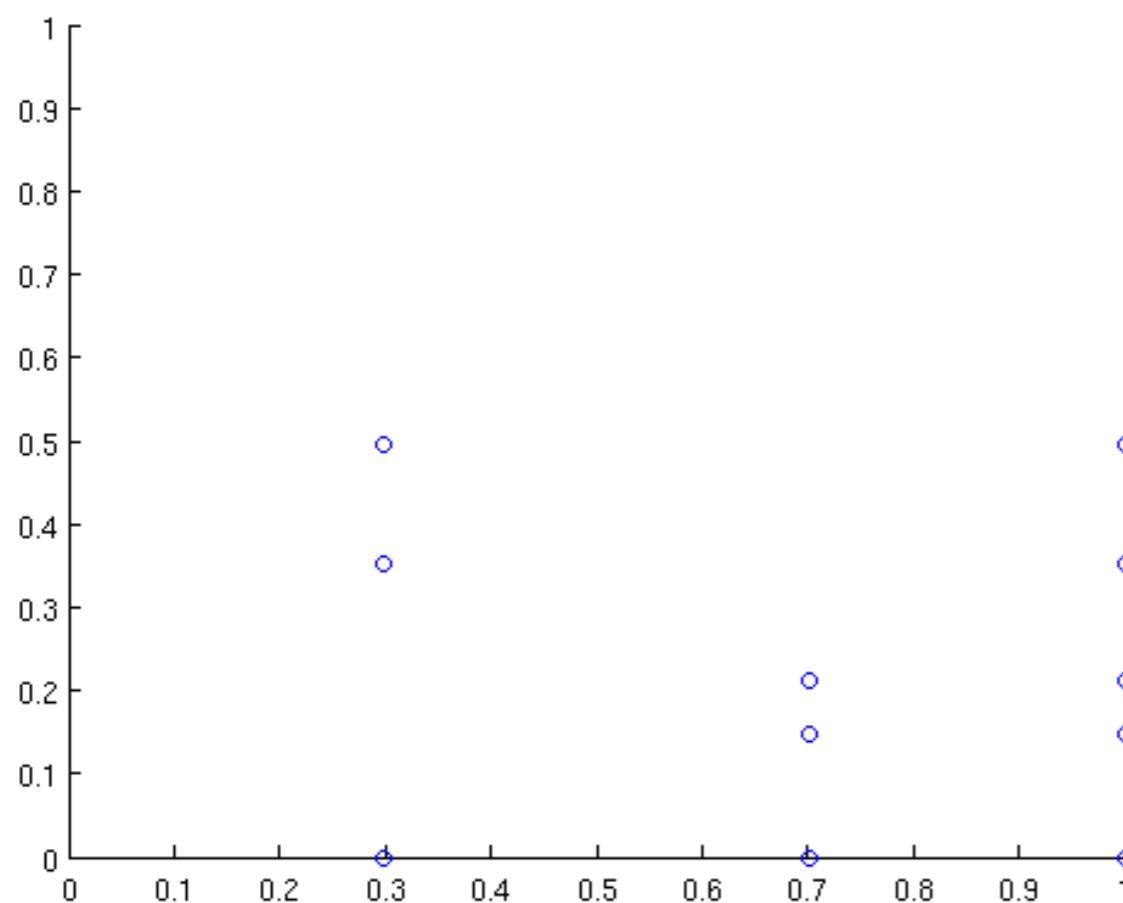
Intensity/gradient magnitude plot



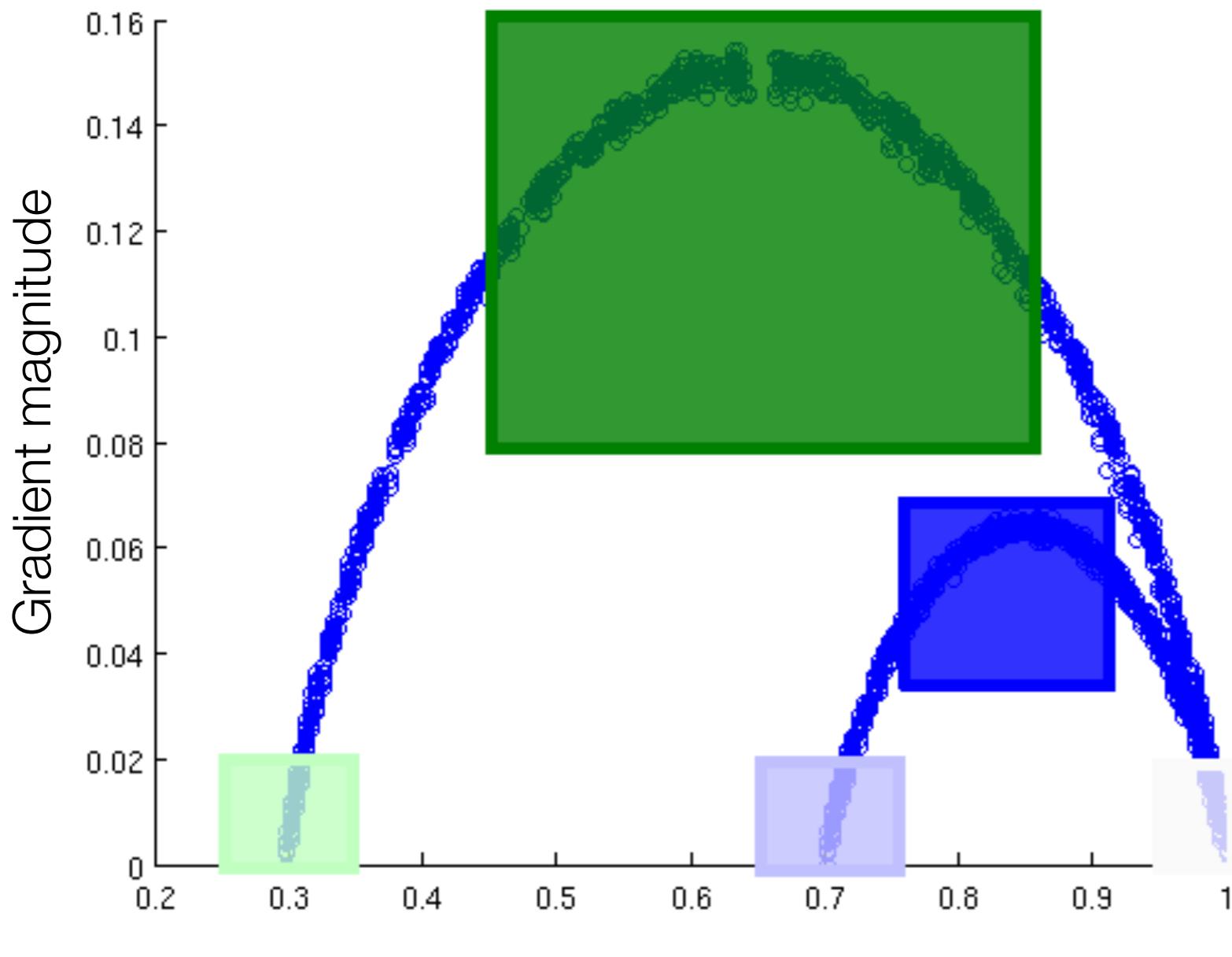
step edges



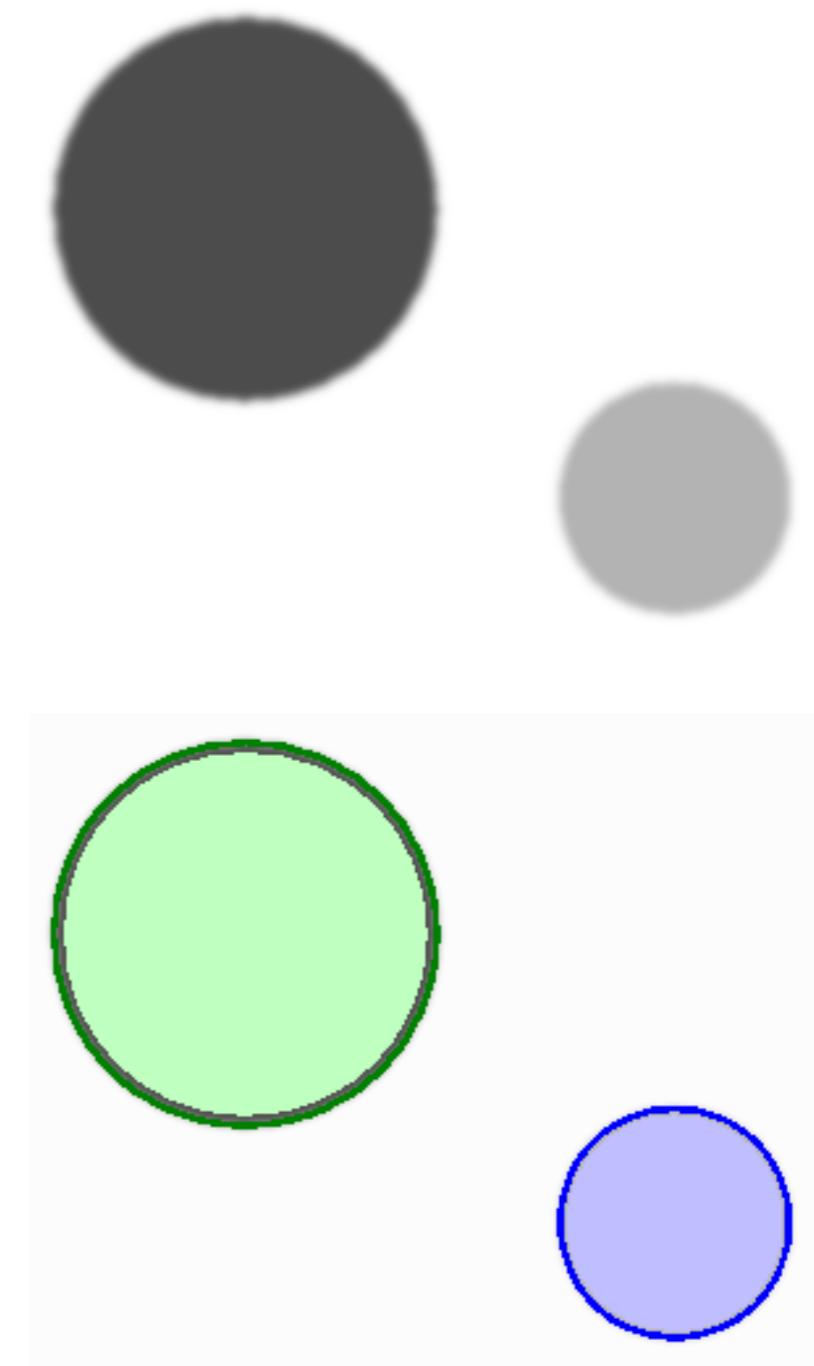
blurred step edges



2D transfer function



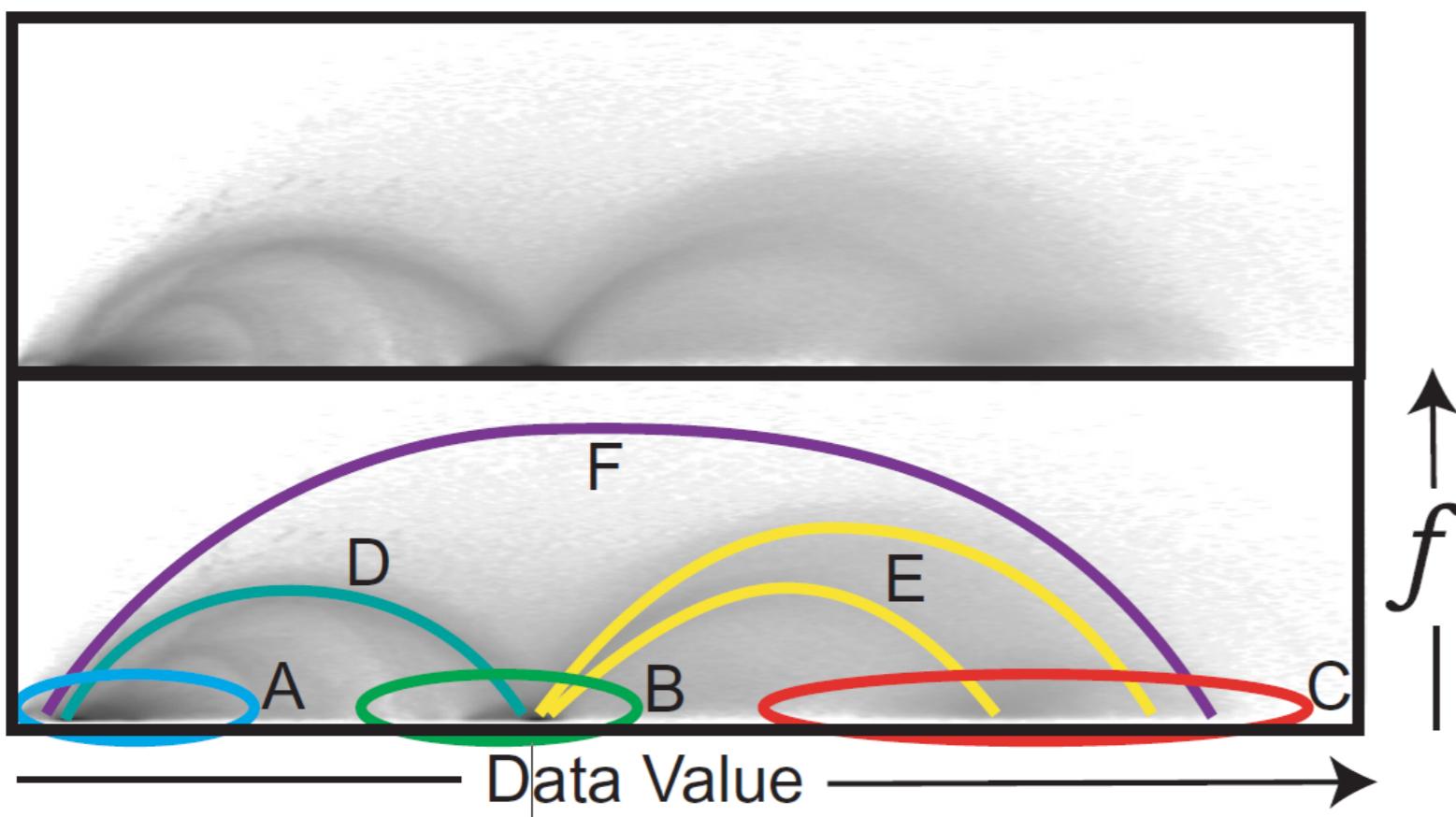
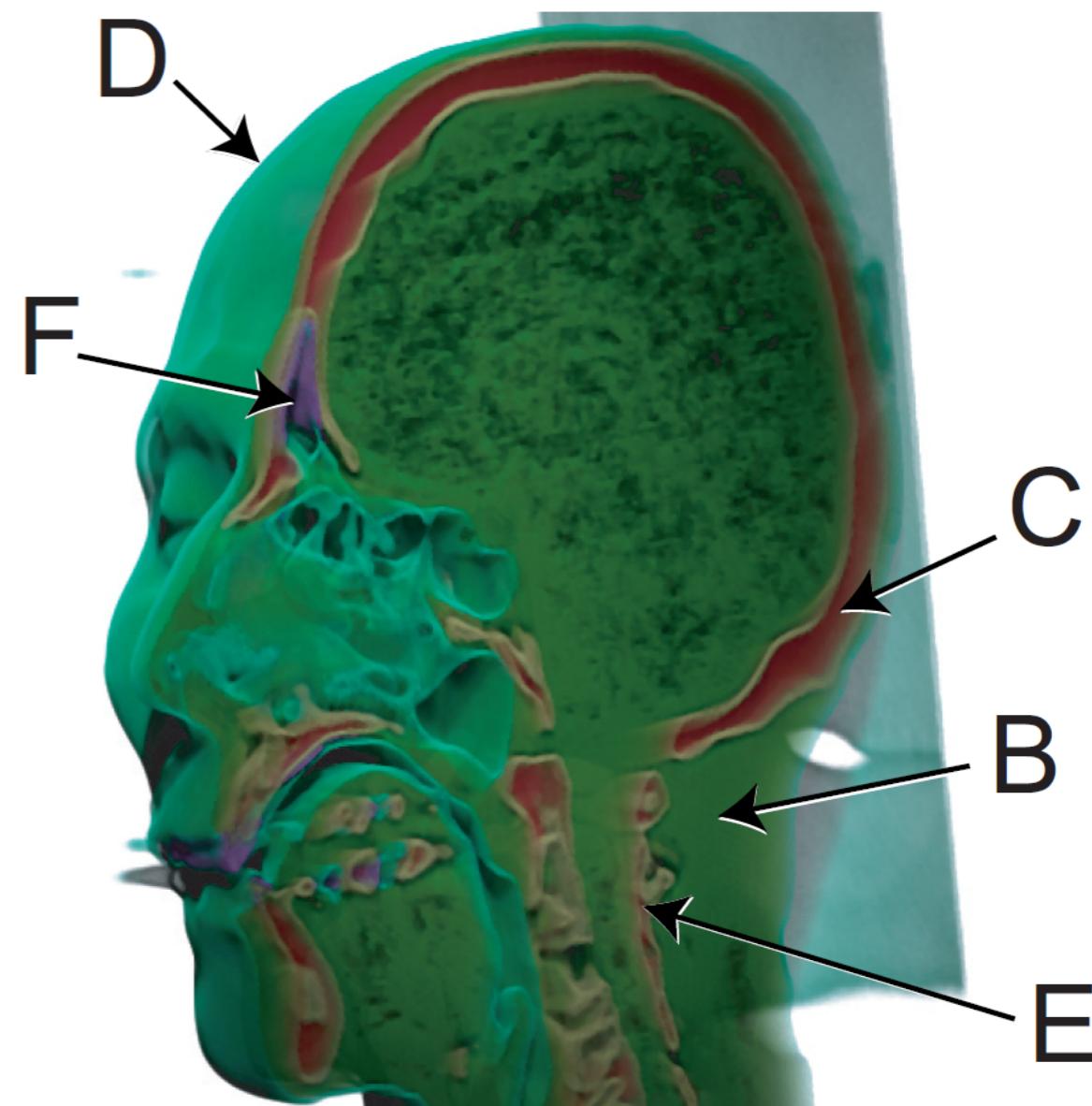
TF design



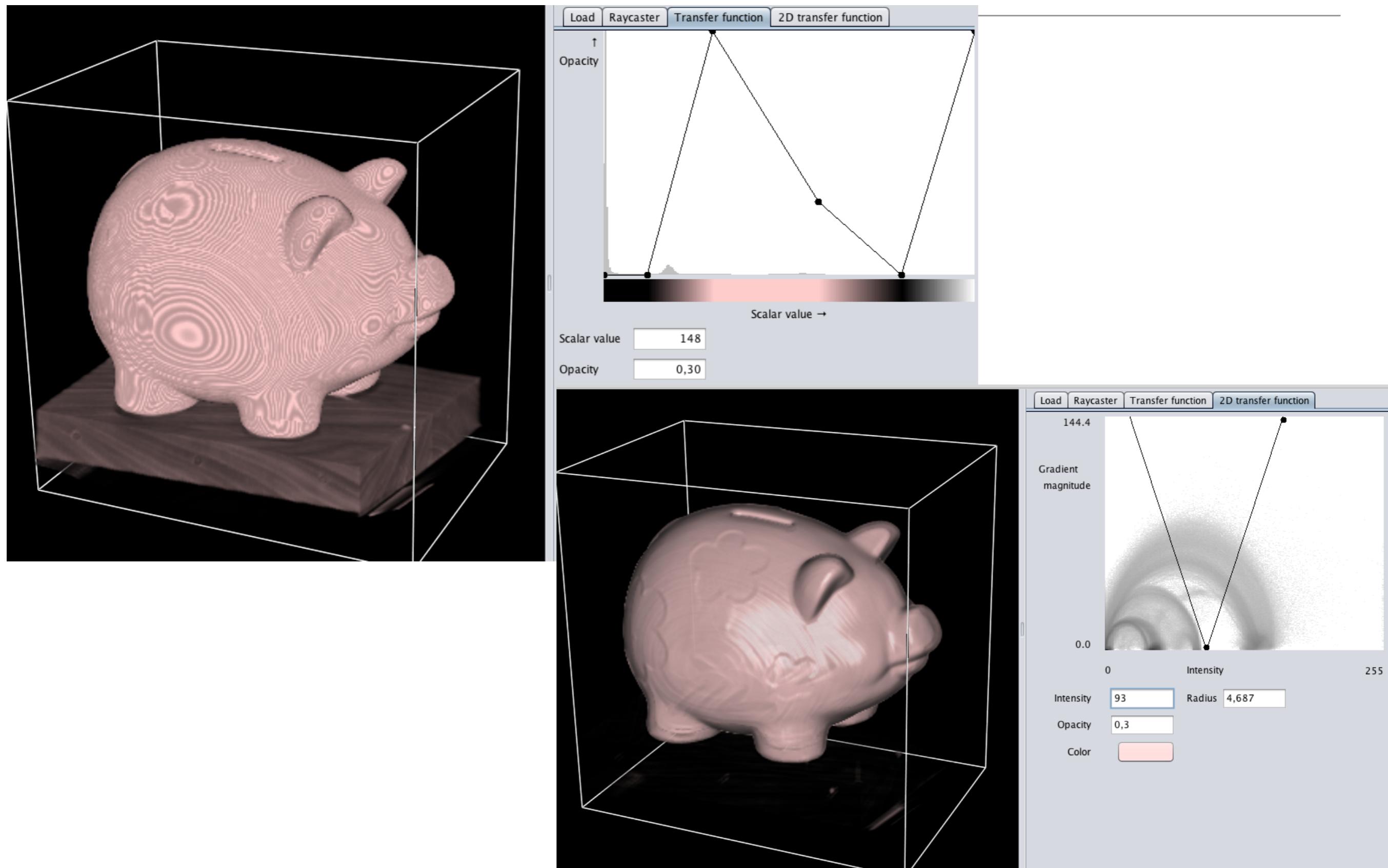
TF applied

2-D transfer functions

- Histogram of voxel intensity and gradient magnitude
- Identify arcs



Transfer functions



Levoy's method

$$\alpha(\mathbf{x}_l) = \alpha_v \begin{cases} 1 & \text{if } |\nabla f(\mathbf{x}_l)| = 0 \text{ and } \\ & f(\mathbf{x}_l) = f_v \\ 1 - \frac{1}{r} \frac{|f_v - f(\mathbf{x}_l)|}{|\nabla f(\mathbf{x}_l)|} & \text{if } |\nabla f(\mathbf{x}_l)| > 0 \text{ and } \\ & f(\mathbf{x}_l) - r |\nabla f(\mathbf{x}_l)| \leq f_v \leq \\ & f(\mathbf{x}_l) + r |\nabla f(\mathbf{x}_l)| \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Computation opacity

