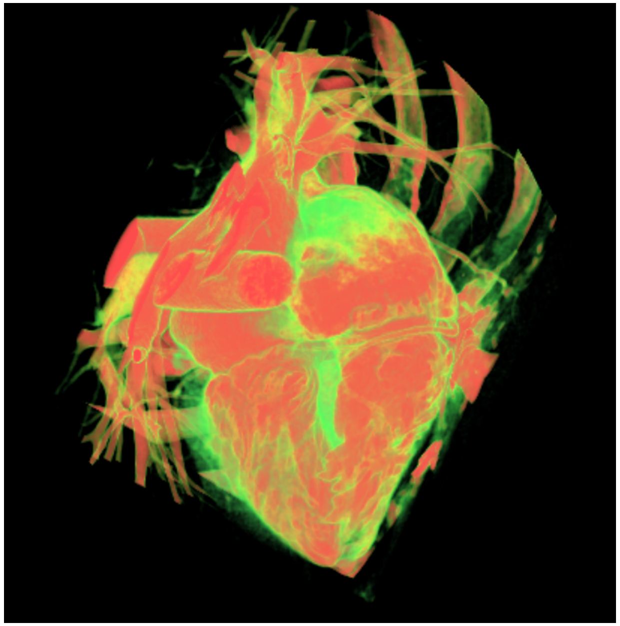
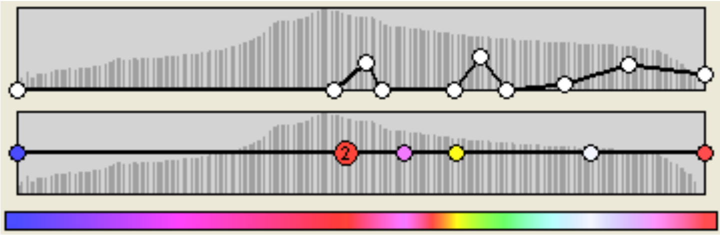
Module 12b:
Texture-based Transfer Functions

Motivation

- Visualization of volumetric data faces the difficult task of finding effective parameters for the transfer functions
- Those parameters are crucial for:
  - The overall image understanding
  - Determining the effectiveness and accuracy

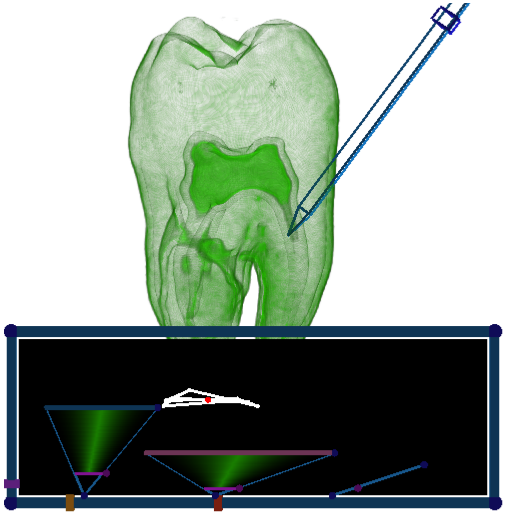




Previous Work

- The design of transfer functions (TFs) is still an active research area

- Transfer Functions:
  - Intensity-based TFs
  - Gradient-based TFs [Levoy, 1988]
  - Multi-dimensional TFs [Kniss et al., 2001]
  - Curvature-based TFs [Kindlmann et al., 2003]



Kindelmann et al, 2003

- Most TFs are still attached to voxel's properties including:
  - Intensity
  - Gradient

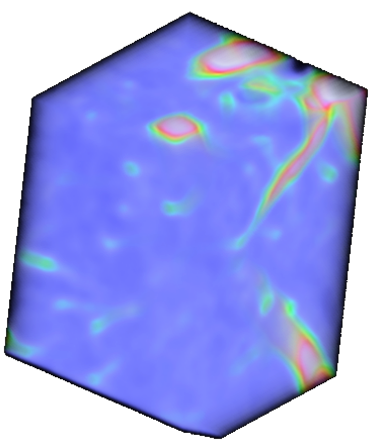
Previous Work

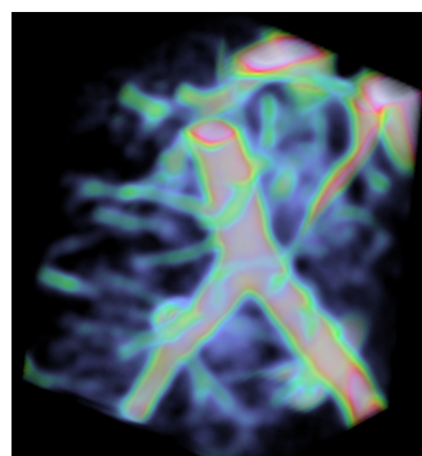
- Recently, design of TFs with spatial and/or local neighborhood characteristics
  - Tissue classification based on 3D local intensity structures [Sato et al., 00]
  - Supervised learning technique [Tzeng et al., 03]
  - Voxel barycenter and region variance [Roettger et al., 05]
  - Scale-based filtering, local analysis, and parallel coordinates [Lum et al, 06]