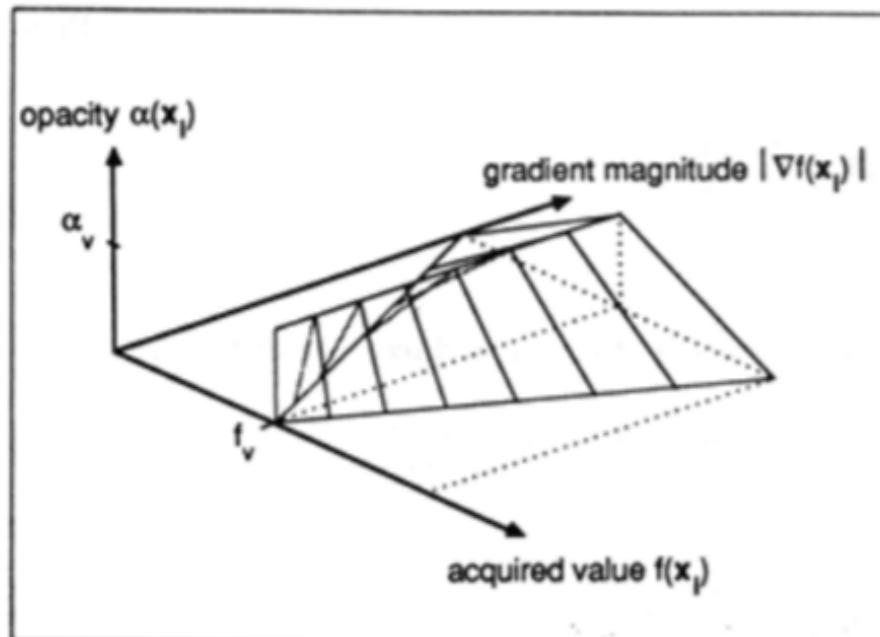
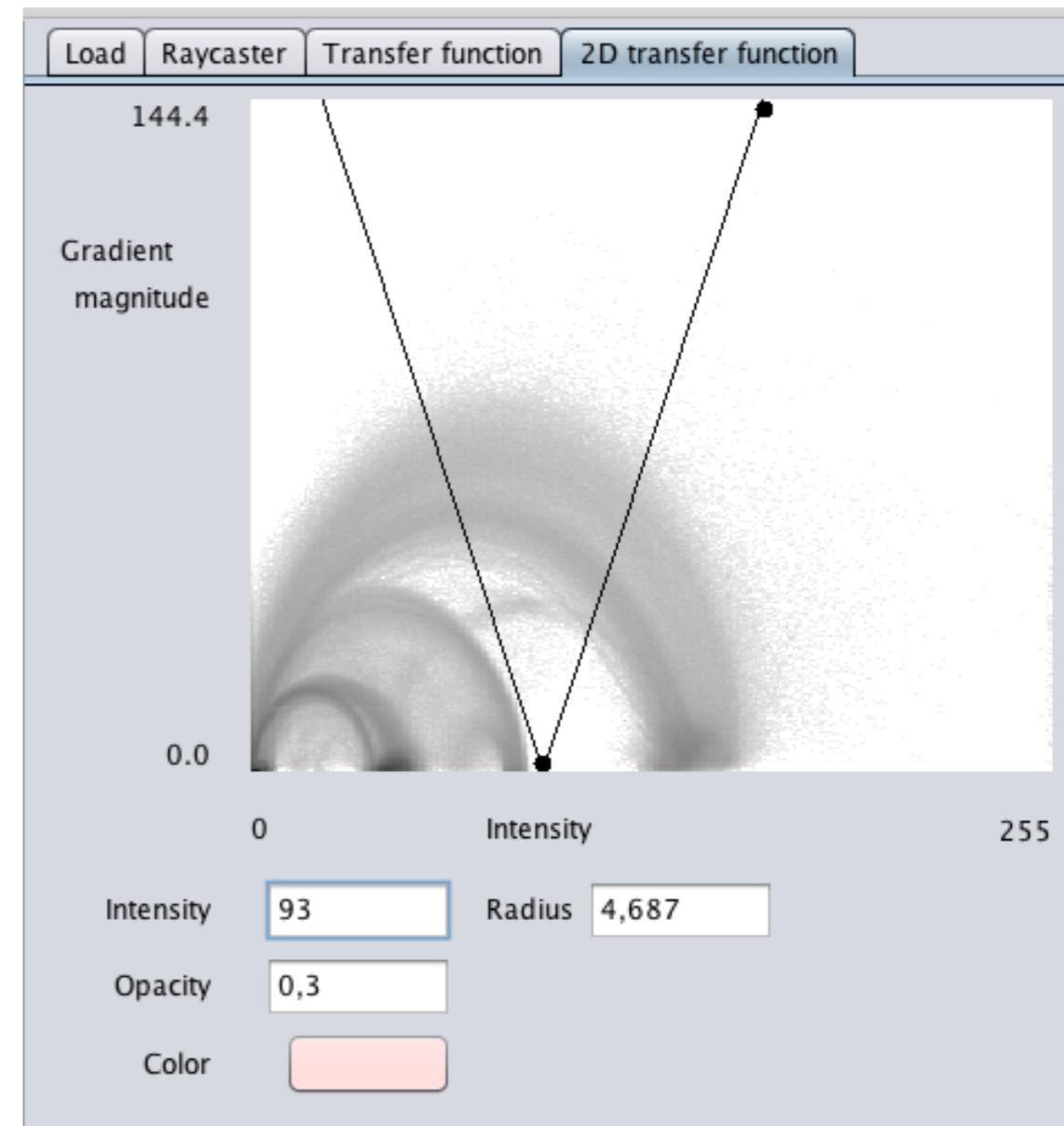


Figure 3. Calculation of opacities for isovalue contour surfaces.

Volume Rendering

Display of Surfaces from Volume Data

Marc Levoy, University of North Carolina



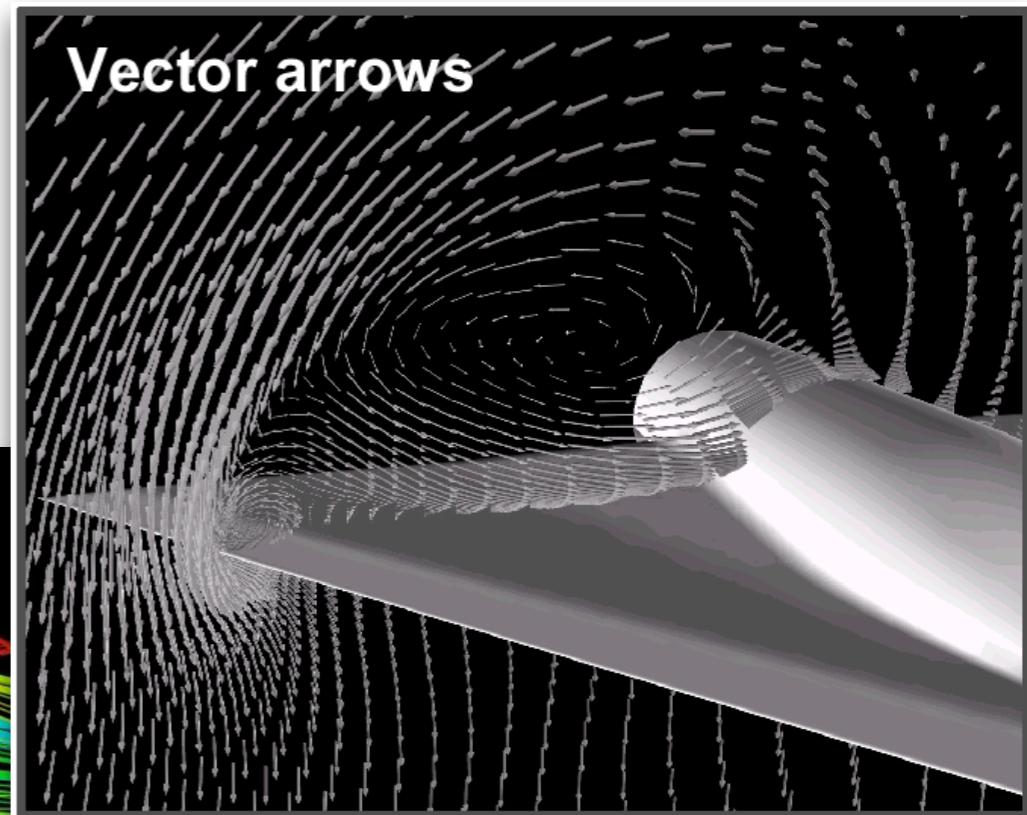
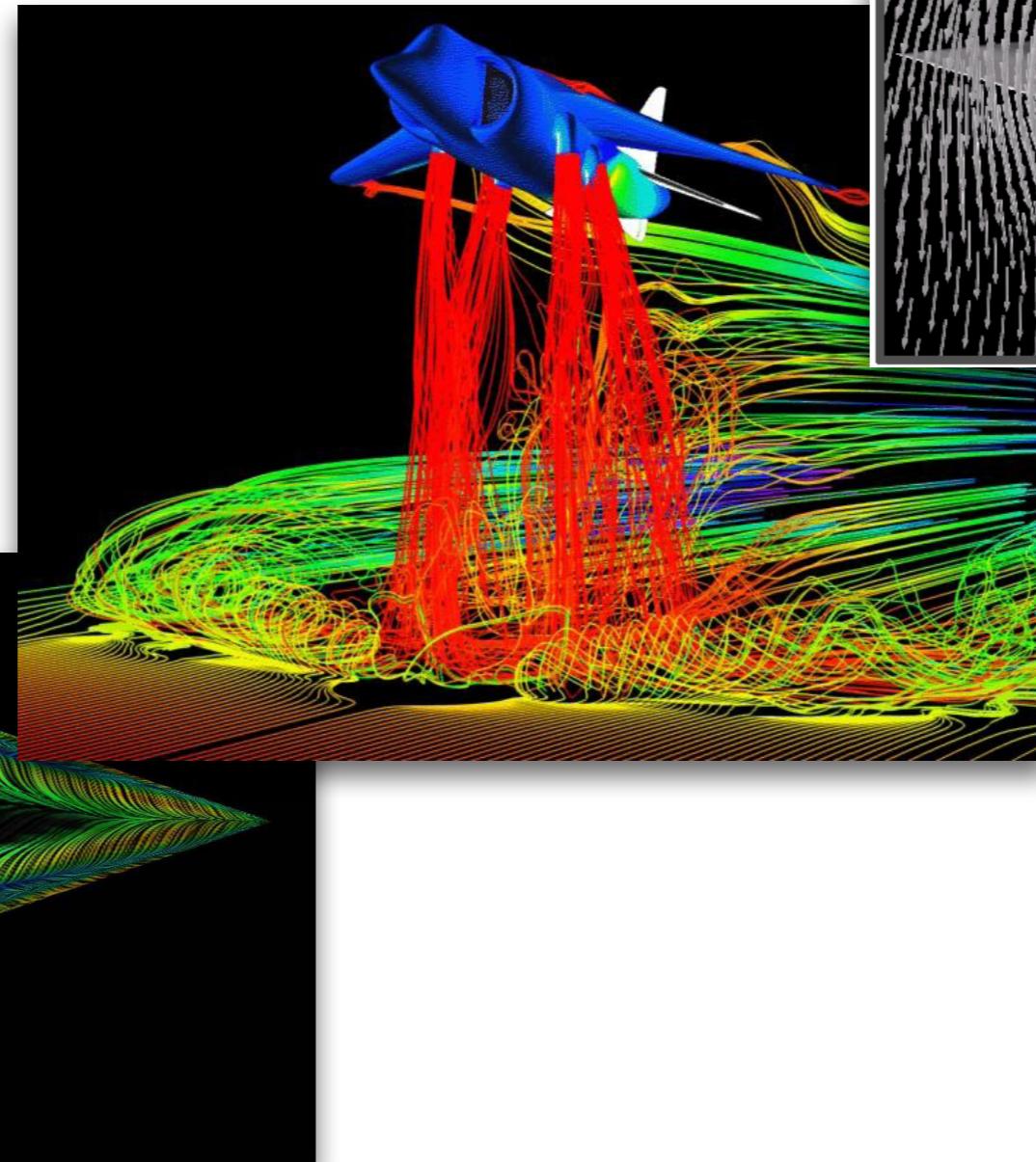
Local illumination in volume rendering

- Use standard Phong model $I = I_a k_{\text{ambient}} + I_d k_{\text{diff}}(\mathbf{L} \cdot \mathbf{N}) + I_s k_{\text{spec}}(\mathbf{V} \cdot \mathbf{R})^\alpha$
- Estimate normal vector \mathbf{N} by computing gradient in each voxel



Vector visualization techniques

- Glyphs
- Streamlines
- Texture based



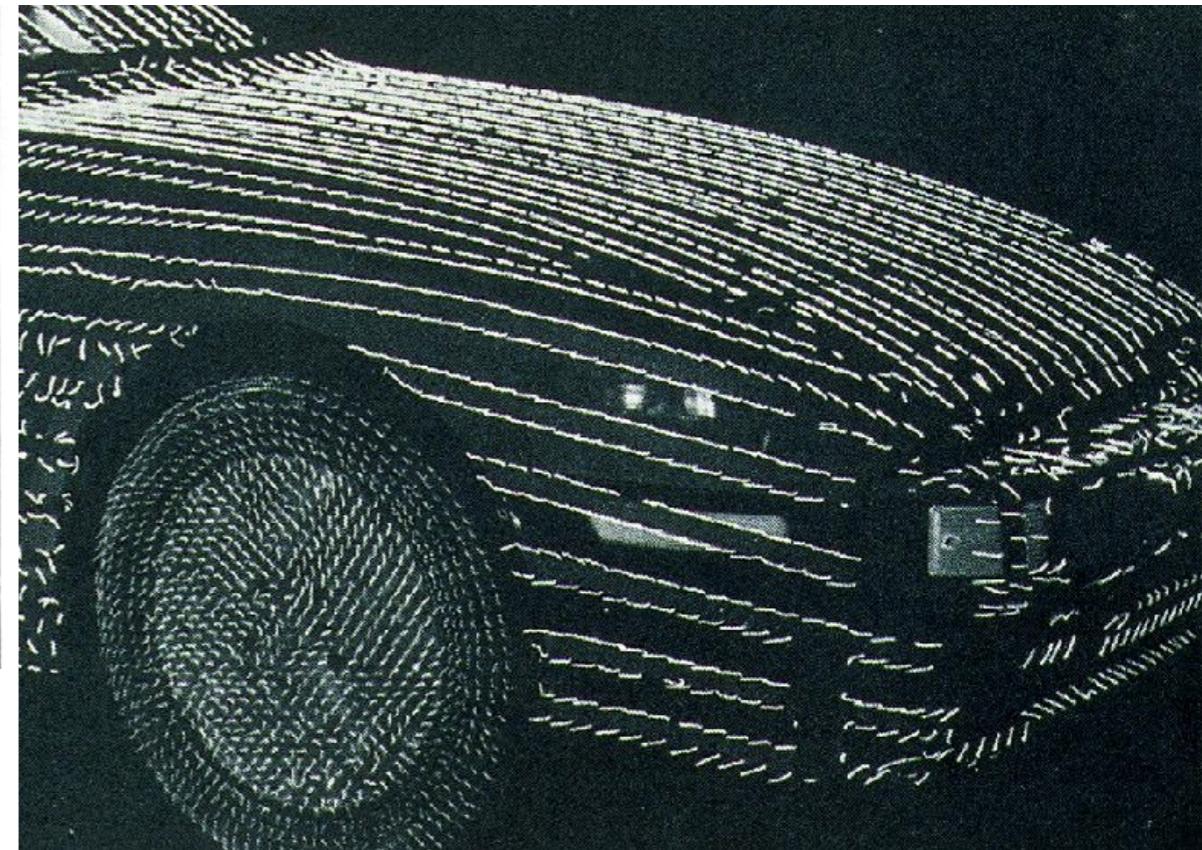
Insight into vector fields

- Properties to visualize
 - global view
 - local view
 - derived properties
- Challenges
 - 2 or 3 components per data point
 - temporal aspects
 - data density

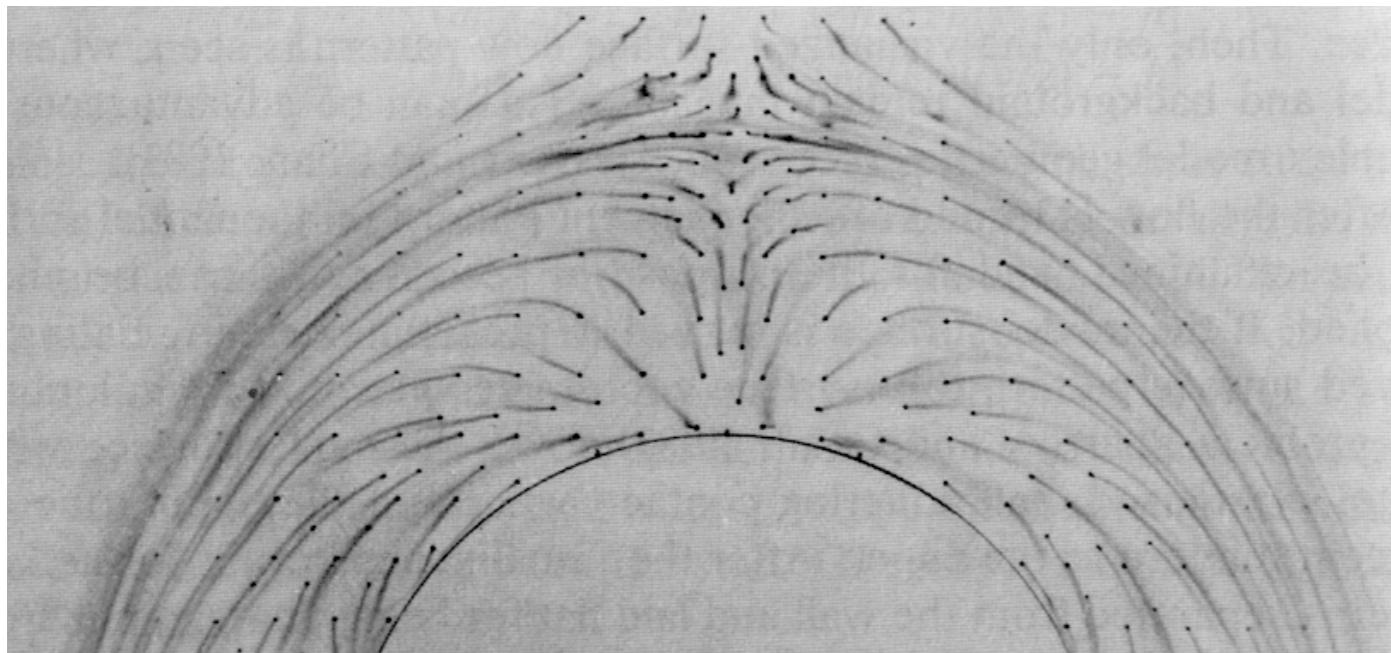
Techniques inspired by experimental visualization



Smoke lines



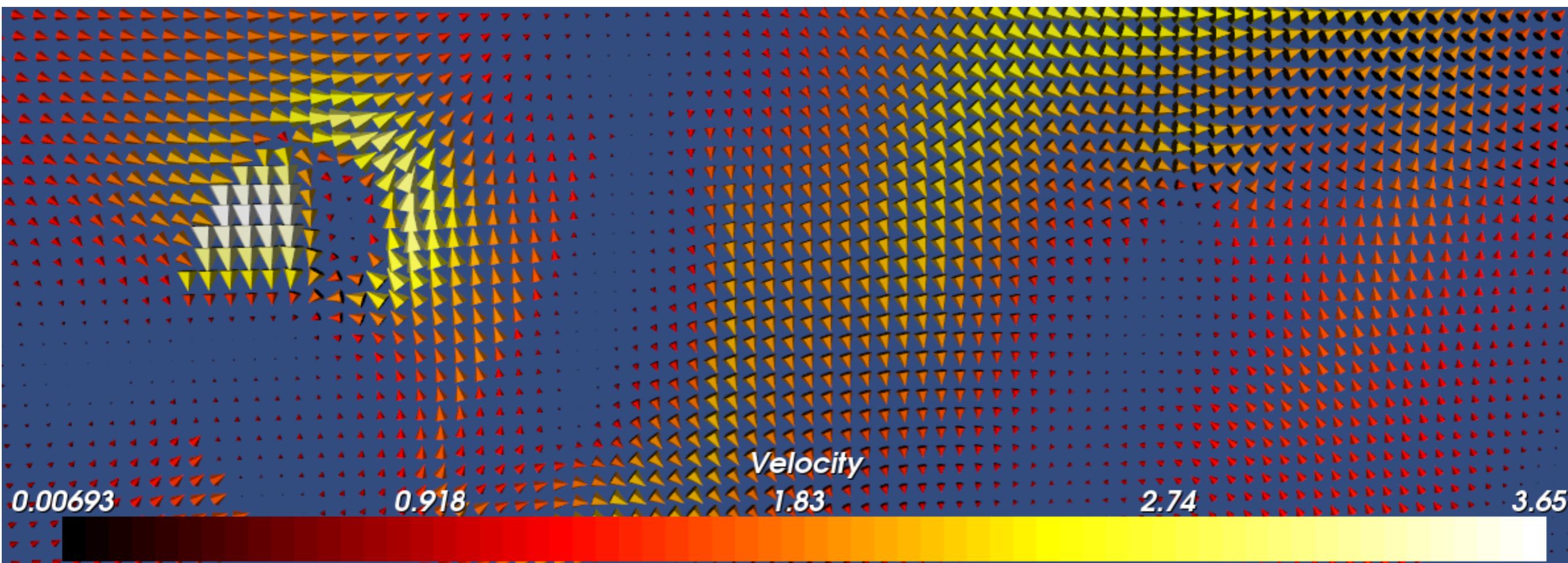
Tufts



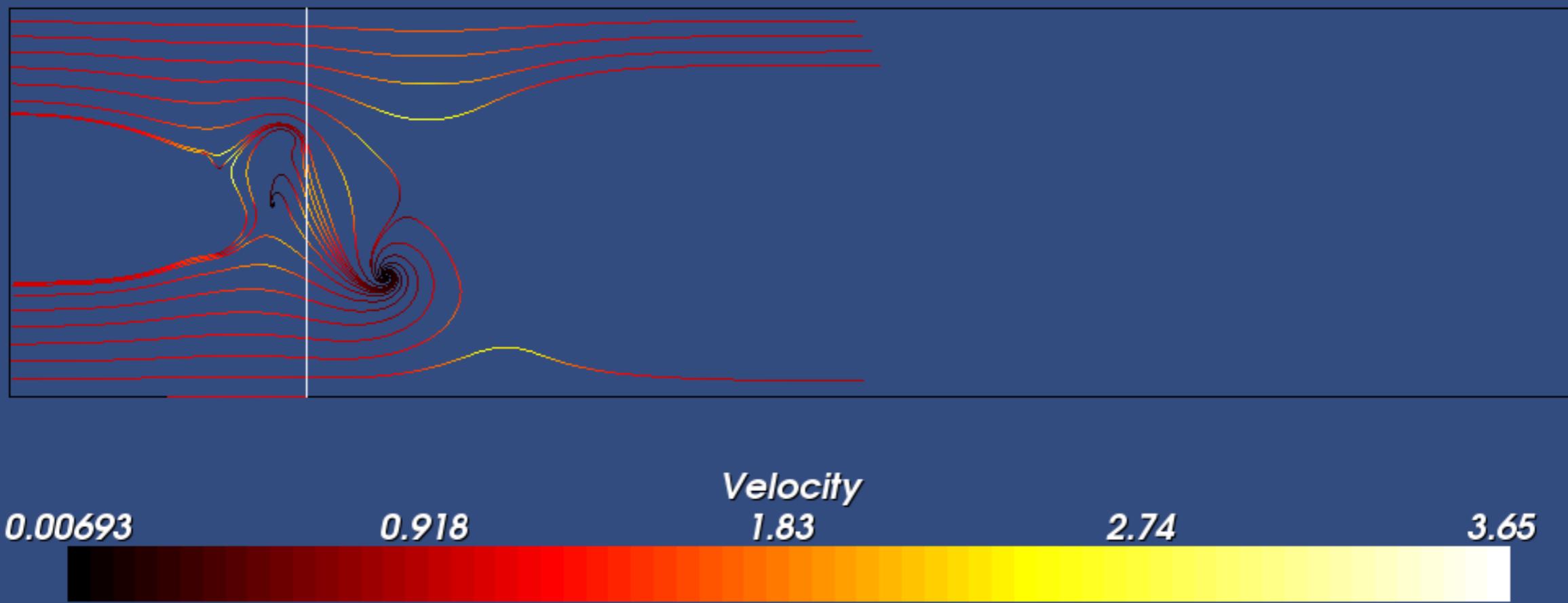
Oil streaks

Vector glyphs

- Assign icon to each sample point
- Icon properties: size, location, direction, orientation, color
- Icons: line segment, arrow, cone, ...



Streamlines



Streamlines

- Line followed by one particle during a certain period
- Motion of particle

$$\frac{d\mathbf{x}}{dt} = \vec{v}(\mathbf{x})$$

- Integration required to get next position

$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t) + \int \vec{v}(\mathbf{x}(t)) dt$$

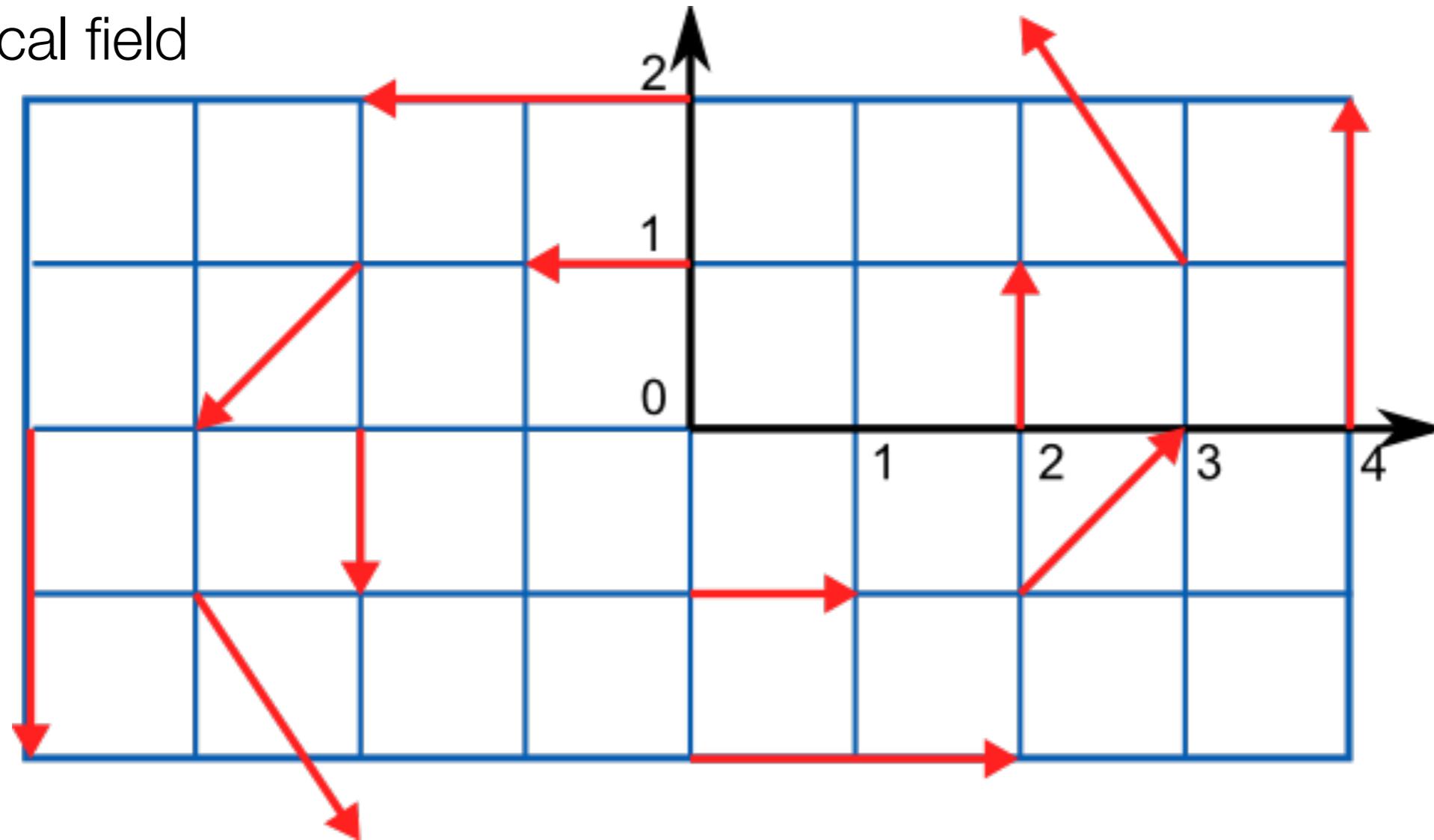
Euler method (simplest numerical scheme)

$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t) + \vec{v}(\mathbf{x}(t))\Delta t$$

Euler integration example

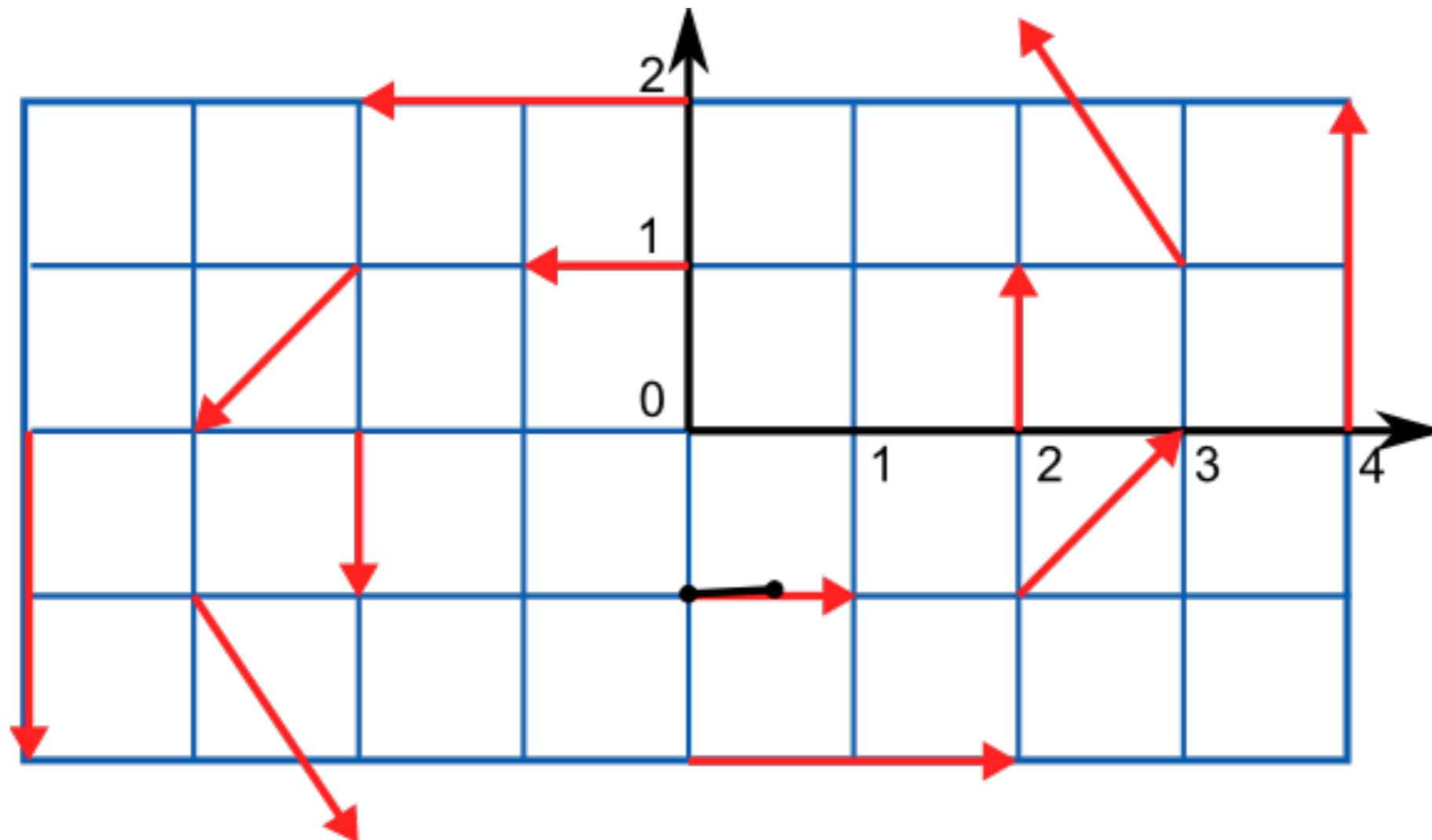
- Model data
- Some sample vectors in red
- Elliptical field

$$\vec{v}(x, y) = \begin{pmatrix} -y \\ x/2 \end{pmatrix}$$



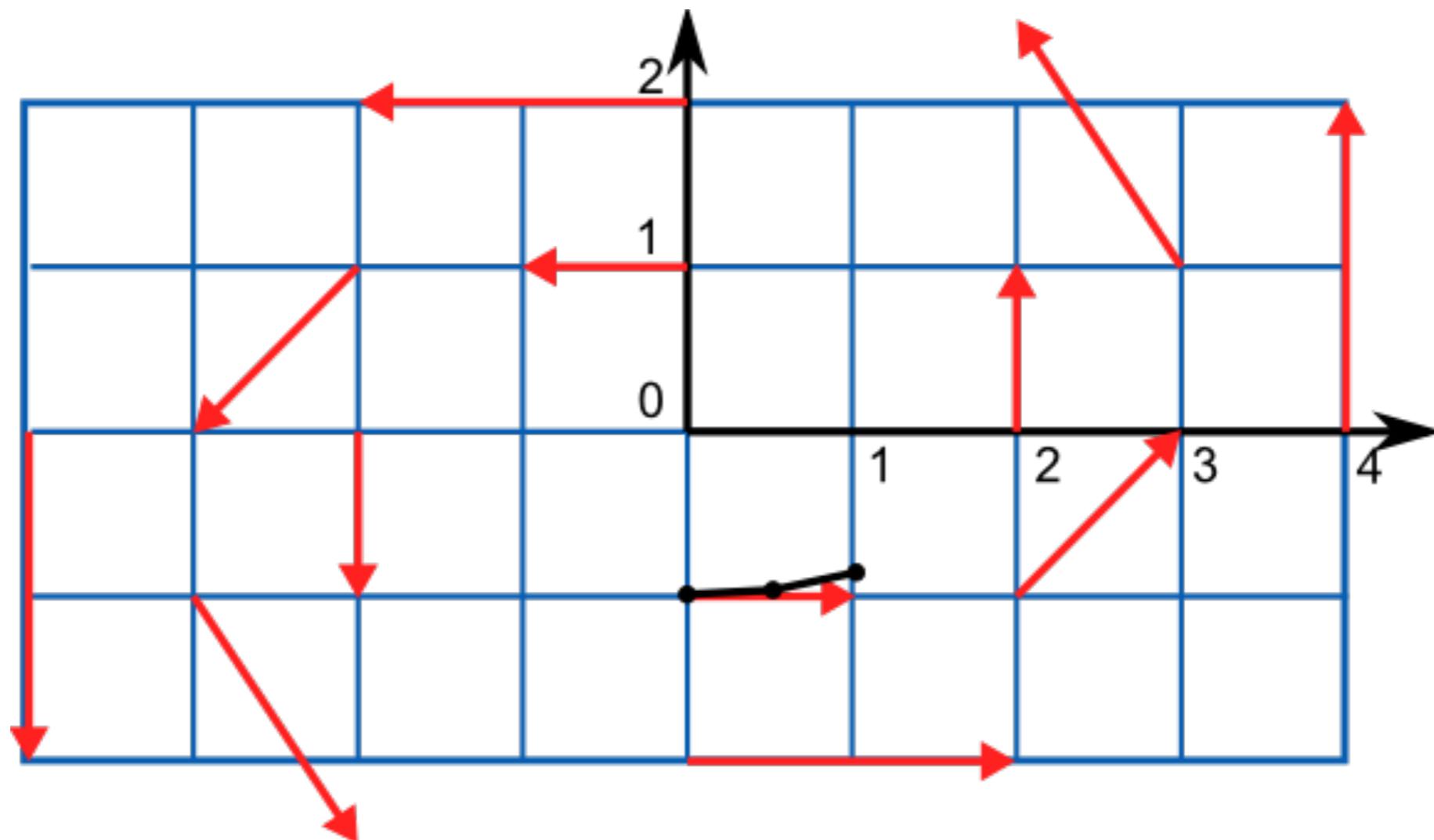
Euler integration example

$$\mathbf{x}(0) = \begin{pmatrix} 0 \\ -1 \end{pmatrix} \quad \Delta t = \frac{1}{2}$$