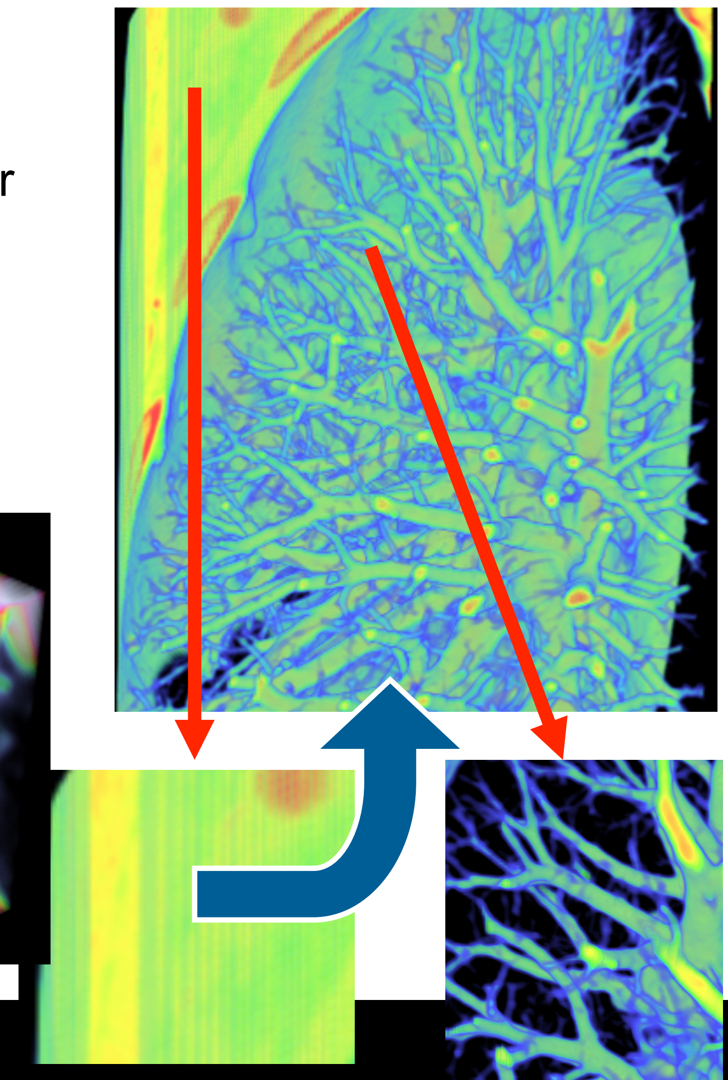
Existing transfer functions are limited at effectively illustrating features with the same intensity and gradient values

Observation: Textures

- Observations:
  - Like images, volumes contain characteristic patterns and small textures – textons - that our visual system can clearly identify
  - Combination of those textons create different structures and characteristic regions

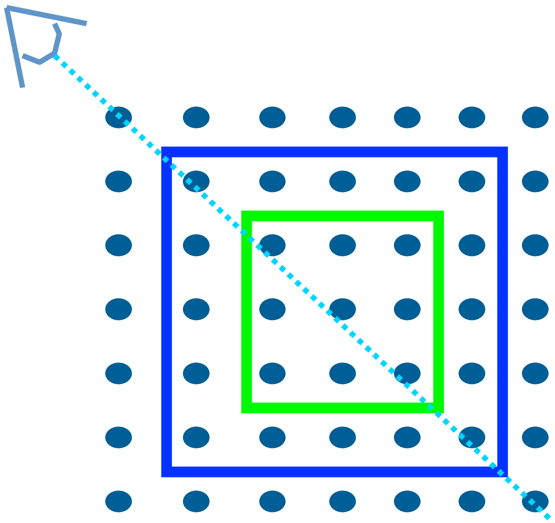






Texture-based Transfer Functions

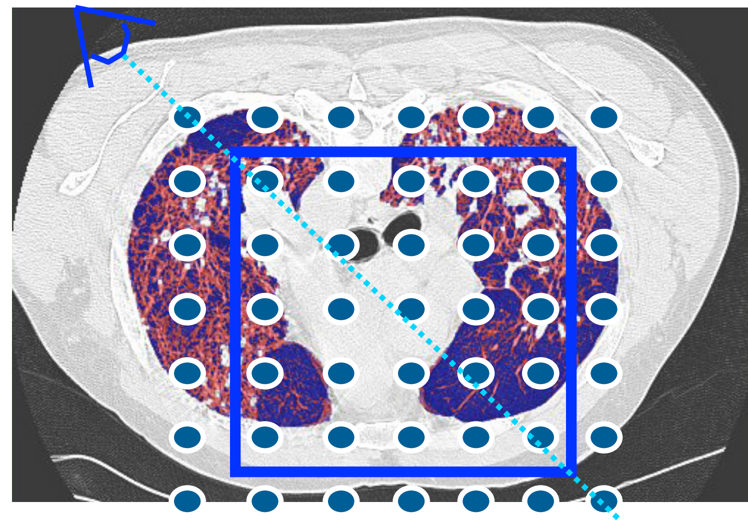
- We introduce Texture-based Transfer Functions (TbTFs)
- The voxel's properties are not attached to intensity or gradient values
- Instead on a set of statistical metrics estimated from local textural analysis



What's Texture Analysis?

- Technique used in medical imaging and image processing to identify, characterize, and compare regions with distinct patterns

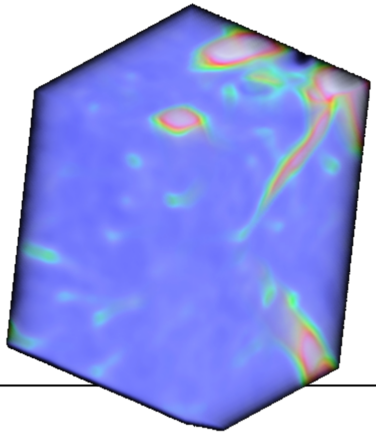
- Measure and capture local image properties which are not necessarily based on intensity properties



- We use a combination of first-, second-, and high-order statistics:
  - 1st Order: Histogram Statistics
  - 2nd Order: Co-occurrence Matrices
  - High-Order: Run-length matrices

First-Order Statistics

- The simplest textural measurements that can be obtained from 2D/3D images
  - Metrics estimated from a histogram



- Histogram Statistics:
  - Measure the probability of observing a particular pixel value at a randomly chosen location in the image.

- Variance:

$$\vartheta^2 = \frac{1}{(XY-1)} \sum_{x=1}^{X} \sum_{y=1}^{Y} [I(xy) - \mu]^2$$

- Standard Deviation:

$$\sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2}.$$

- Skewness:

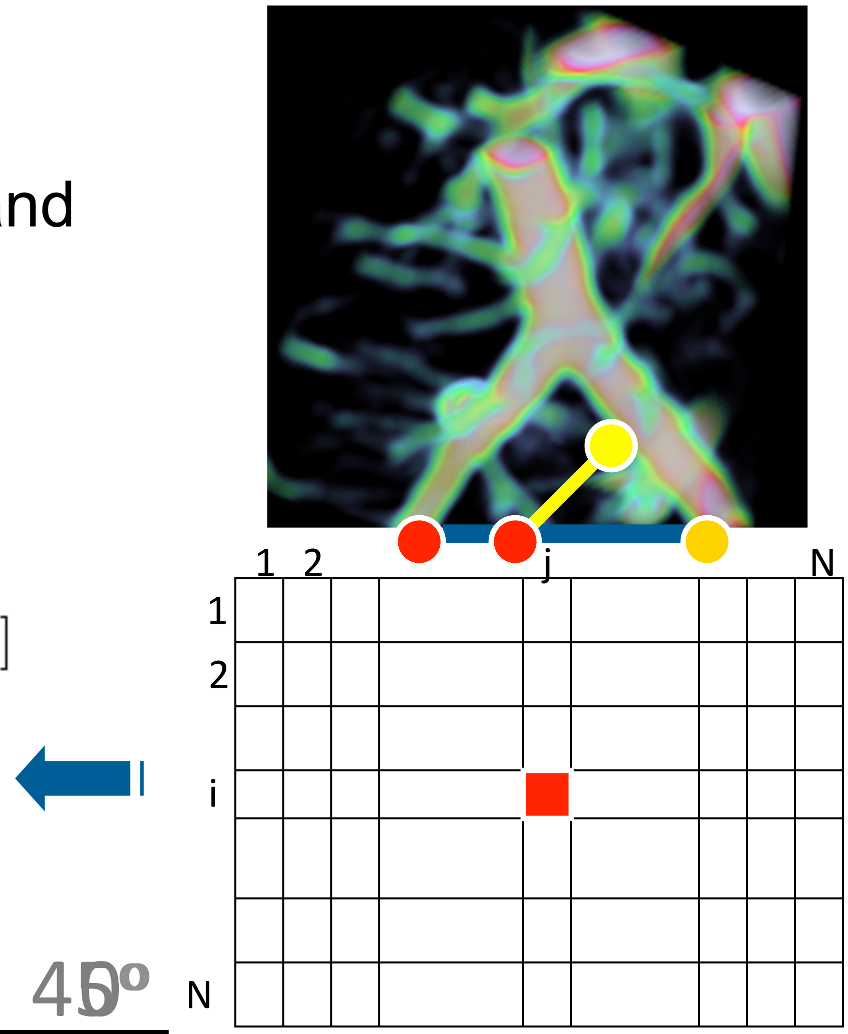
$$\frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} \left[\frac{I(xy) - \mu}{\vartheta}\right]^3$$

- Kurtosis:

$$\left\{\frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} \left[\frac{I(xy) - \mu}{\vartheta}\right]^4\right\} - 3$$

Second-Order Statistics

- Second-order statistics
  - Measure the likelihood of observing an intensity value *i* and *j* at an average distance



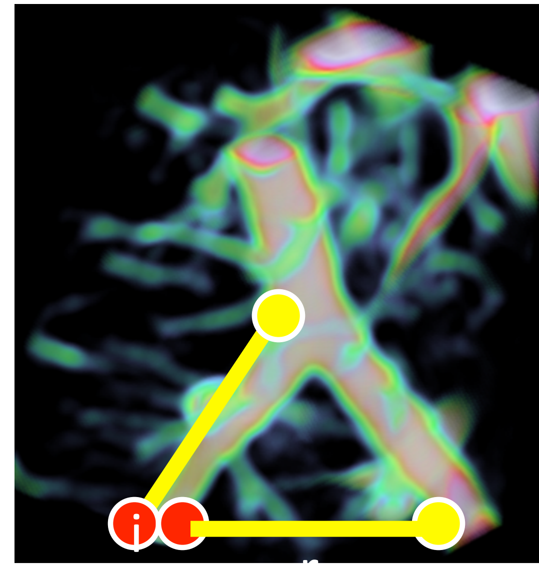
Energy: $$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)^2$$

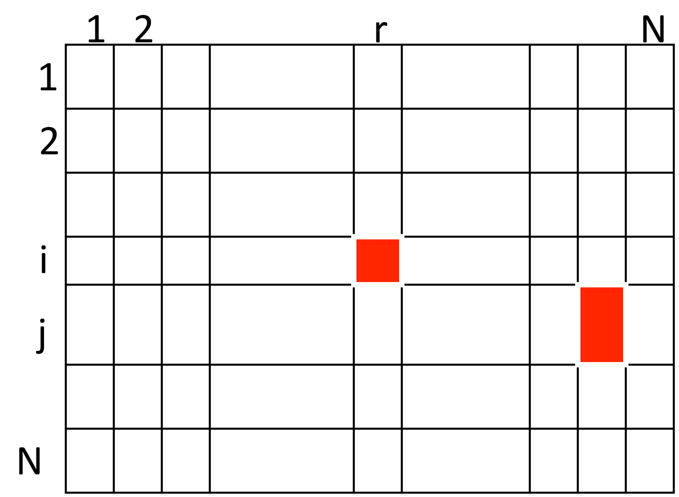
Entropy: $$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} [p(i,j)log(p(i,j))]$$

Contrast: $$\sum_{n=0}^{N_{g-1}} n^2 \left\{ \sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j) \right\}$$

Higher-Order Statistics

- Run-length matrices
  - Finds gray-level runs within the volume
  - Consecutive pixels that have the same