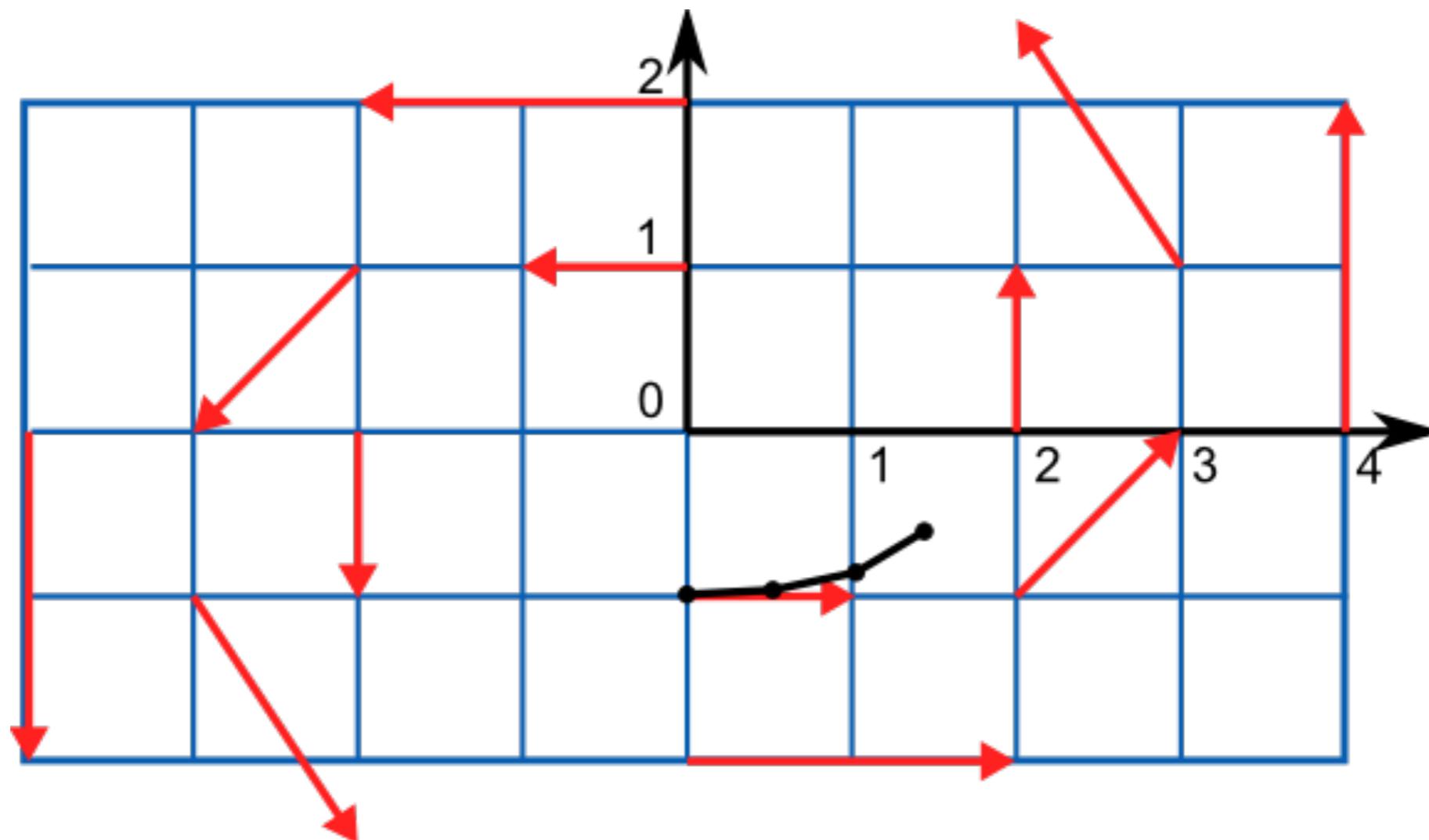
$$\mathbf{x}(1) = \mathbf{x}(0) + \vec{v}(\mathbf{x}(0))\Delta t = \begin{pmatrix} 0 \\ -1 \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} \frac{1}{2} = \begin{pmatrix} 0.5 \\ -1 \end{pmatrix}$$

Euler integration example

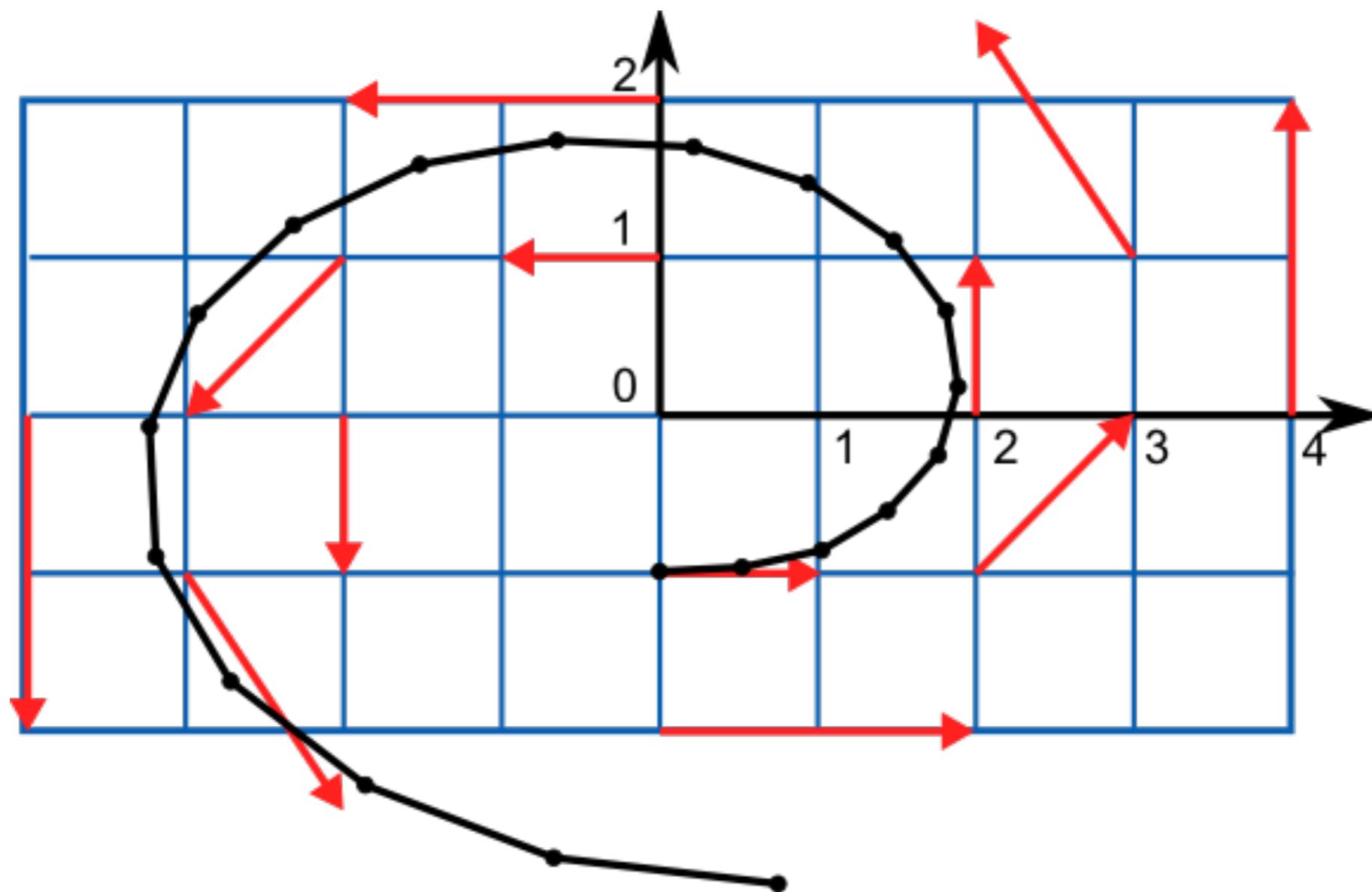


$$\mathbf{x}(2) = \mathbf{x}(1) + \vec{v}(\mathbf{x}(1))\Delta t = \begin{pmatrix} 0.5 \\ -1 \end{pmatrix} + \begin{pmatrix} 1 \\ 0.25 \end{pmatrix} \frac{1}{2} = \begin{pmatrix} 1 \\ -0.875 \end{pmatrix}$$

Euler integration example

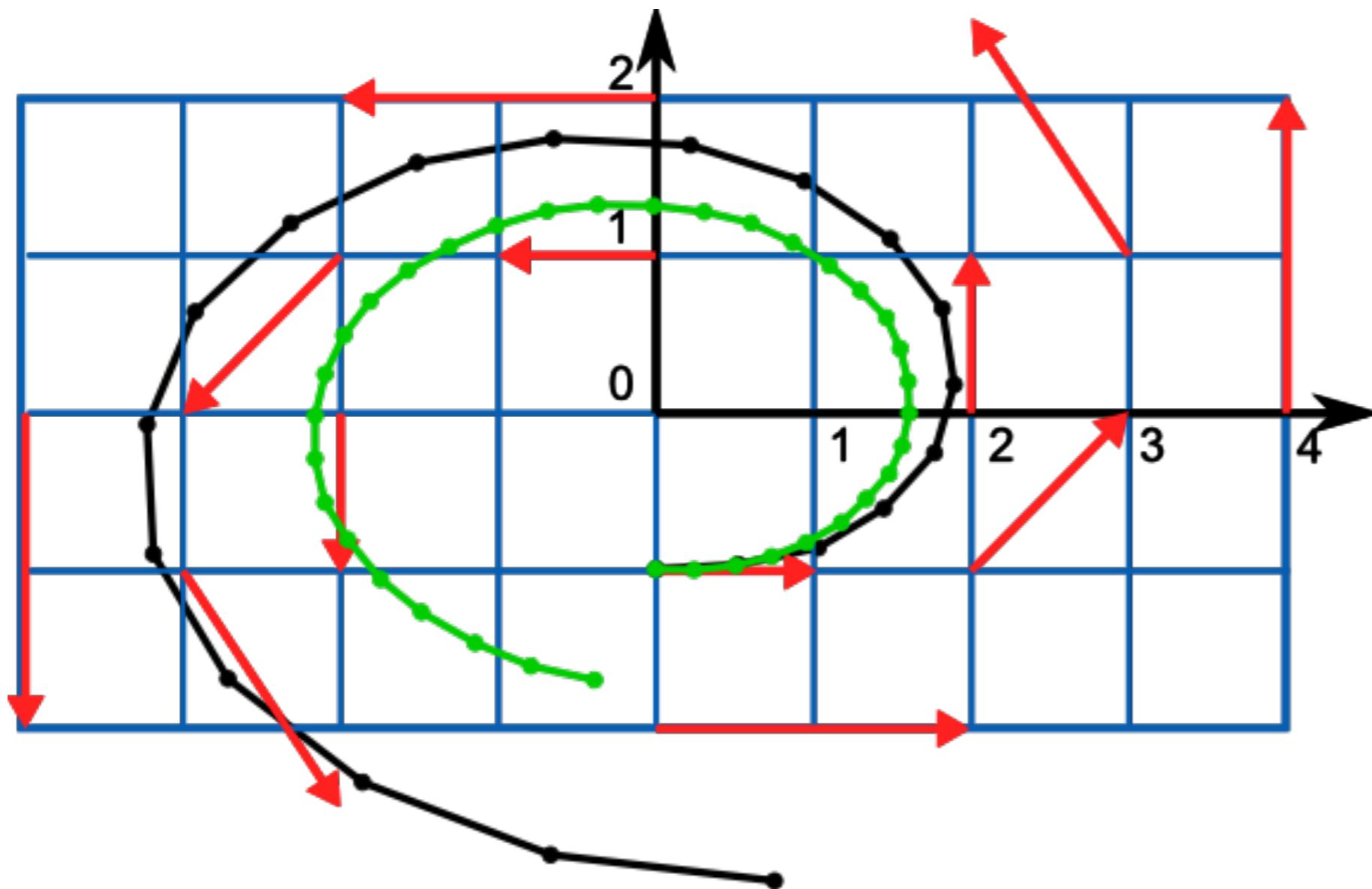


Euler integration example



Euler integration example

Green line: smaller step size $\Delta t = \frac{1}{4}$



Runge-Kutta integration (second order)

- Predictor-corrector approach

$$\mathbf{x}^*(t + \Delta t) = \mathbf{x}(t) + \vec{v}(\mathbf{x}(t))\Delta t \quad \text{predictor}$$

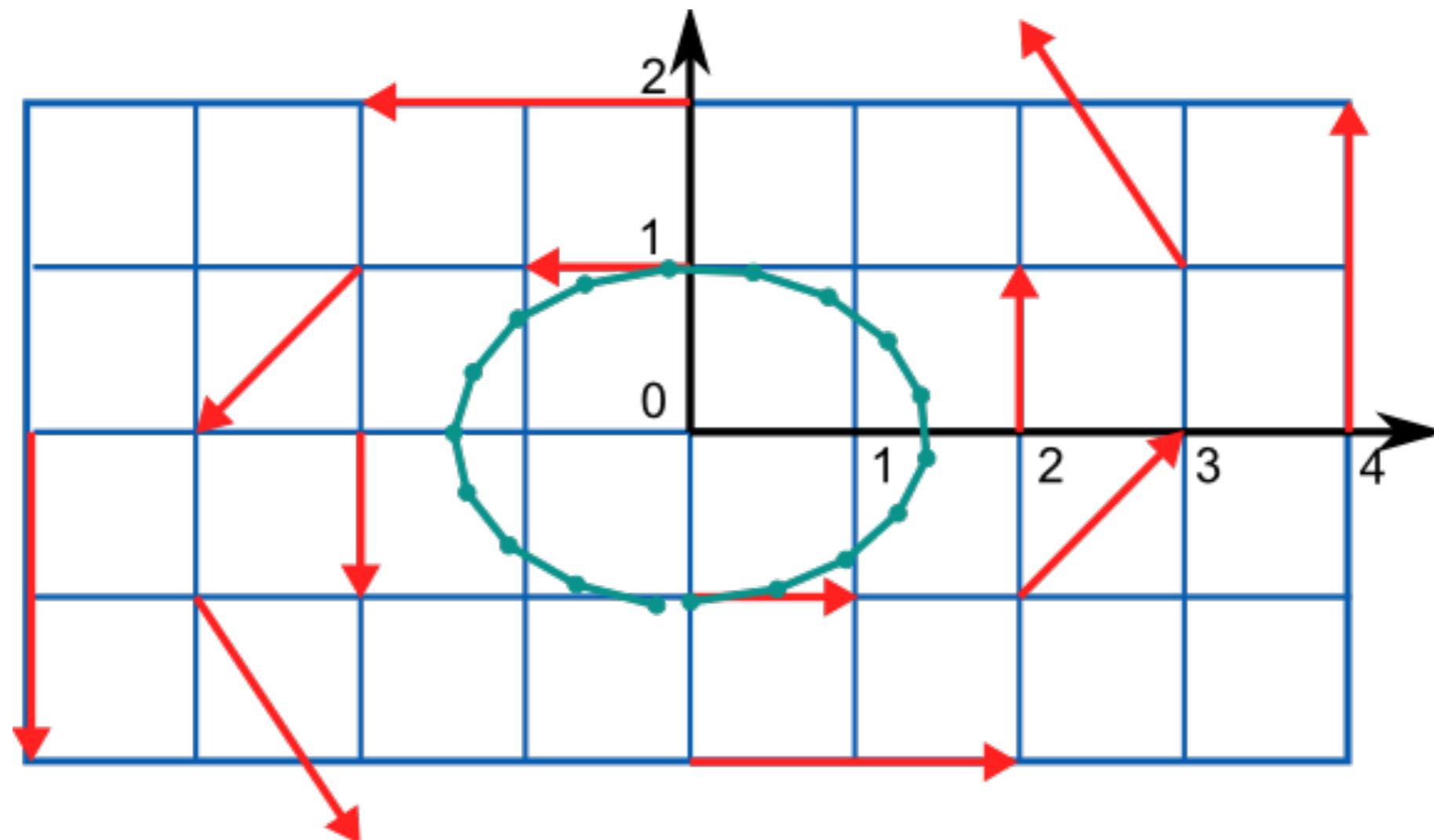
$$\mathbf{x}(t + \Delta t) = \mathbf{x}(t) + \frac{\vec{v}(\mathbf{x}(t)) + \vec{v}(\mathbf{x}^*(t + \Delta t))}{2} \Delta t \quad \text{corrector}$$