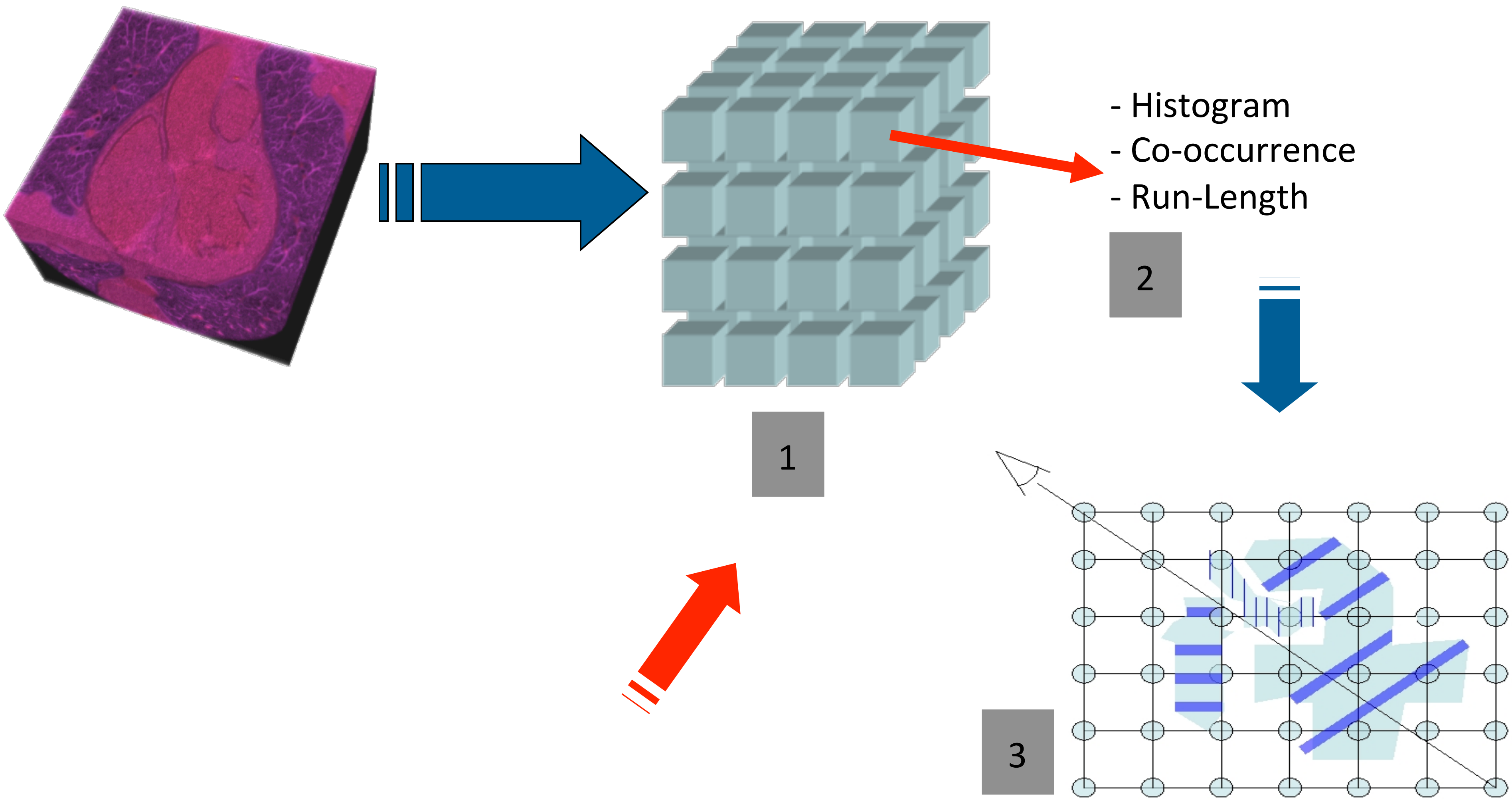
Short Run:

$$SRE = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \frac{p(i,j)}{j^2}}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}$$

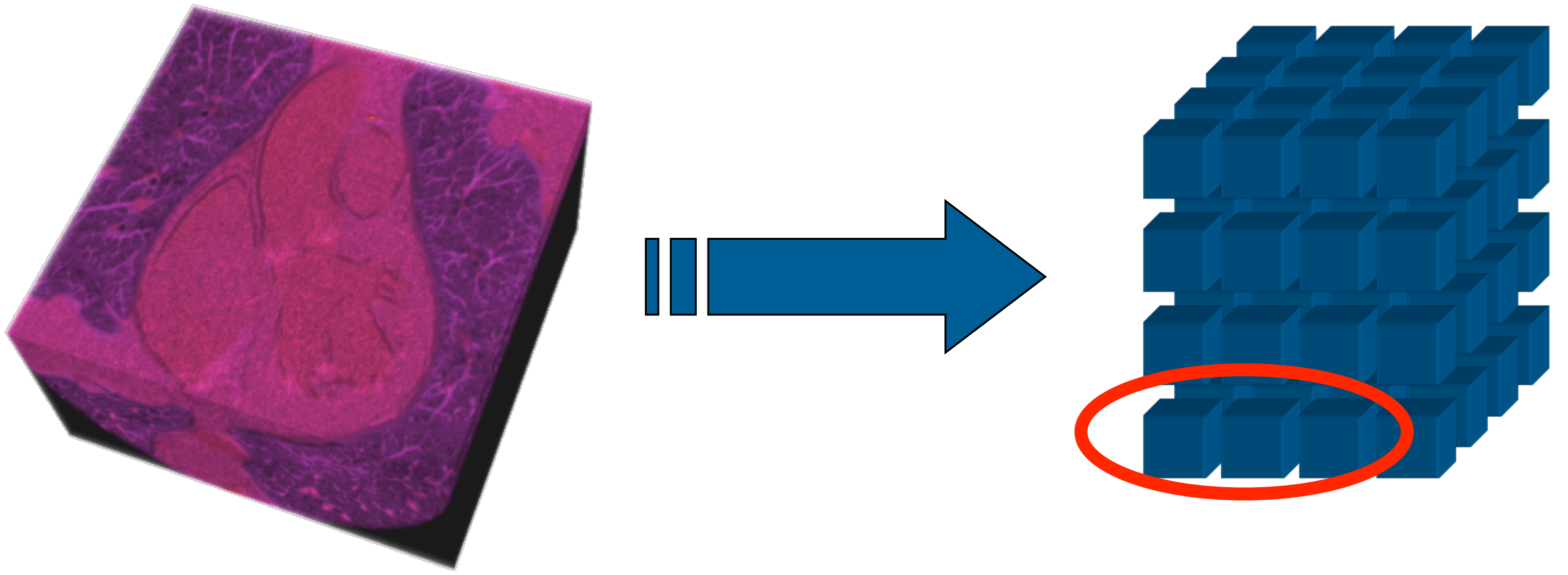
Long Runs:

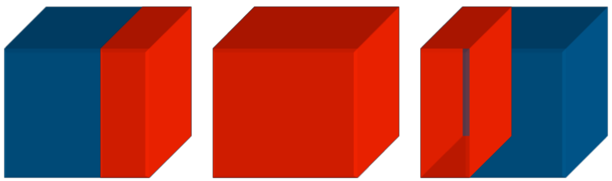
$$LRE = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} j^2 p(i,j)}{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} p(i,j)}$$

Approach – General Idea



1. Volume Partition

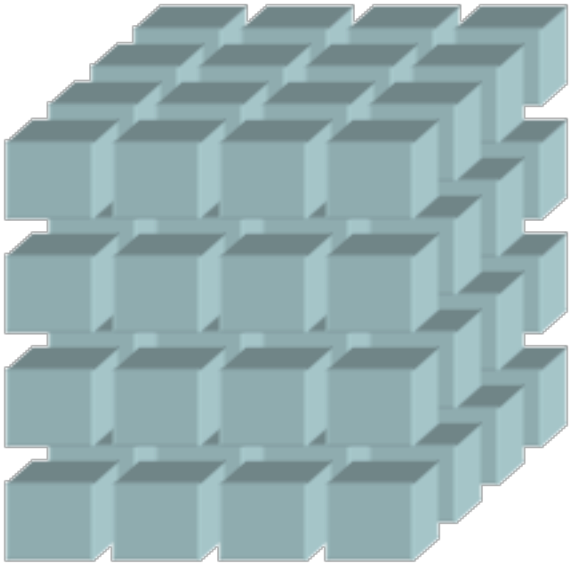




Size: $p \geq 1$

Overlap: $o \geq 0$

2. Pre-computed Properties

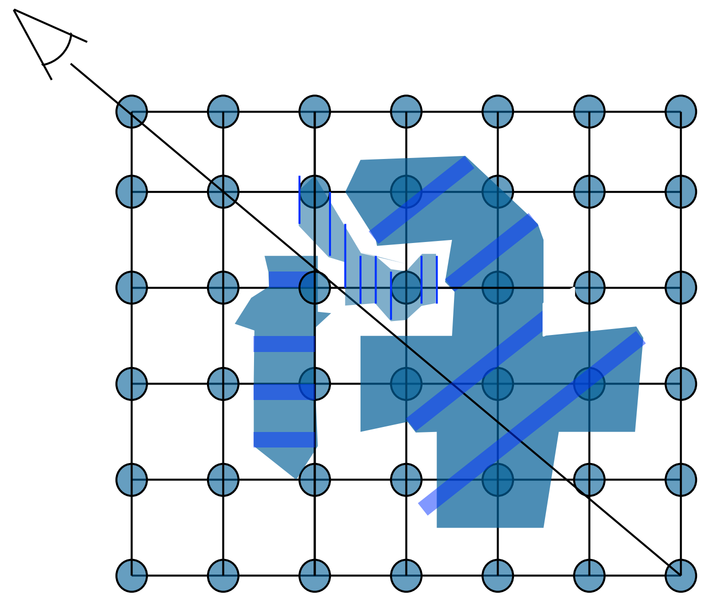


1^{st} Order Statistics	2^{nd} Order Statistics	Run Length Matrices
Mean	Energy	Short Run (SRE)
Variance	Inertia	Long Run (LRE)
Skewness	Inverse Diff	Gray Level Nonuniform (GLNE)
Kurtosis	Entropy	Low Gray Run (LGRE)
Absolute Deviation	Correlation	High Gray Run (HGRE)
Standard Deviation	Contrast	Short Run Low Gray (SRLGE)
	Sum Entropy	Long Run Low Gray (LRLGE)

- Textural metrics are stored in a vector image V'
- Vector image can be either pre-computed or computed during initialization

3. Texture-based Transfer Functions

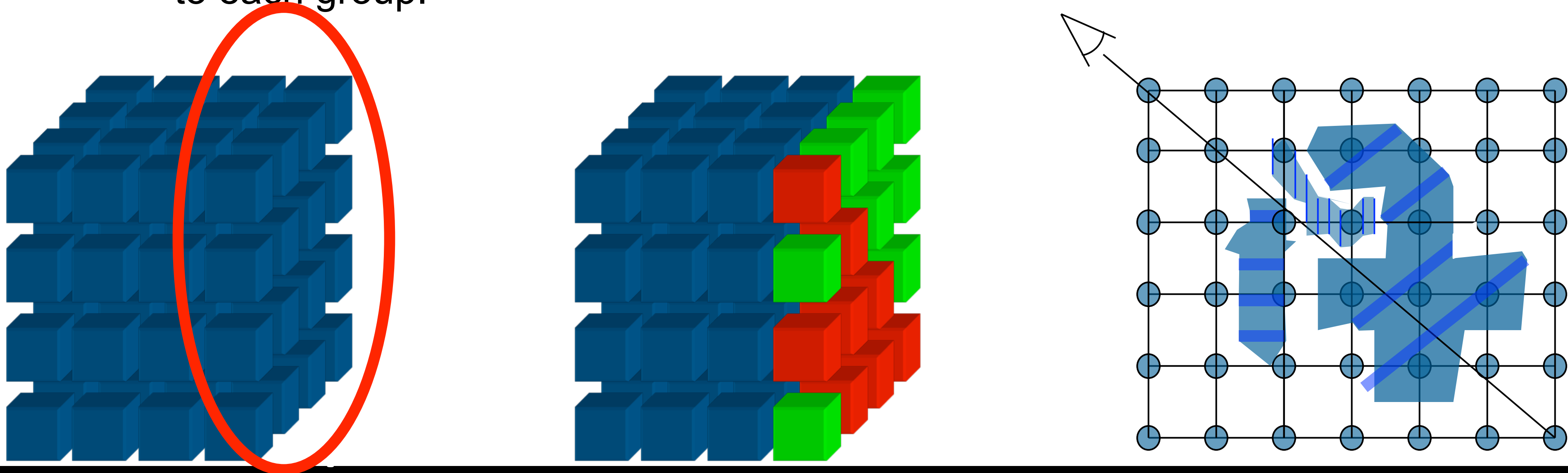
- During the rendering process, a voxel is represented by its local textural properties
- Flexibility of enhancing regions with similar density and gradient values



- Four ways to use TbTFs:
  1. Automatic Classification
  2. Individual Weighted Metrics
  3. Similarity Measurements
  4. Non-uniform Weights

1. Automatic

- Automatic enhancement of individual regions
  1. The user specify a value k (number of structures to highlight)
  2. The entire collection of vectors or a set of vectors $v_i \in V'$ are extracted
  3. An inequality-based fast *k-means* implementation is used to quickly clustered in k groups.
  4. During the rendering process, different rendering properties are assigned to each group.