Runge-Kutta example

Runge-Kutta $\Delta t = \frac{1}{2}$

$\Delta t = \frac{1}{4}$

$\Delta t = \frac{1}{2}$

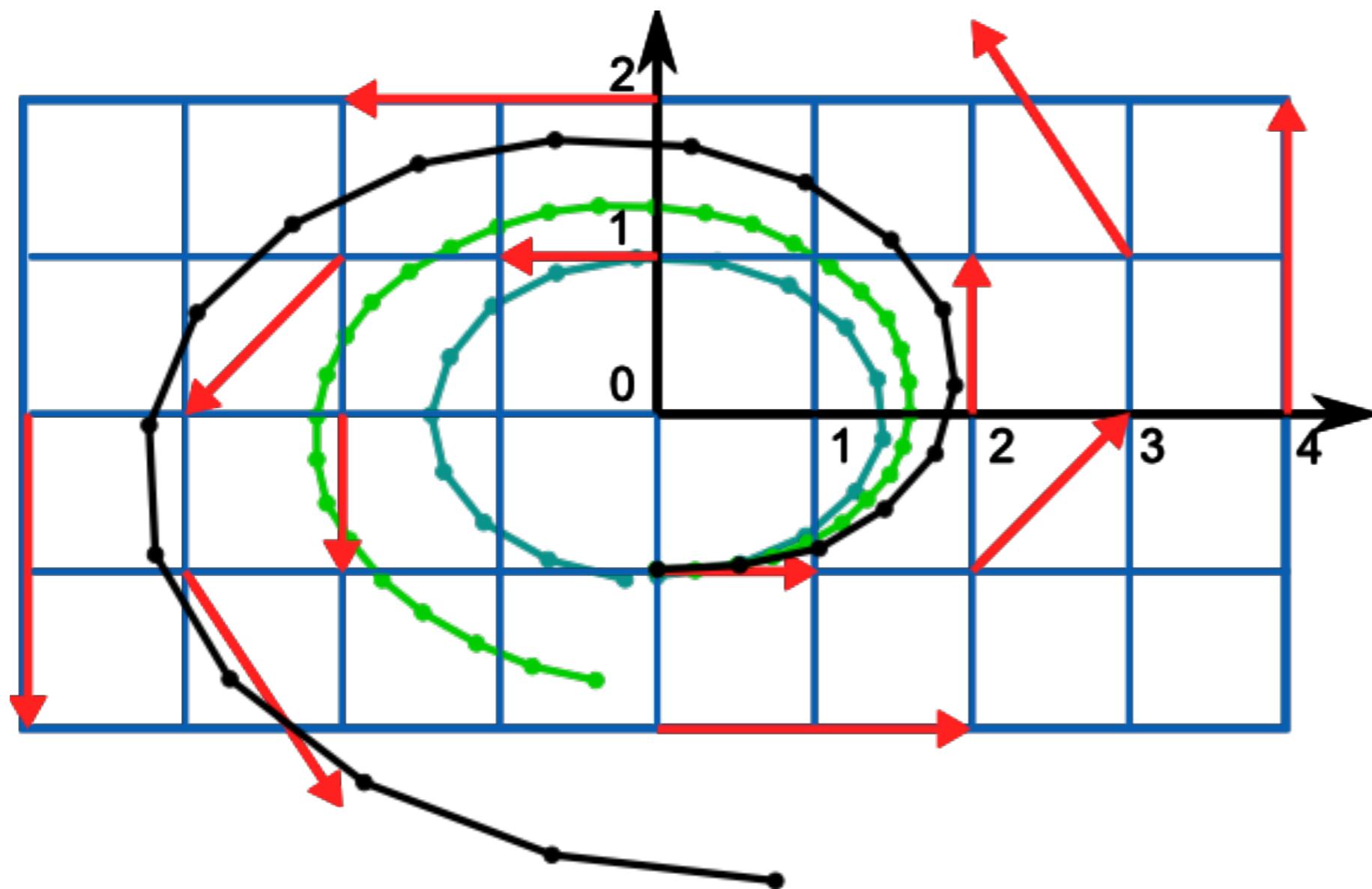


Runge-Kutta example

Runge-Kutta $\Delta t = \frac{1}{2}$

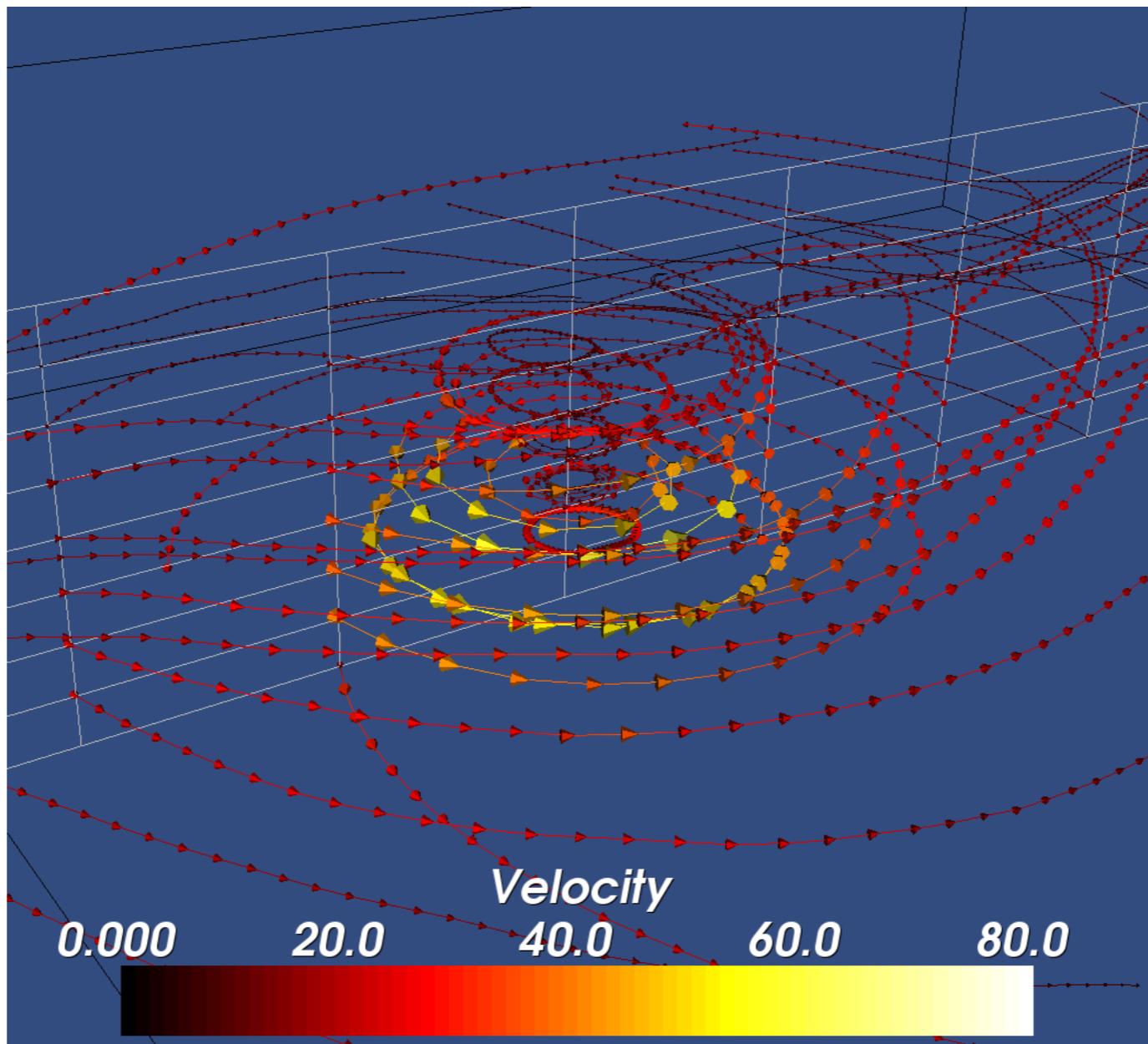
Euler $\Delta t = \frac{1}{4}$

Euler $\Delta t = \frac{1}{2}$



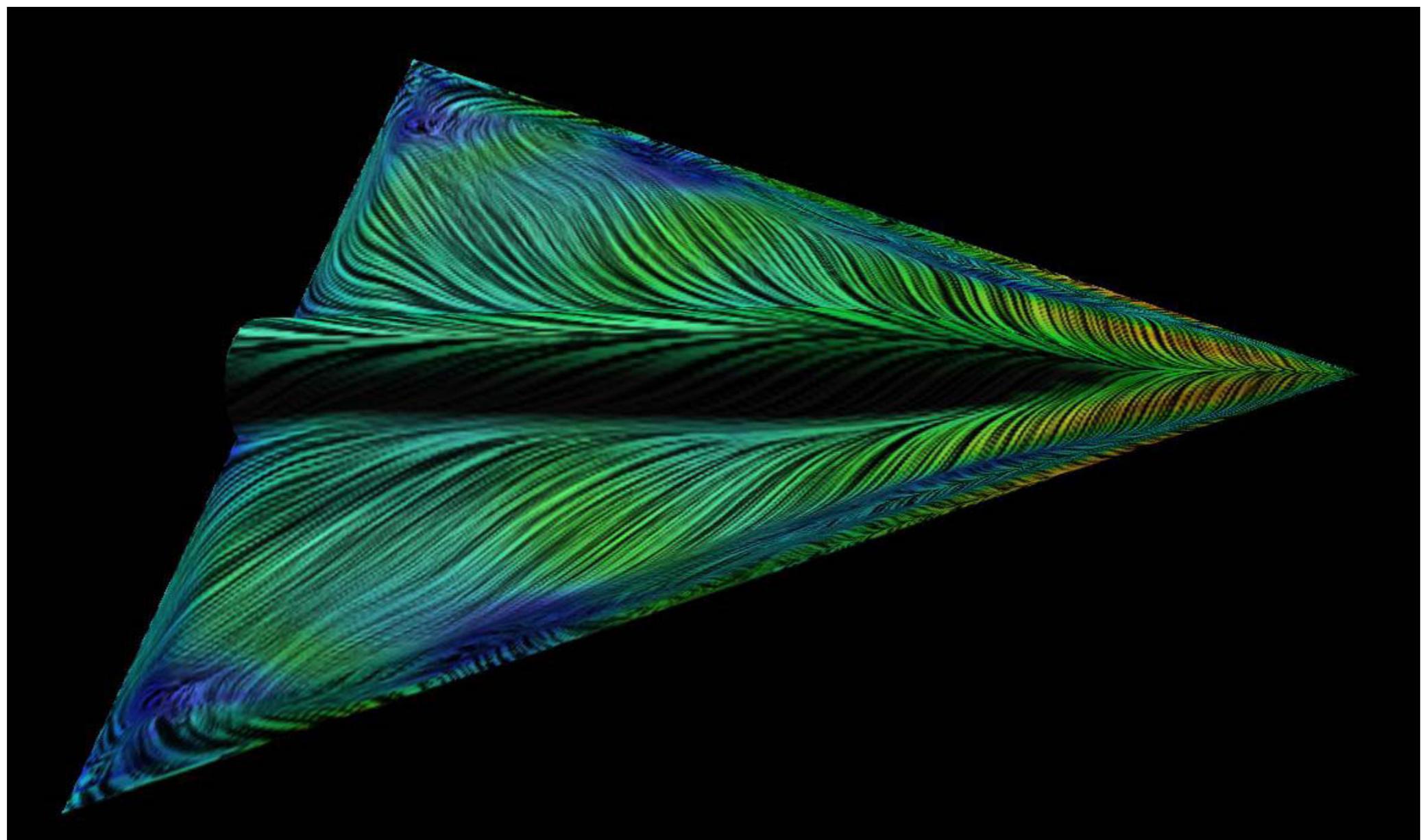
Hurricane Isabel demo

- Simulation of hurricane Isabel
- Grid dimensions $250 \times 250 \times 50$
- Physical scale $2138 \text{ km} \times 2004 \text{ km} \times 19.8 \text{ km}$



Texture-based visualization

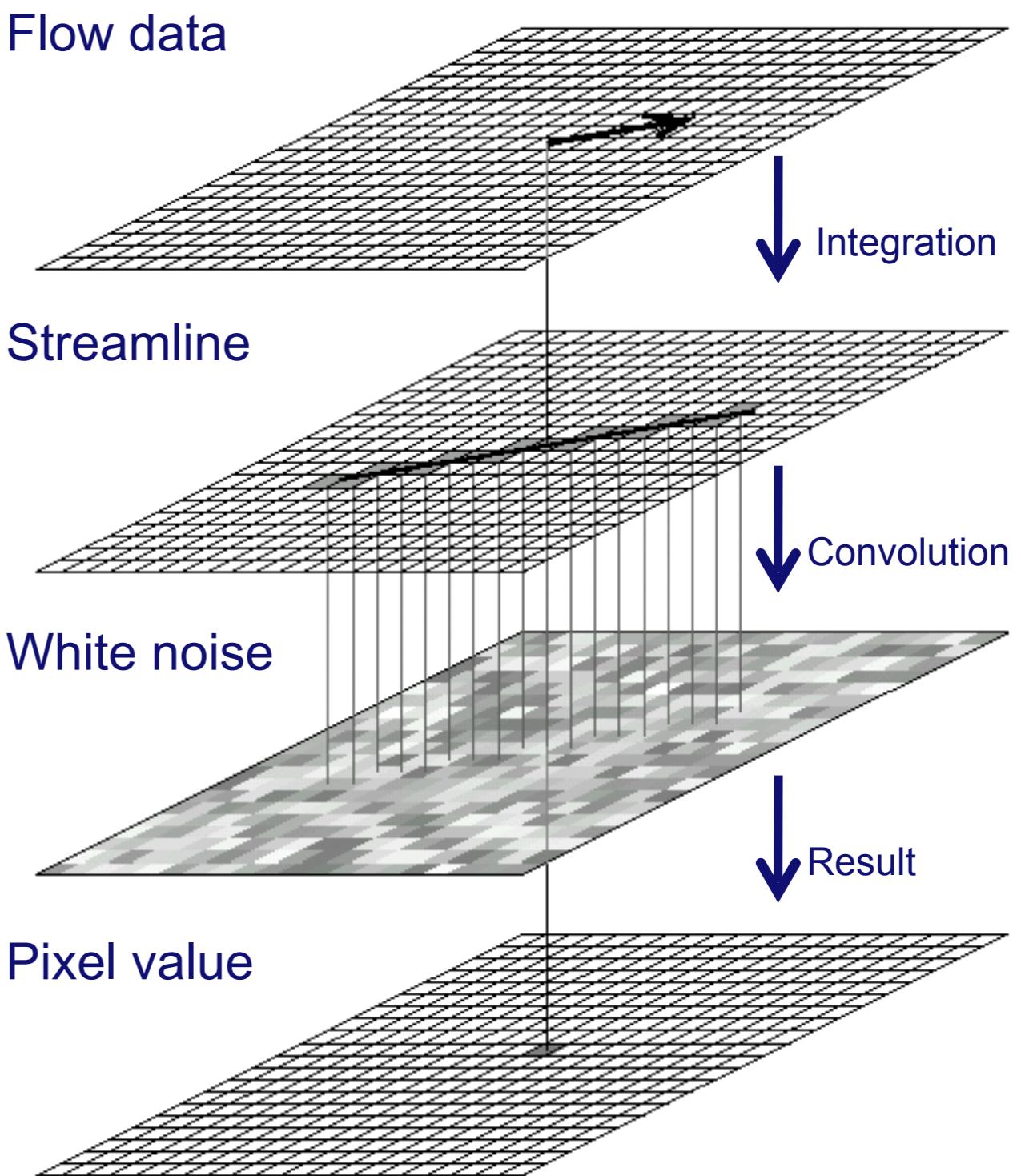
- Goal: generate overview image of the flow
- Approach: blur a noise texture locally according to the vector field



LIC: approach

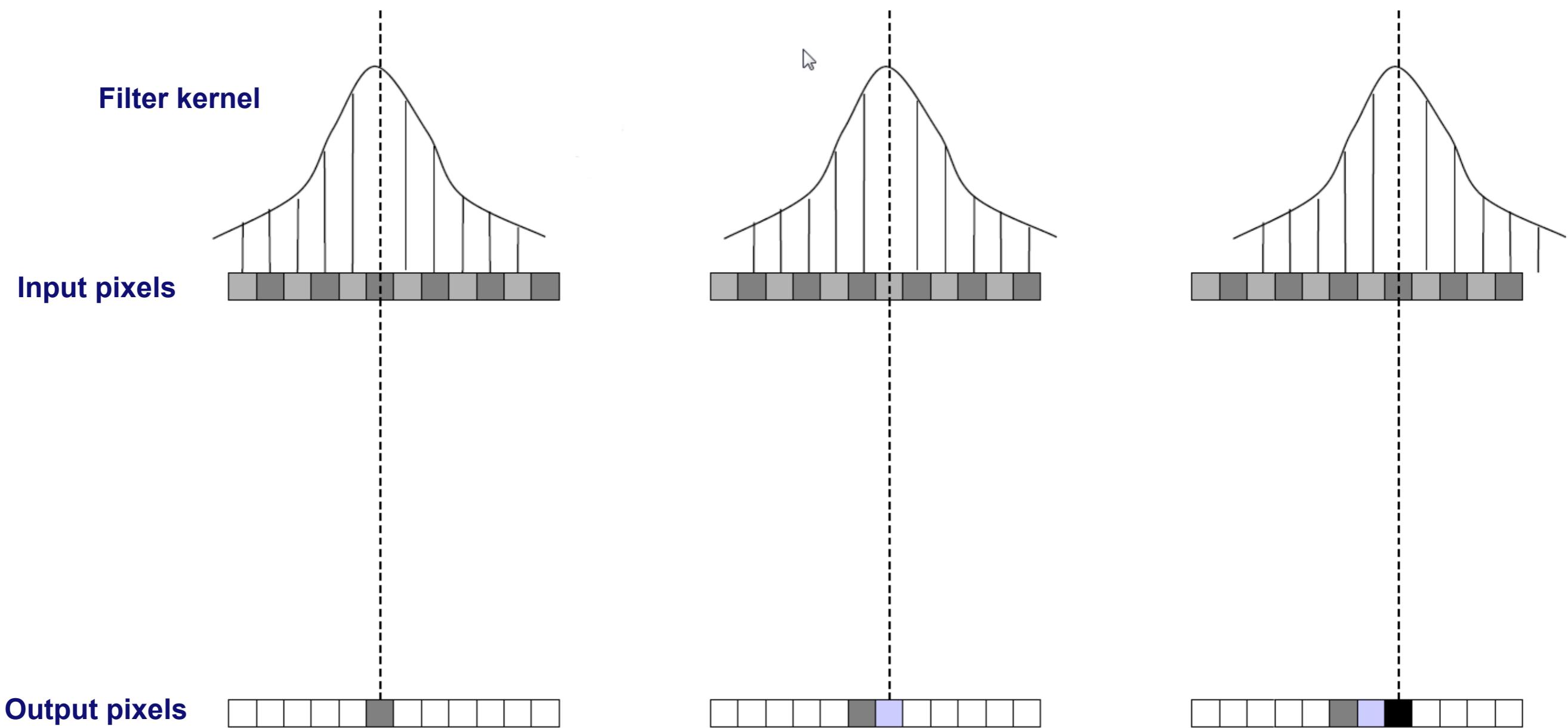
Line integral convolution (LIC)

- Integrate streamline from point in forward and backward direction over some length L
- Compute weighted sum of noise texture values at pixel locations of streamline



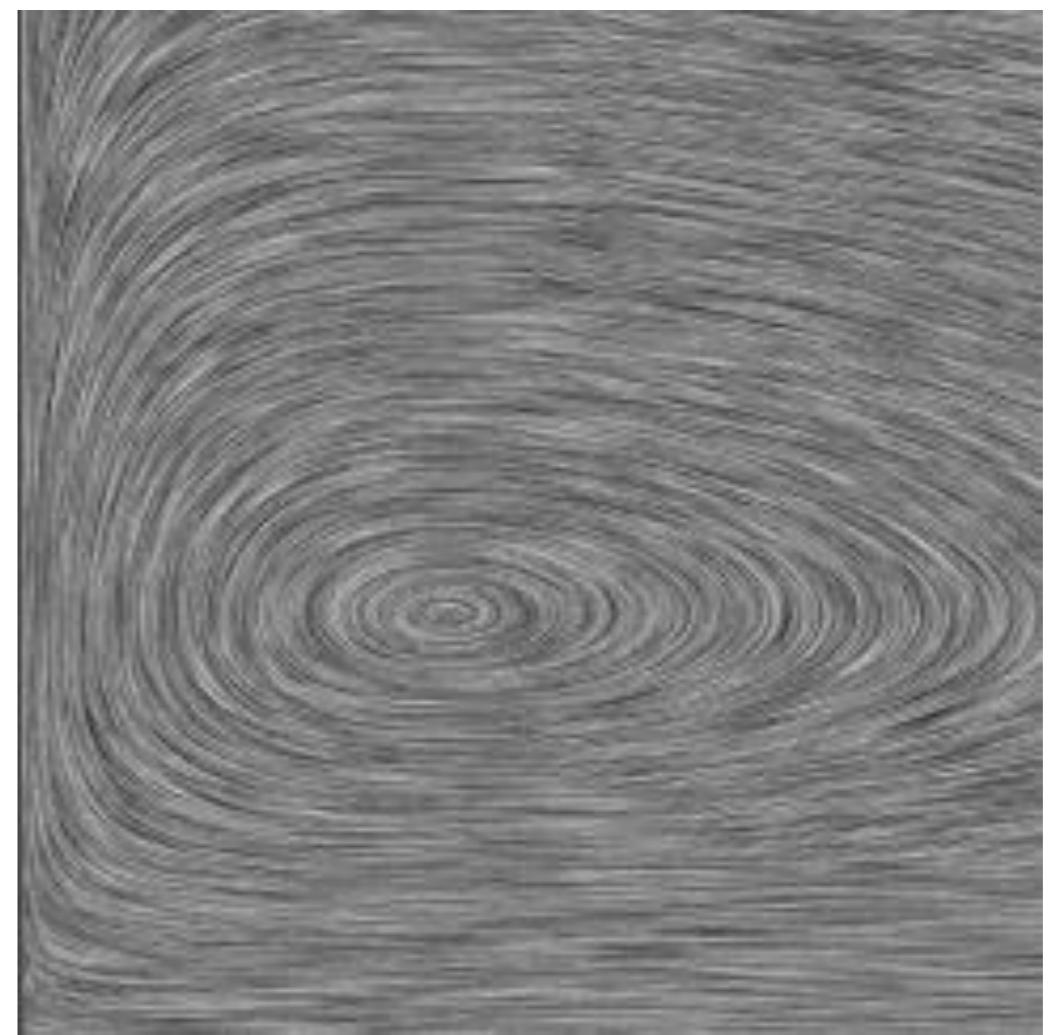
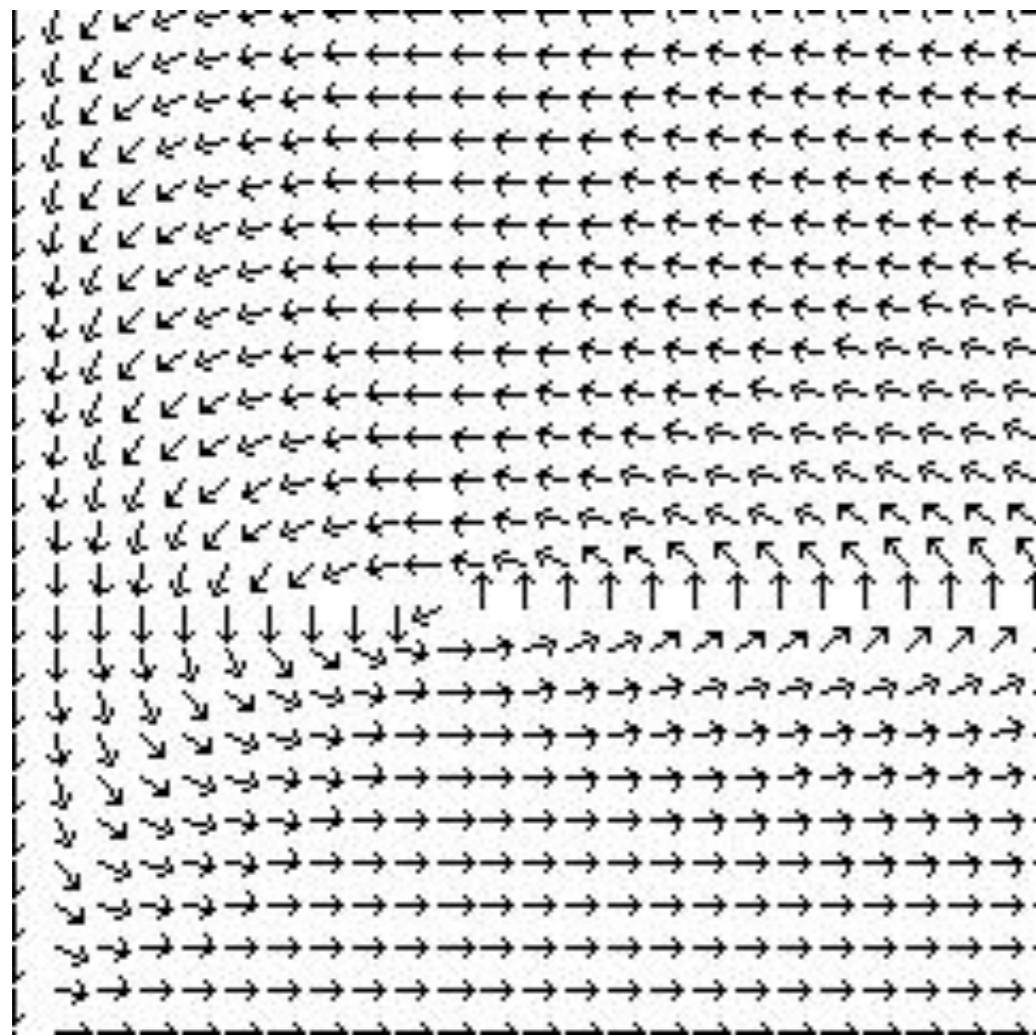
Convolution

- Output pixel p' computed as weighted sum of pixel neighborhood of input pixel p