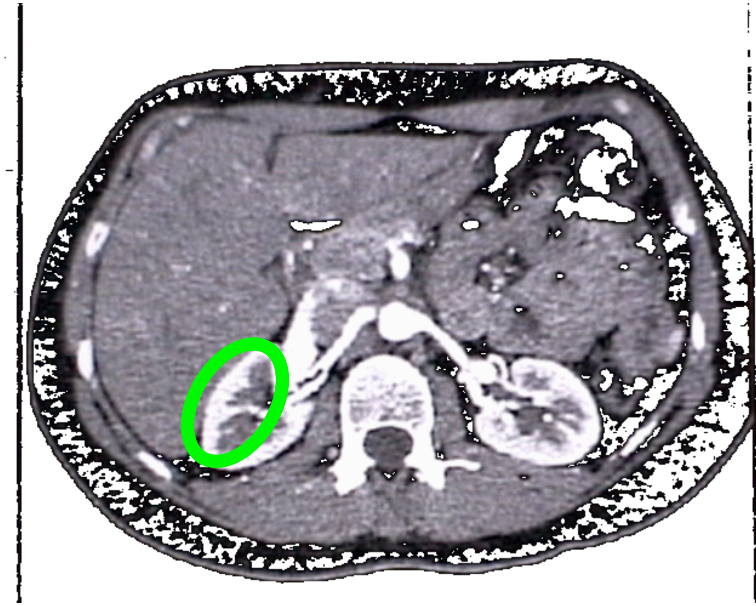
2. Individual Weights

1. User select or change any of the metrics
2. For every region or voxel under consideration:
   1. If the value of the specific metric(s) under consideration is above the user's threshold, assigned particualar opacity and color
   2. Otherwise, default rendering properties

	Kidney	Liver	Spleen	Backbone	Heart
Entropy	.4-.5			.6-.7	
Energy	0-.1		.2-.3		0-.1
Contrast		0-.1			0-.1
Homogeneity	.4-.5				
SumMean	.5-.6	.5-.6	.4-.5	.6-.7 .7-.8	
Variance					.3-.4
Correlation		.2-.3			.3-.4
Max Prob	0-.1		.2-.3	0-.1	.1-.2
IDM		.7-.8			
Cluster Tend					
SRE	.2-.3				
LRE			.2-.3	0-.1	

3. Similarity Measurements

- Given a region of interest, use similarity measurements to enhance alike regions
- Enables easy distinction of structures with similar intensity and gradient values

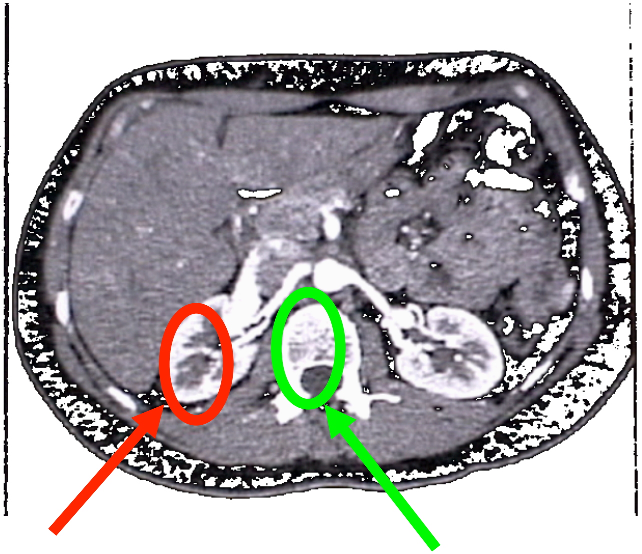


- How?
  1. The user employs a 3D widget to select a specific ROI
  2. During the raycasting process:

$$\text{Rend. Prop} = \begin{cases} \text{If } \|I(x,y,z) - \overline{ROI}\| \leq \tau & \text{Enhance} \\ \text{Otherwise} & \text{Default TF} \end{cases}$$

4. Non-uniform Weights

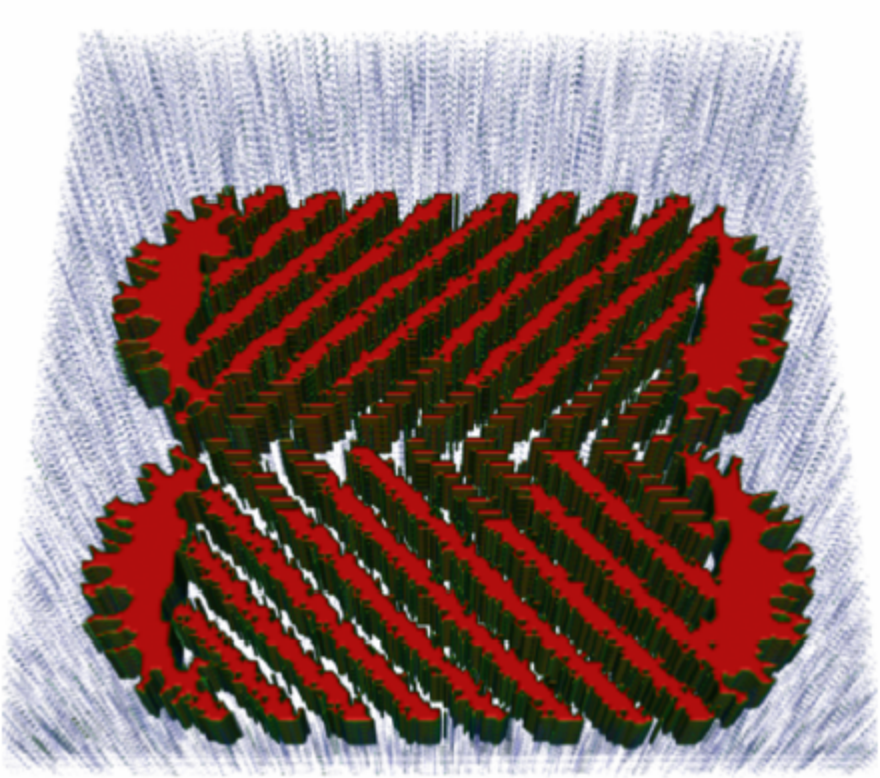
- Select two small ROI, S_1 and S_2 characteristic of the individual regions to enhance.
- Estimate set of textural features and weights to maximize the differences between S_1 and S_2

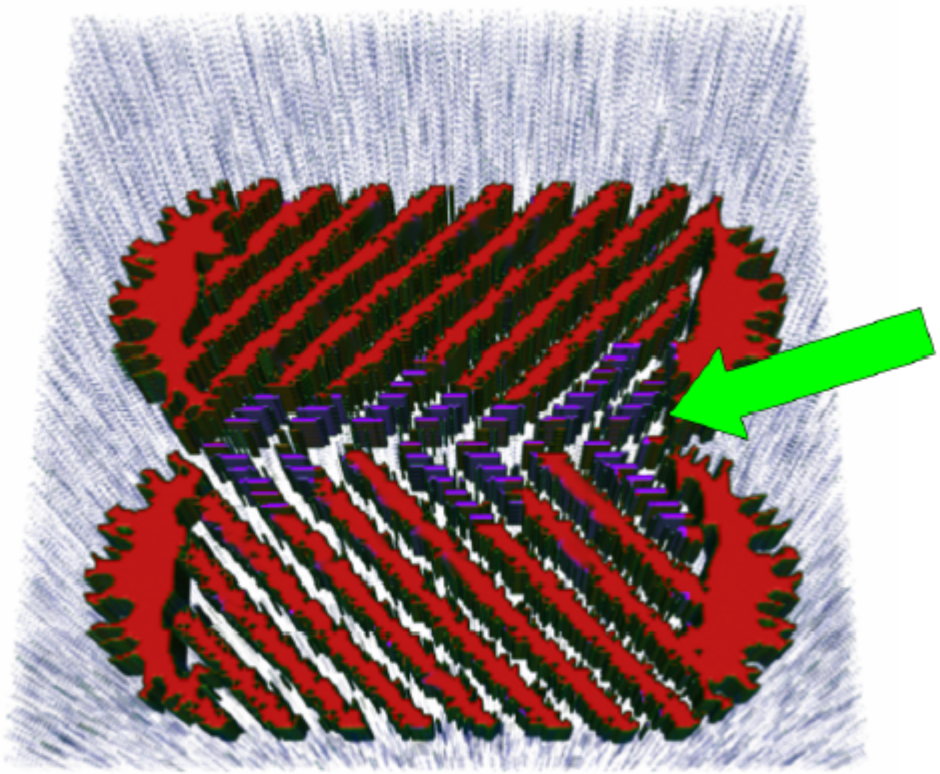


- How?
  1. Employ a 3D widget to select two ROI
  2. Combine texture vectors keeping label/class number
  3. Apply feature selection technique to find most important features that differentiate S1 and S2
  4. Assign weights