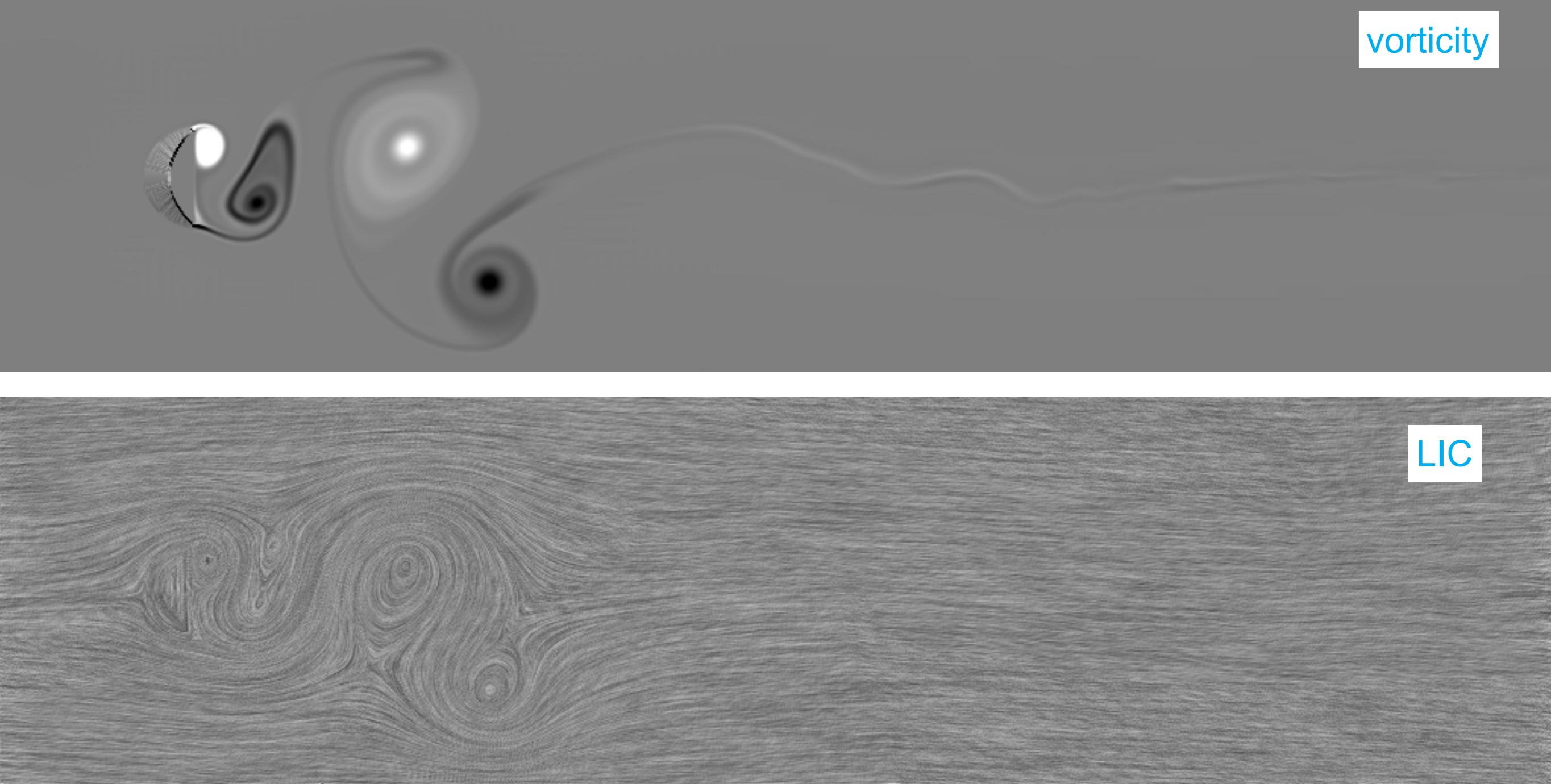
LIC: why it works

- Along streamline: little variation in pixel values
- Neighboring streamlines: strong variation

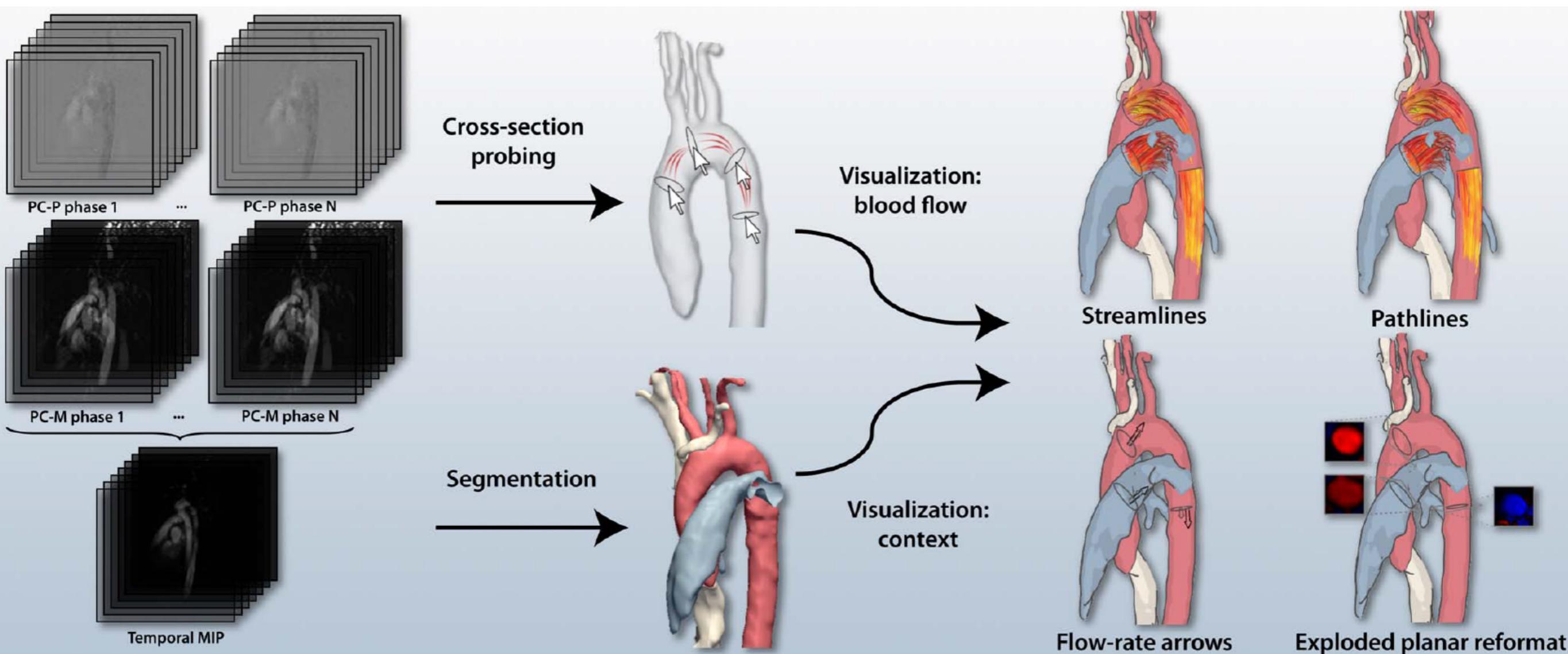


LIC: example

- Flow around half-cylinder



4D blood flow visualization

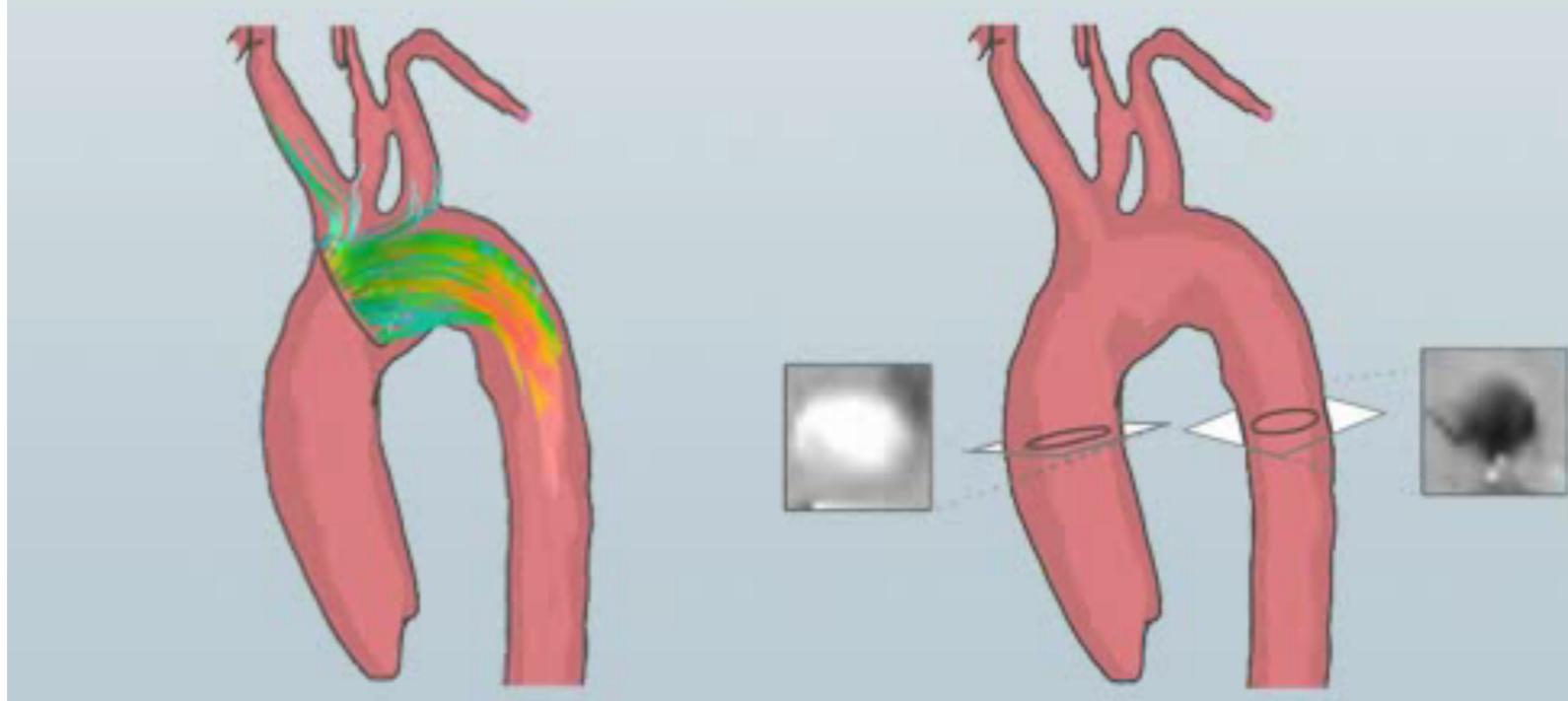


Van Pelt et al., **Exploration of 4D MRI Blood-Flow Using Stylistic Visualization**,
IEEE Trans. Visualization and Computer Graphics 16(6):1339-1347, 2010.

4D blood flow visualization example



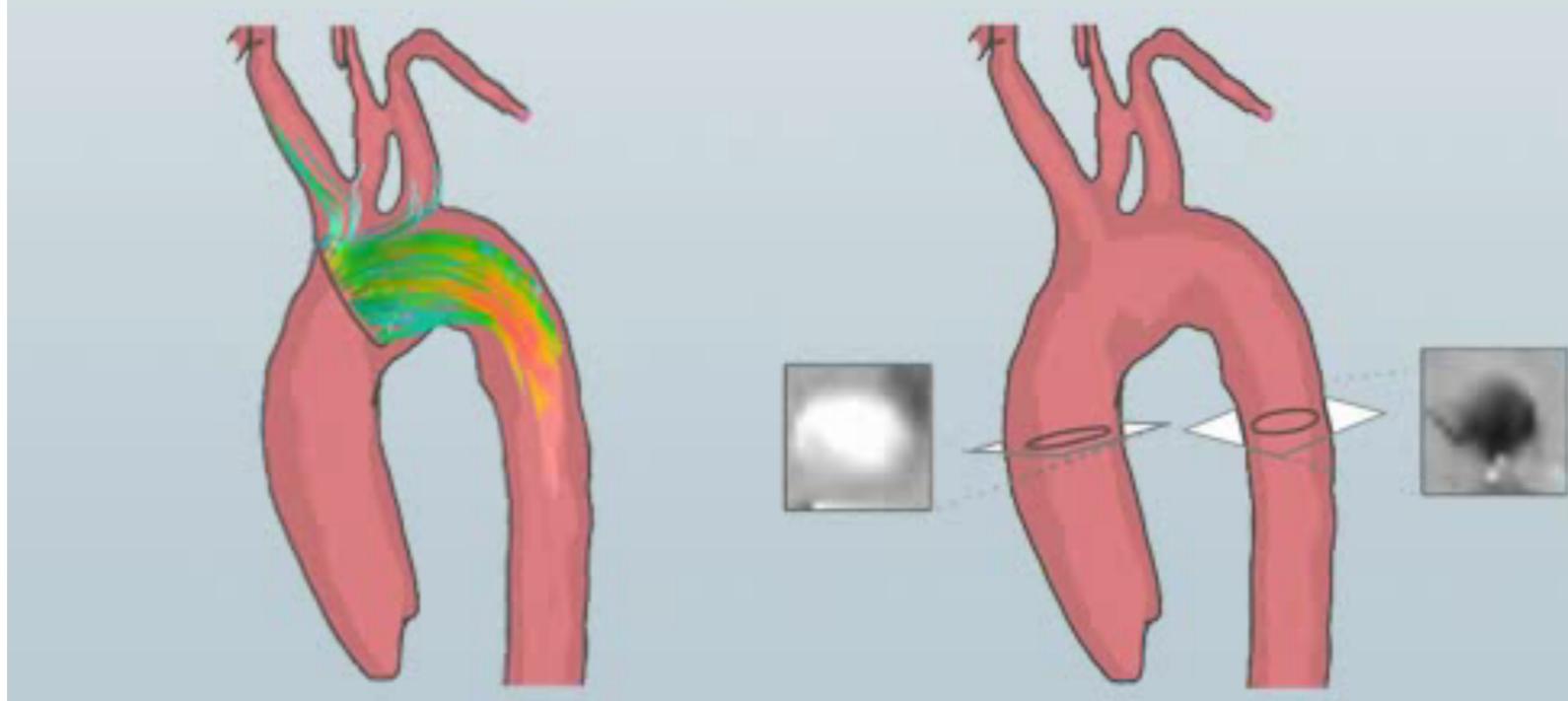
Exploration of 4D MRI Blood-Flow
using Stylistic Visualization



4D blood flow visualization example



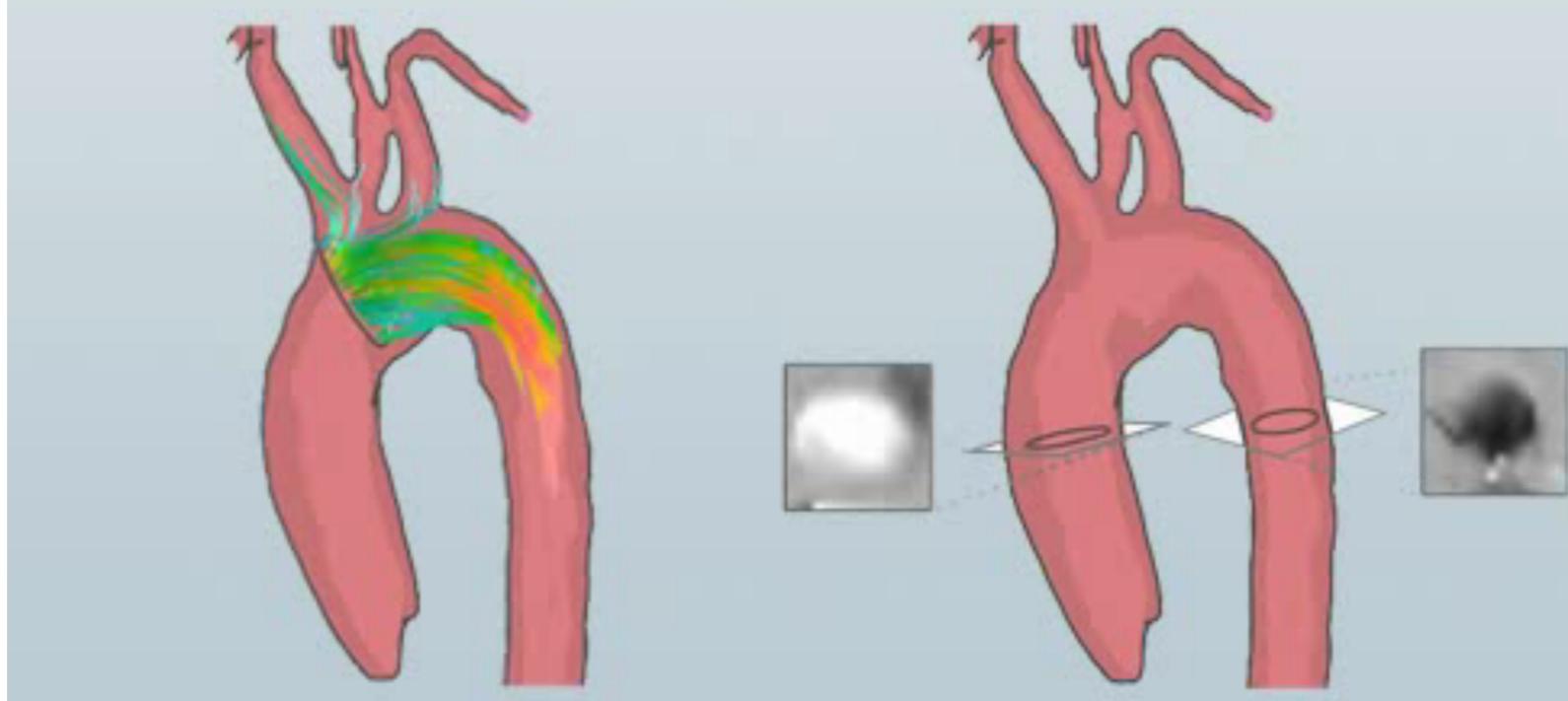
Exploration of 4D MRI Blood-Flow
using Stylistic Visualization



4D blood flow visualization example



Exploration of 4D MRI Blood-Flow
using Stylistic Visualization



Diffusion tensor imaging

- Measure diffusion of water by MRI
- Diffusion velocity and direction depend on tissue type
- Fluid-filled compartments show **isotropic** diffusion
- Neural fibers show **anisotropic** diffusion

DTI data

- Diffusion tensor

$$D = \begin{pmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yx} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{pmatrix}$$

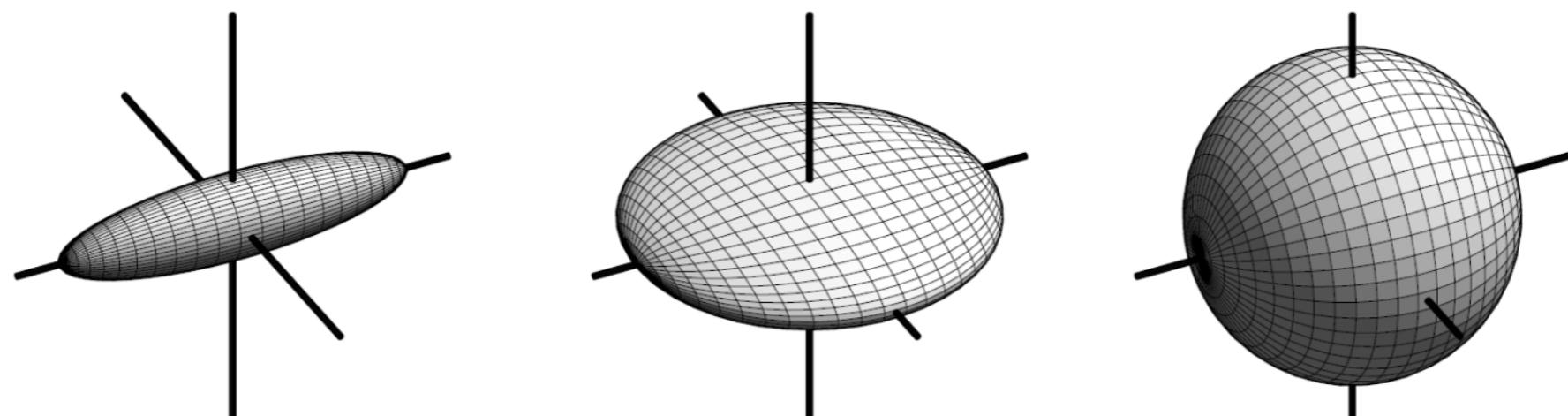
- Low spatial resolution (128x128 and 30-60 slices)
- Voxel spacing 2x2x2 mm
- Matrix elements are with respect to **global** coordinate system

Eigenanalysis

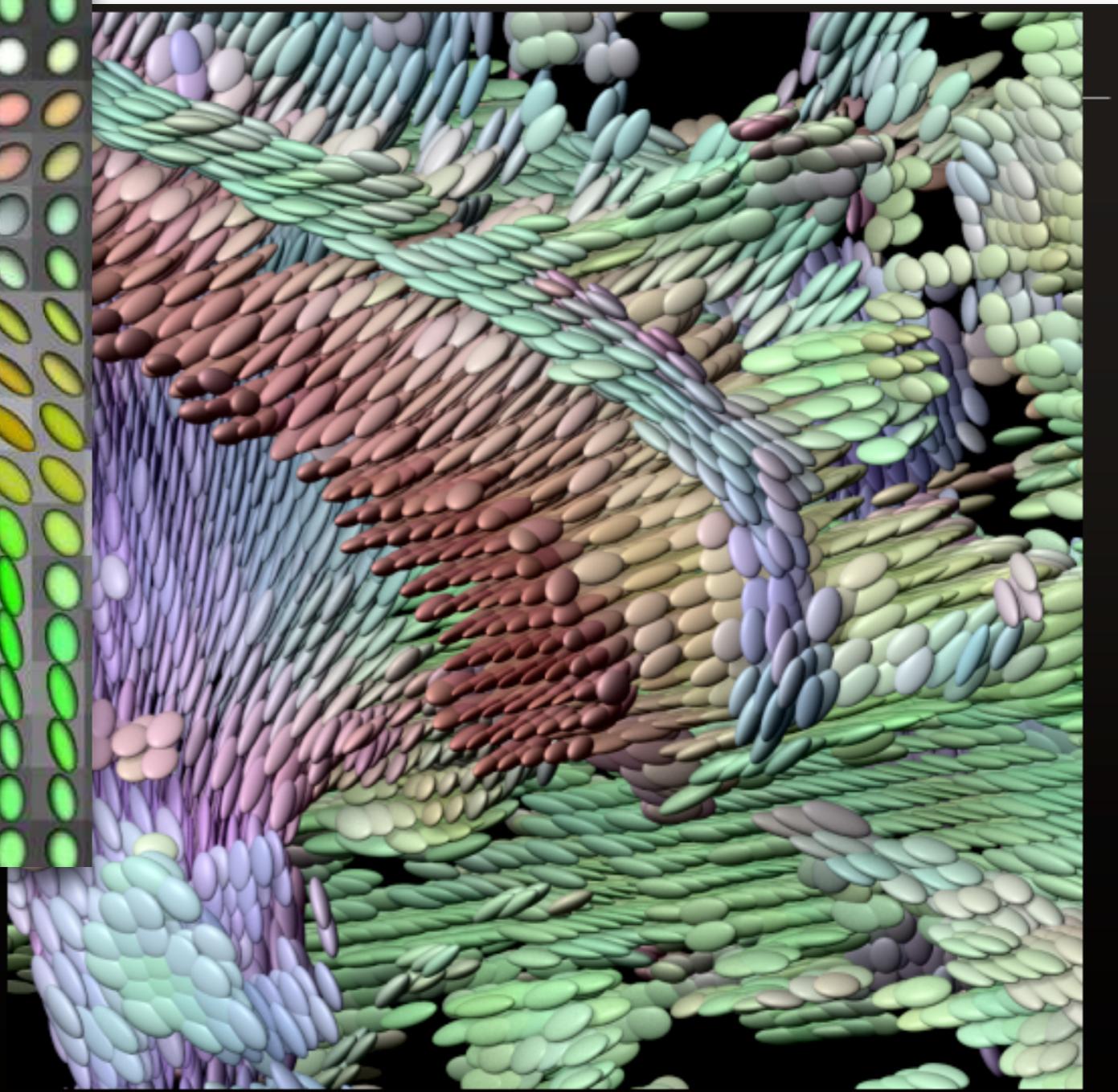
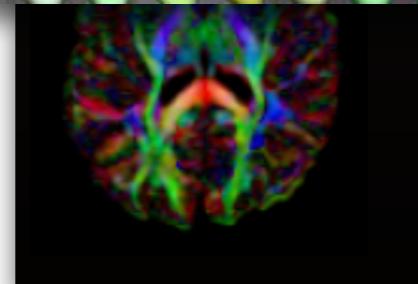
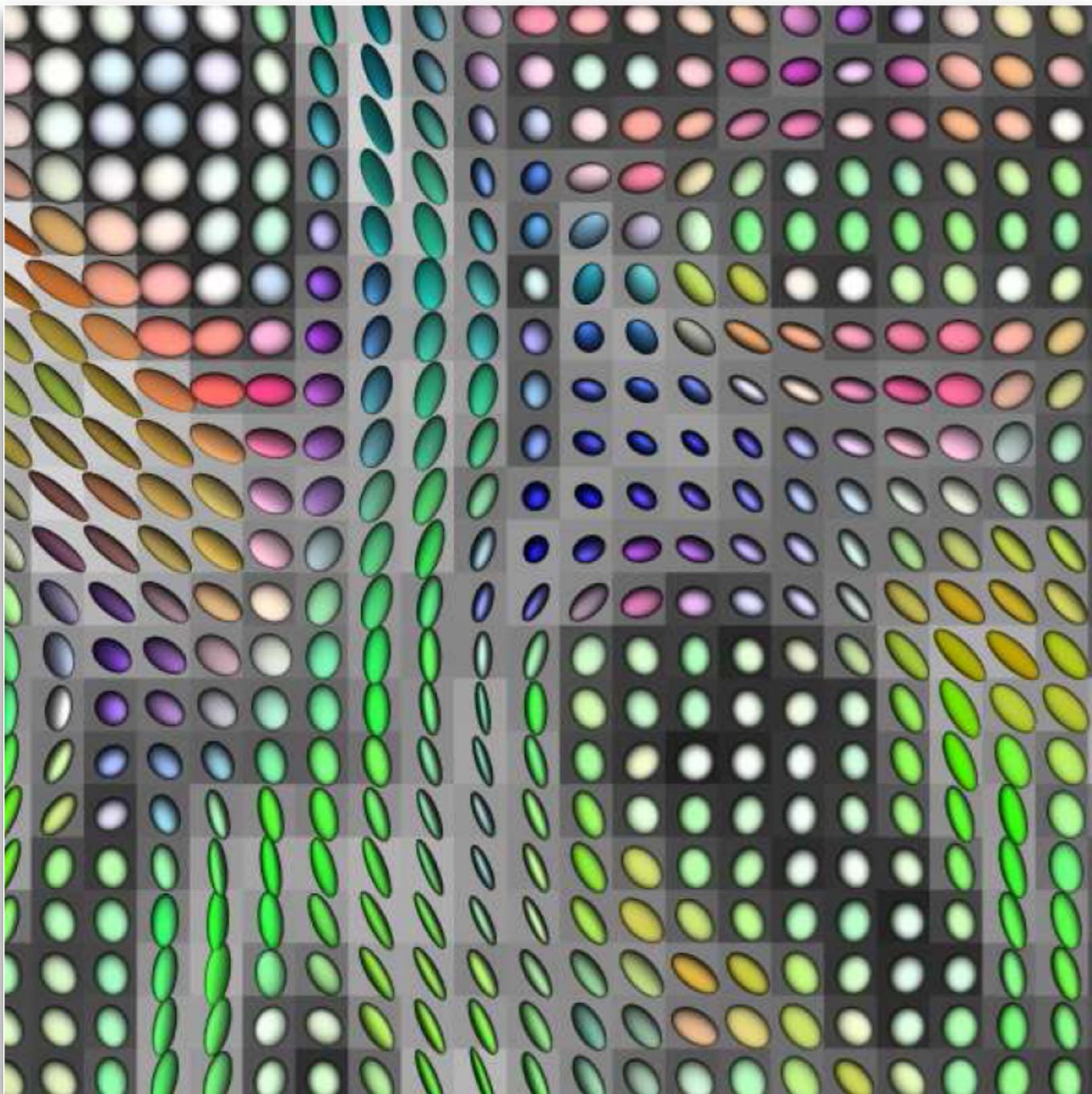
- Diagonal form representation of tensor

$$D = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3\} \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix} \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3\}^T$$

- Geometric interpretation of the diffusion tensor
 - ellipsoid with axes aligned with the three eigenvectors
 - axis length proportional to eigenvalue



Tensor glyphs 2D and 3D



Anisotropy metrics

- Mean diffusivity

$$\lambda_{\text{mean}} = \frac{\lambda_1 + \lambda_2 + \lambda_3}{3}$$

- Fractional anisotropy

$$FA = \sqrt{\frac{3}{2} \frac{\sqrt{\sum_{i=1}^3 (\lambda_i - \lambda_{\text{mean}})^2}}{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}}$$

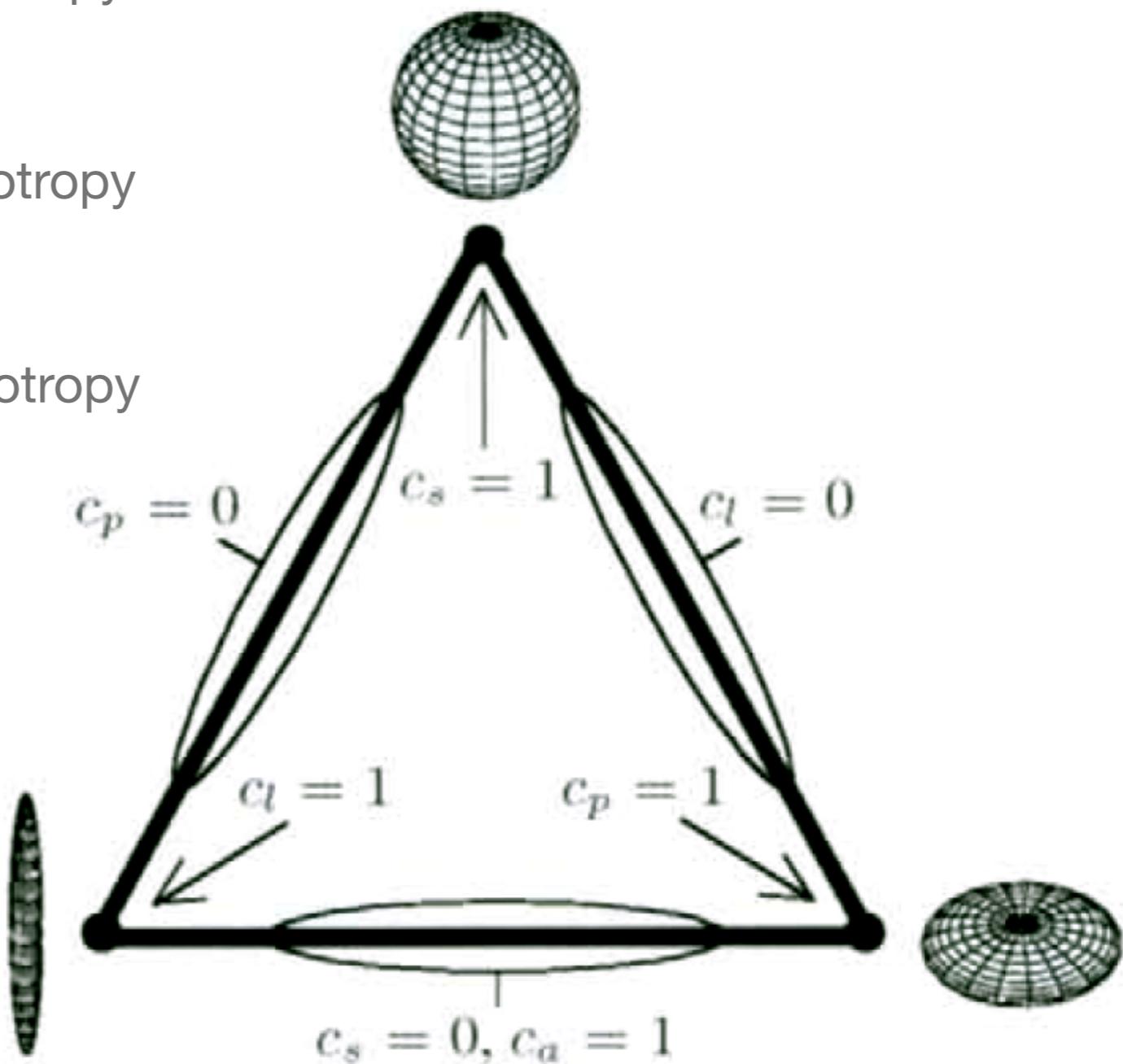
Anisotropy metrics

- Consider sorted eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3$

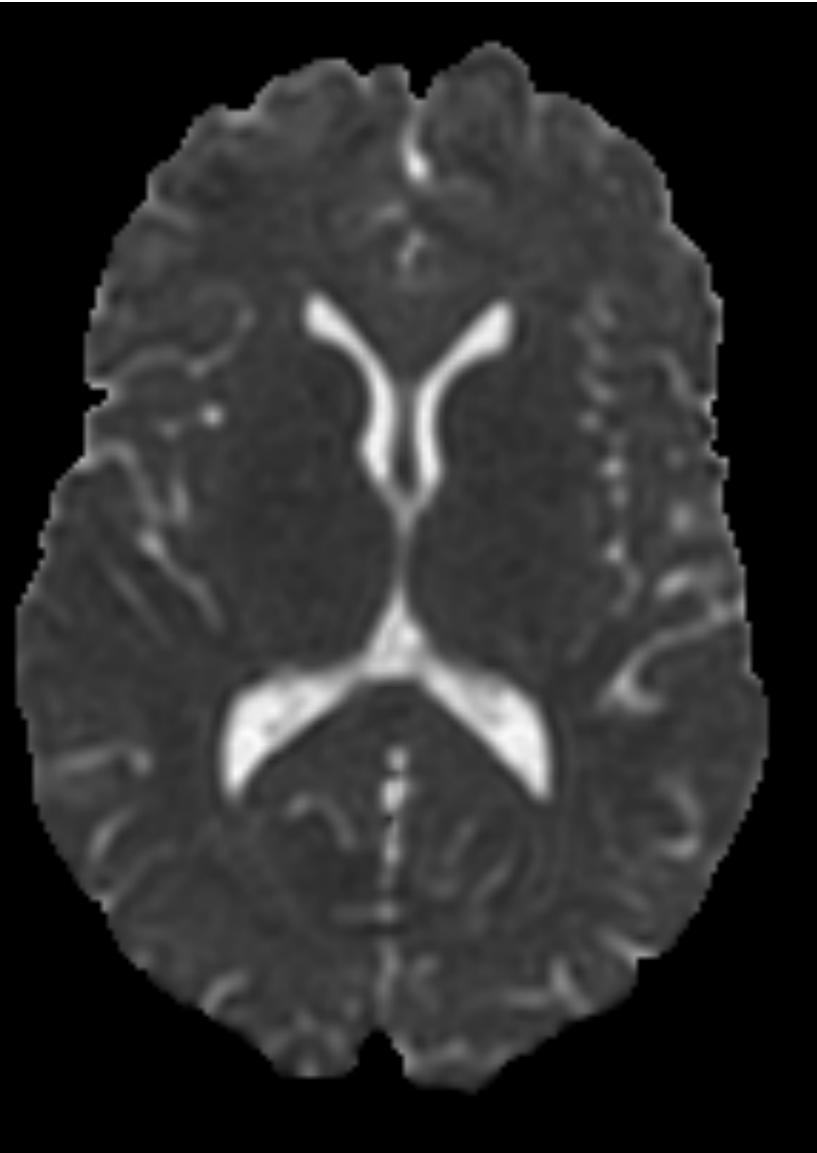
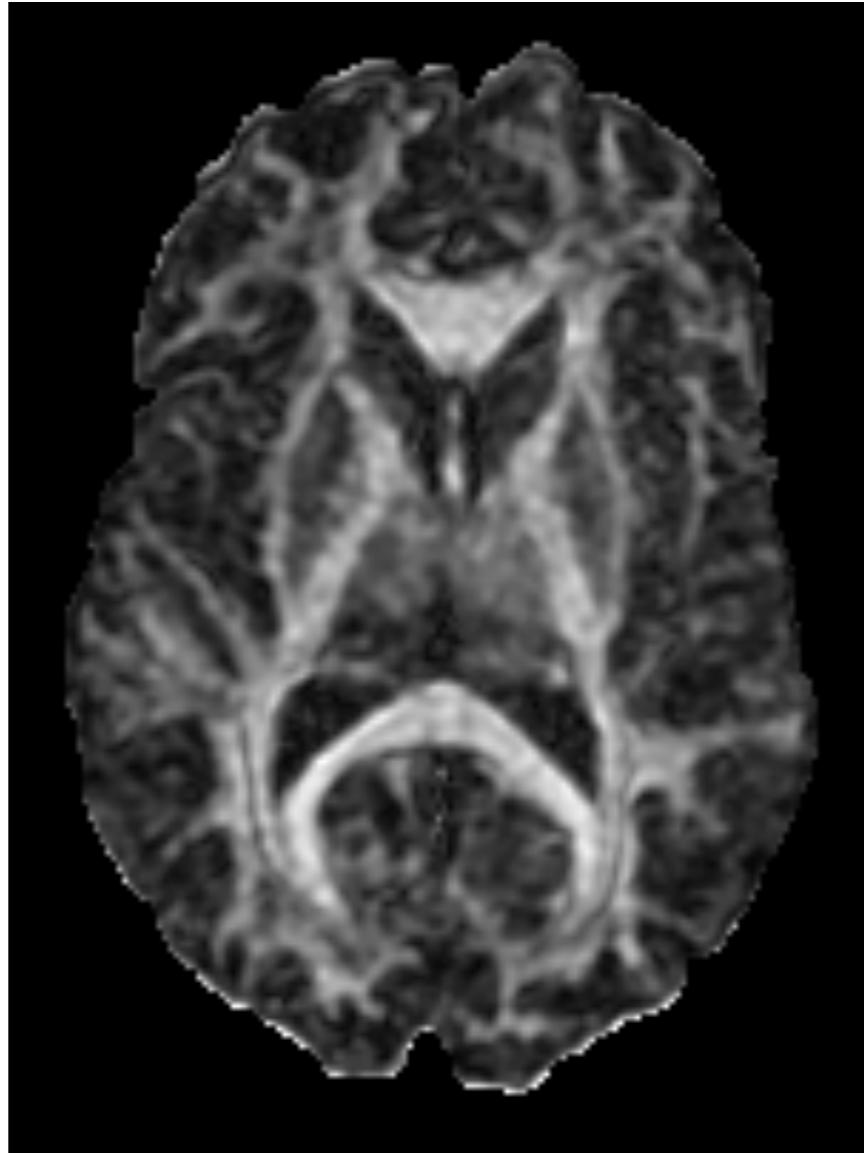
$$c_l = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2 + \lambda_3} \quad \text{linear anisotropy}$$

$$c_p = \frac{2(\lambda_2 - \lambda_3)}{\lambda_1 + \lambda_2 + \lambda_3} \quad \text{planar anisotropy}$$

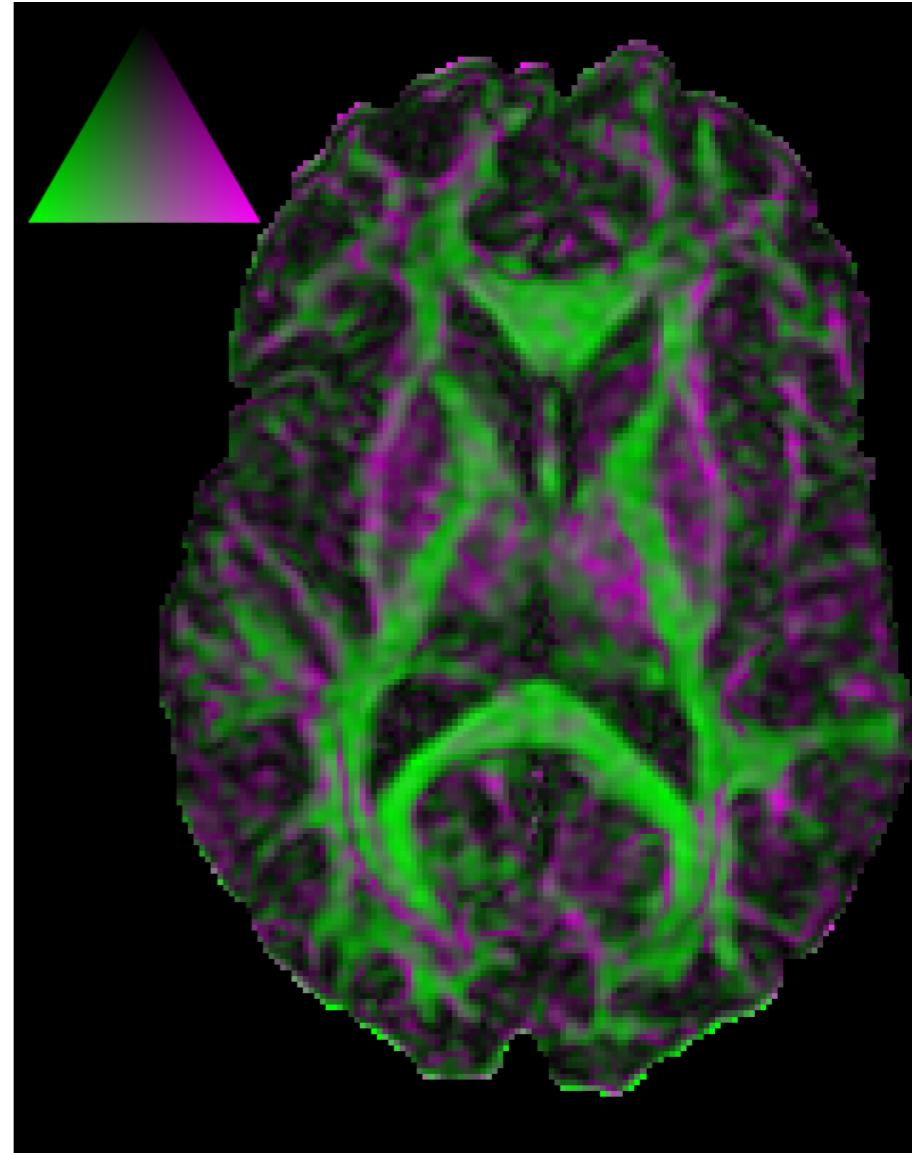
$$c_s = \frac{3\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3} \quad \text{spherical isotropy}$$



Anisotropy metrics

 λ_{mean} 

FA

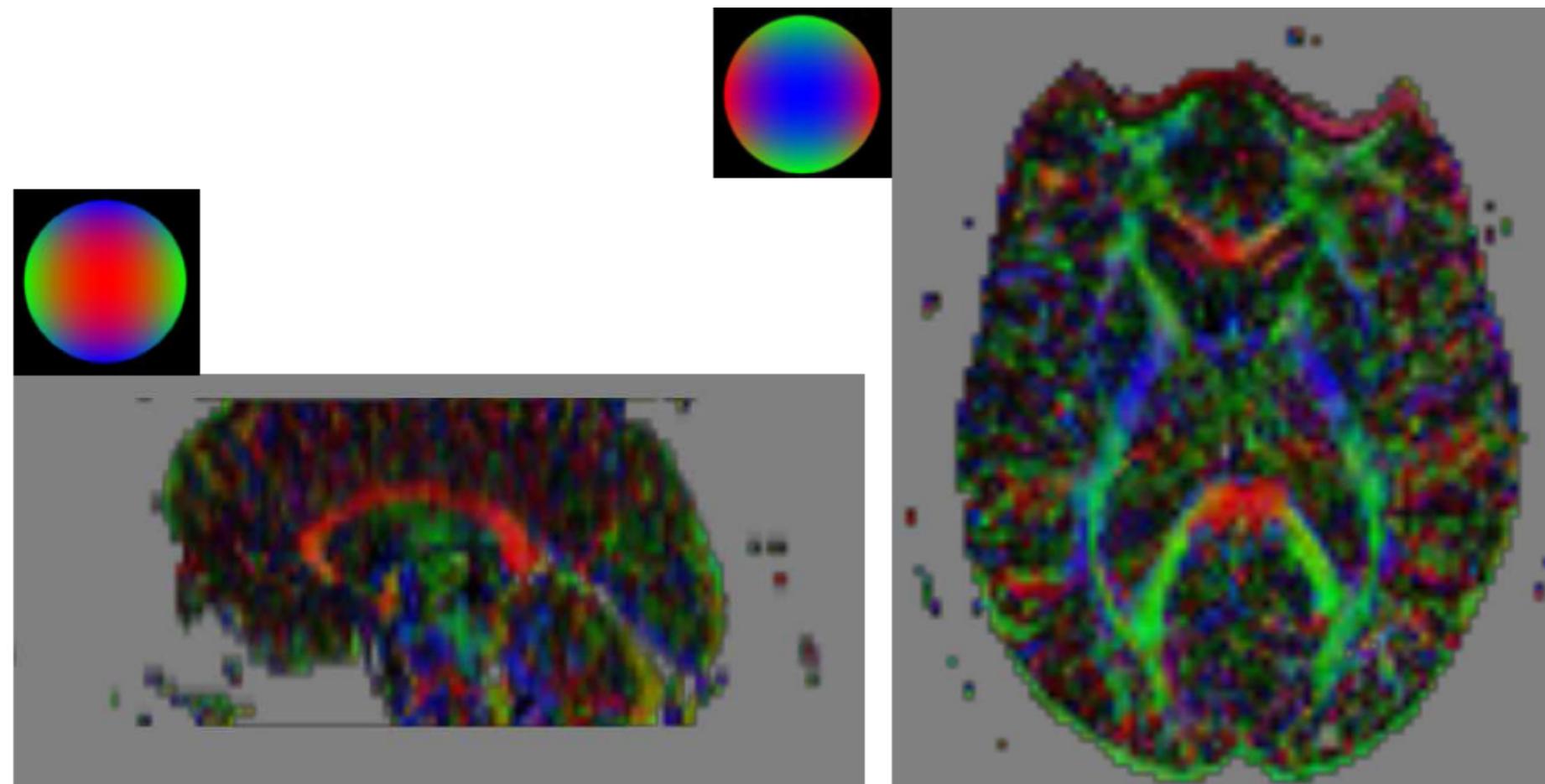
 c_l (green) c_p (magenta)

Major eigenvector direction visualization

- Simplify tensor field to vector field
- Consider only main eigenvector \mathbf{e}_1
- Map components to RGB colors

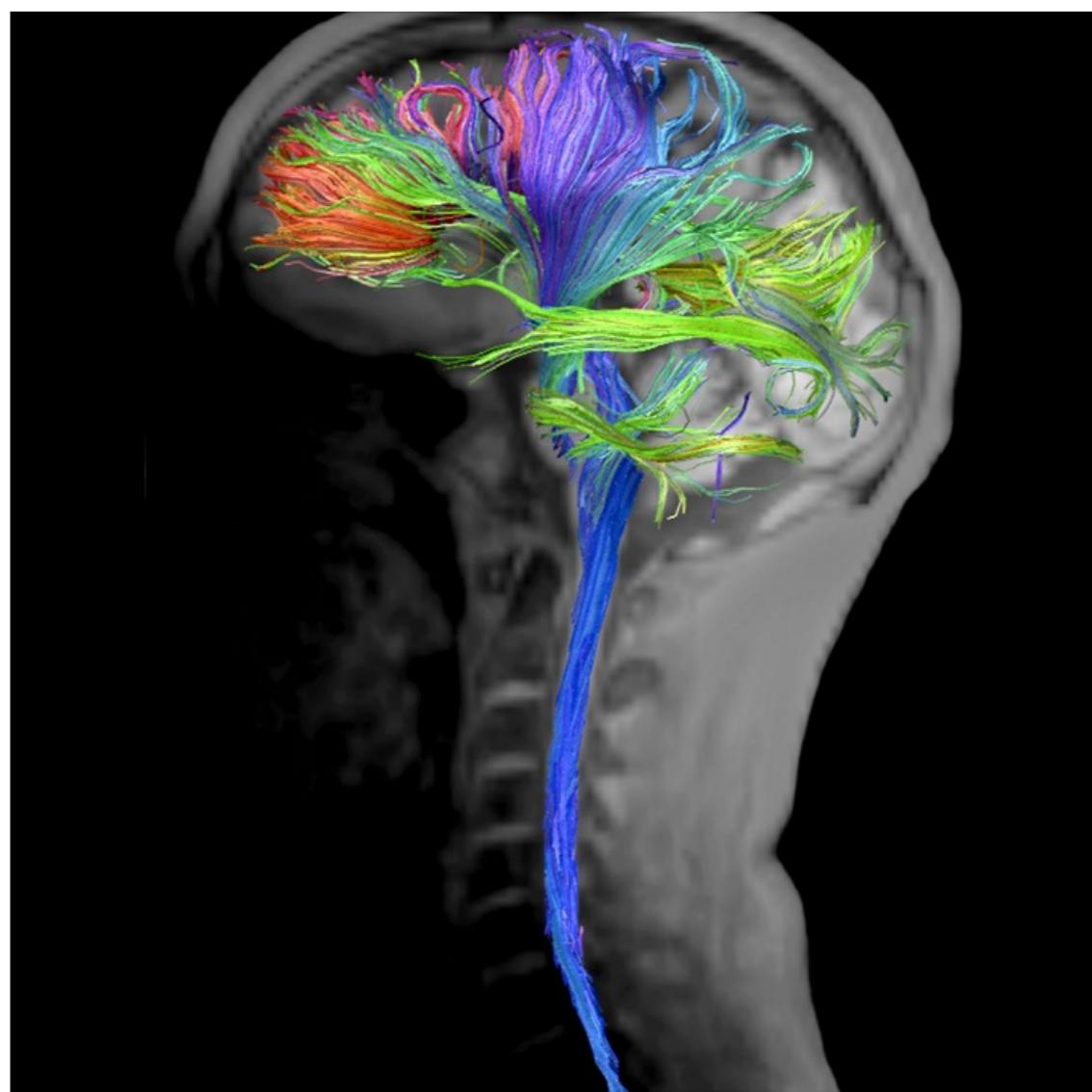
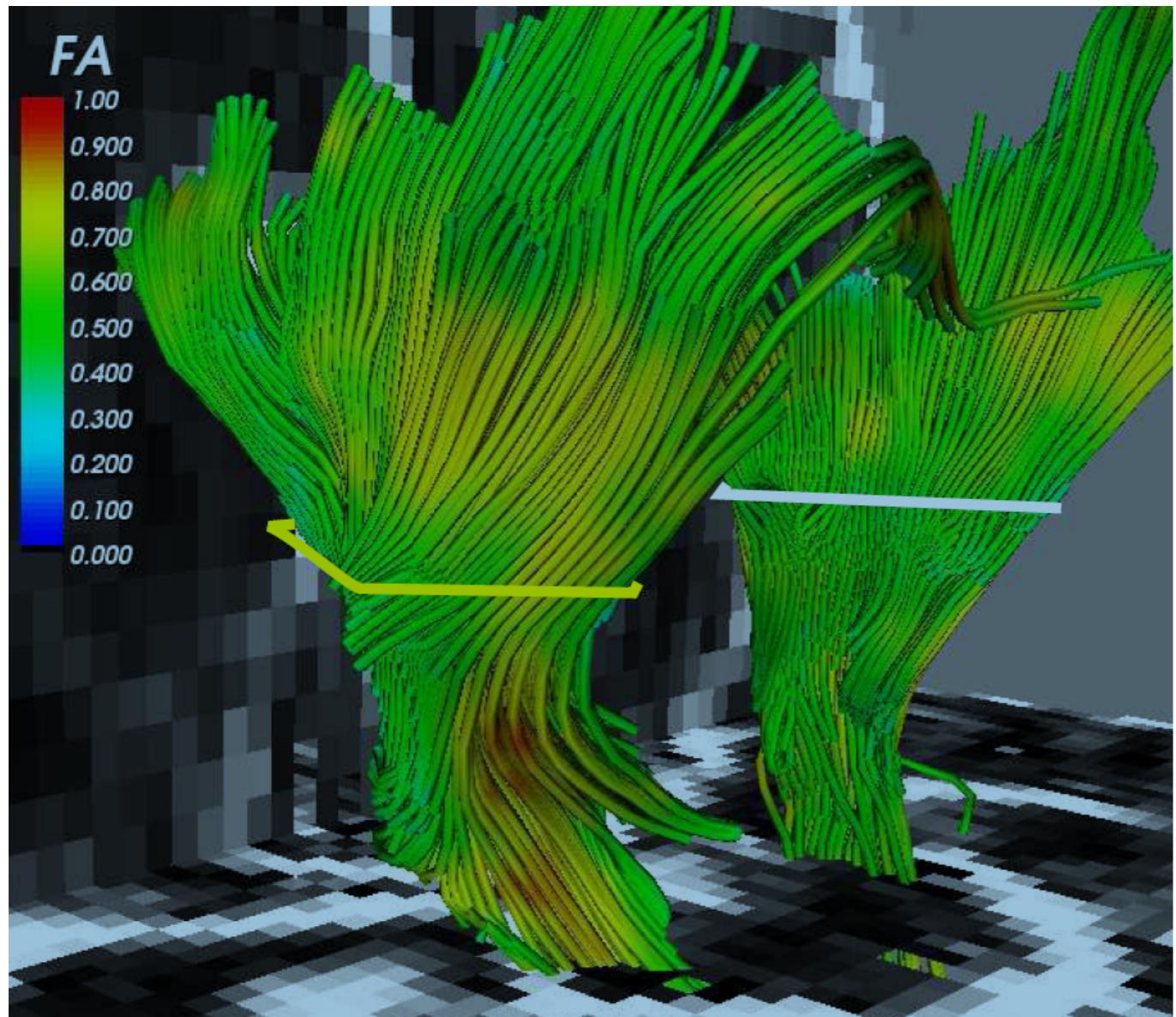
$$R = |\mathbf{e}_1 \cdot \mathbf{x}| \quad G = |\mathbf{e}_1 \cdot \mathbf{y}| \quad B = |\mathbf{e}_1 \cdot \mathbf{z}|$$

- Saturation weighted by anisotropy



Fiber tracking

- Trace streamlines in the e_1 vector field
- Terminology: fiber tracking, tractography



Readings

Volume Rendering

Display of Surfaces from Volume Data

Marc Levoy, University of North Carolina

In this article we will explore the application of *volume rendering* techniques to the display of surfaces from sampled scalar functions of three spatial dimensions. It is not necessary to fit geometric primitives to the sampled data. Images are formed by directly shading each sample and projecting it onto the picture plane.

Surface-shading calculations are performed at every voxel with local gradient vectors serving as surface normals. In a separate step, surface classification operators are applied to compute a partial opacity for every voxel. We will look at operators that detect isovalue contour surfaces and region boundary surfaces. Independence of shading and classification calculations ensure an undistorted visualization of 3D shape. Nonbinary classification operators ensure that small or poorly defined features are not lost. The resulting colors and opacities are composited from back to front along viewing rays to form an image.

The technique is simple and fast, yet displays surfaces exhibiting smooth silhouettes and few other aliasing artifacts. We will also describe the use of selective blurring and supersampling to further improve image quality. Examples from two applications are given: molecular graphics and medical imaging.



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IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS, VOL. 8, NO. 3, JULY-SEPTEMBER 2002

Multidimensional Transfer Functions for Interactive Volume Rendering

Joe Kniss, Student Member, IEEE Computer Society,
Gordon Kindlmann, Student Member, IEEE Computer Society, and
Charles Hansen, Member, IEEE Computer Society

Abstract—Most direct volume renderings produced today employ one-dimensional transfer functions which assign color and opacity to the volume based solely on the single scalar quantity which comprises the data set. Though they have not received widespread attention, multidimensional transfer functions are a very effective way to extract materials and their boundaries for both scalar and multivariate data. However, identifying good transfer functions is difficult enough in one dimension, let alone two or three dimensions. This paper demonstrates an important class of three-dimensional transfer functions for scalar data, and describes the application of multidimensional transfer functions to multivariate data. We present a set of direct manipulation widgets that make specifying such transfer functions intuitive and convenient. We also describe how to use modern graphics hardware to both interactively render with multidimensional transfer functions and to provide interactive shadows for volumes. The transfer functions, widgets, and hardware combine to form a powerful system for interactive volume exploration.

Index Terms—Volume visualization, direct volume rendering, multidimensional transfer functions, direct manipulation widgets, graphics hardware.

1 INTRODUCTION

DIRECT volume rendering has proven to be an effective and flexible visualization method for three-dimensional (3D) scalar fields. Transfer functions are fundamental to direct volume rendering because their role is essentially to make the data visible. By assigning optical properties like color and opacity to the voxel data, the volume can be rendered with traditional computer graphics methods. Good transfer functions reveal the important structures in the data without obscuring them with unimportant regions. To date, transfer functions have generally been limited to one-dimensional (1D) domains, meaning that the 1D space of scalar data value has been the only variable to which opacity and color are assigned. One aspect of direct volume rendering which has received little attention is the use of multidimensional transfer functions.

In the medical field, it is common to apply thresholding to binary representations of 3D scalar fields. If this binary representation is opaque, then a user can see the underlying gray scale grid. Improvements in segmentation algorithms have led to the ability to slice through a volume to yield a set of regions of interest. Then a user can connect the centers of these regions to form a scale of voxels appropriate for displaying

The currently dominant techniques for displaying

May 1988

0272-1716/88/0500-0029\$01.00 1988 IEEE

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For information on obtaining reprints of this article, please send e-mail to: tovg@computer.org, and reference IEEECS Log Number 116208.

1077-2626/02/\$17.00 © 2002 IEEE

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EuroVis 2016

R. Maciejewski, T. Ropinski, and A. Vilanova
(Guest Editors)

Volume 35 (2016), Number 3
STAR – State of The Art Report

State of the Art in Transfer Functions for Direct Volume Rendering

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Abstract

A central topic in scientific visualization is the transfer function (TF) for volume rendering. The TF serves a fundamental role in translating scalar and multivariate data into color and opacity to express and reveal the relevant features present in the data studied. Beyond this core functionality, TFs also serve as a tool for encoding and utilizing domain knowledge and as an expression for visual design of material appearances. TFs also enable interactive volumetric exploration of complex data. The purpose of this state-of-the-art report (STAR) is to provide an overview of research into the various aspects of TFs, which lead to interpretation of the underlying data through the use of meaningful visual representations. The STAR classifies TF research into the following aspects: dimensionality, derived attributes, aggregated attributes, rendering aspects, automation, and user interfaces. The STAR concludes with some interesting research challenges that form the basis of an agenda for the development of next generation TF tools and methodologies.

Categories and Subject Descriptors (according to ACM CCS): I.3.8 [Computer Graphics]: Applications—Volume Rendering I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Color, shading, shadowing, and texture I.4.10 [Computer Graphics]: Image Representation—Volumetric

Introduction

Transfer function (TF) maps volumetric data to optical properties part of the traditional visualization pipeline: data acquisition, processing, visual mapping, and rendering. Volumetric data is often a scalar function from a three-dimensional spatial domain with a one-dimensional range (e.g., density, flow magnitude, etc.). Image generation involves mapping data samples through the TF where they are given optical properties such as color and opacity, and then compositing them into the image.

TF simultaneously defines (1) which parts of the data are essential to depict and (2) how to depict these, often small, portions of the volumetric data. Considering the first step, a TF is a special, important case of a segmentation or classification. With classification, certain regions in a three-dimensional domain are identified according to the same material, such as bone, vessel, or soft tissue, etc. In medical imaging, a plethora of classification and segmentation methods have been developed over the last decades, with semi-automatic approaches often tailored to specific application scenarios. Segmentation algorithms can be quite intricate since information about the three-dimensional spatial domain and the one-dimensional range are taken into account. TFs in their basic form are, on the other hand, restricted to using only the data ranges. In comparison to general classification algorithms, this characteristic makes a

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TF less powerful with respect to identifying relevant parts of the data. The advantage of a TF is, however, a substantial performance gain as classification based on the one-dimensional data range reduces the complexity tremendously. This gain is the result of the three-dimensional domain being typically two orders of magnitude larger than the small data range. Histograms are an example of discarding potentially complex spatial information and aggregating only the data values to binned-frequency information. In the same spirit, TFs classify interesting parts of the data by considering data values alone. The second functionality of a TF deals with specifying optical properties for portions of the data range previously identified as being relevant.

A survey of the works published in the field of TFs reveals that in the three decades since the earliest published techniques for direct volume rendering [KVN84, DCH88, Lev88], over a hundred studies have been published in the most influential journals and conferences. In 2001, the Transfer Function Bake-Off examined four of the then most promising approaches to TF design [PLB*01]: trial and error with a TF editor; data-centric using computed metrics over the scalar field; data-centric using a material boundary model; and image-centric using an organized sampling of exemplar images. In 2010, Arens and Domik [AD10] authored a survey of TFs for volume rendering in which they subdivided TFs into the following