Results:
Synthetic Data

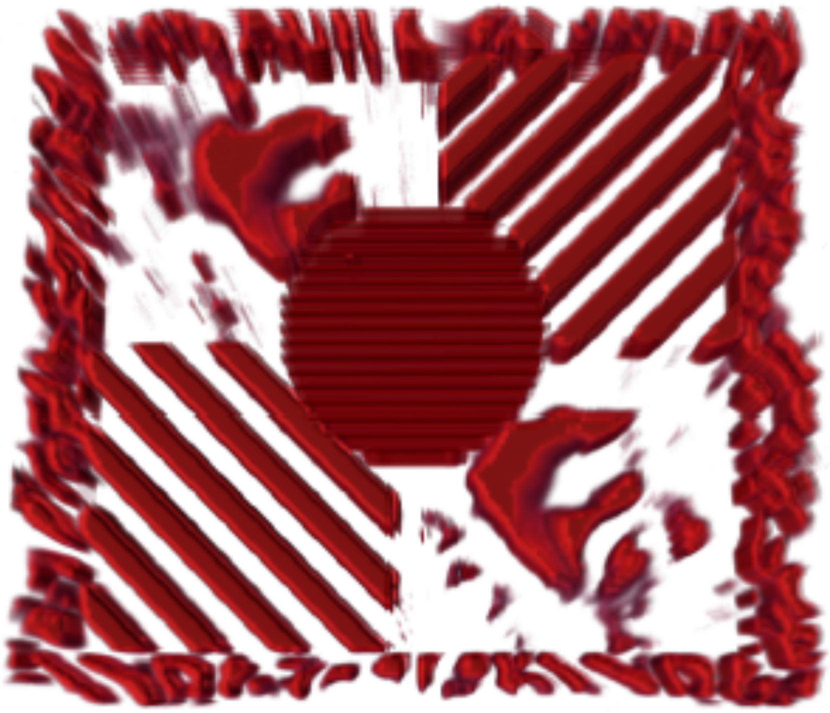
Results - Synthetic Data

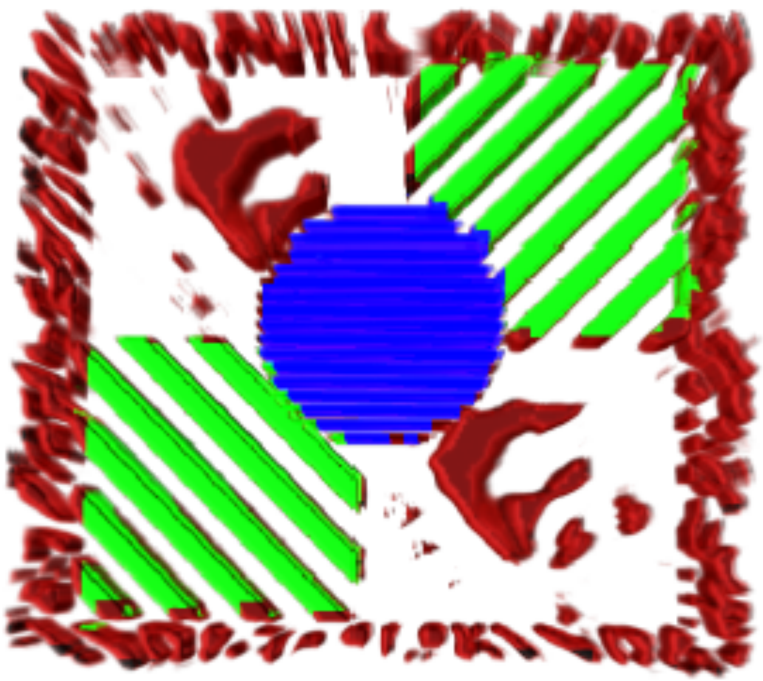




$p = 4 \qquad o = 0 \qquad k = 3$

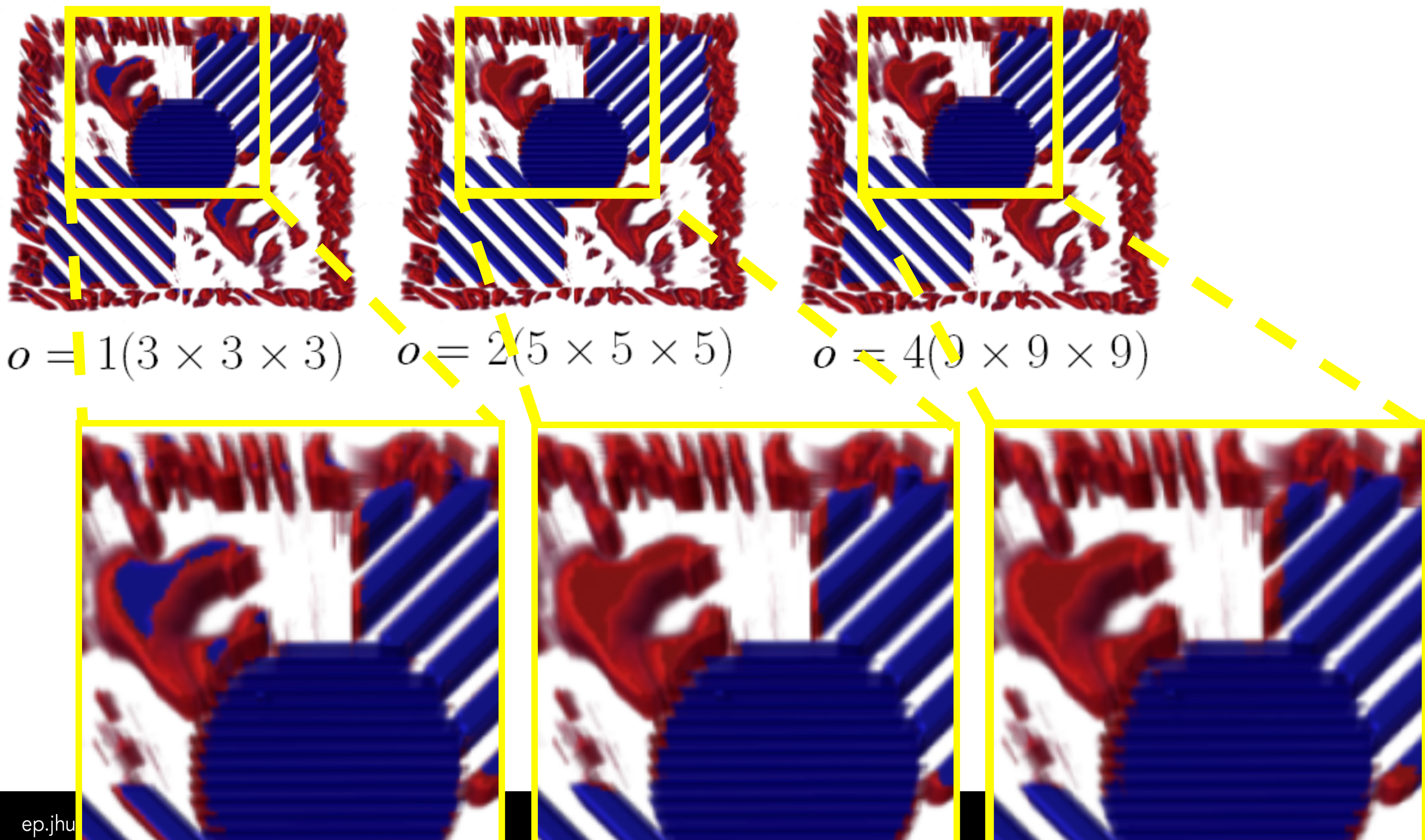
Results - Synthetic Data





$p = 2$ $o = 2$ $k = 4$

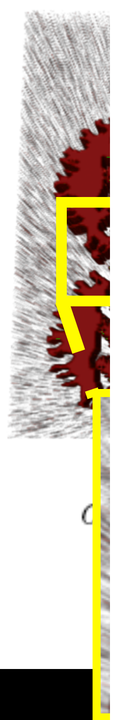
Texture/Window Size

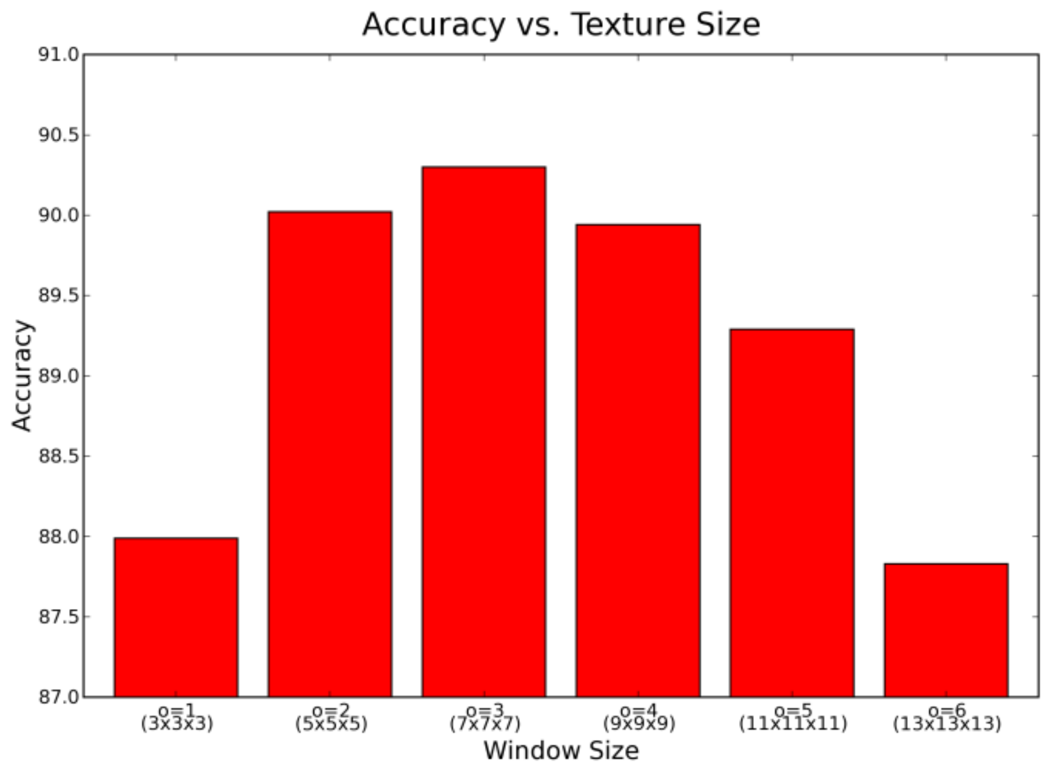


Texture/Window Size

- Regions of 5x5x5 – 7x7x7 are large enough to capture neighborhood properties and small enough to capture only local structures

- No significant difference between *p =1* and *p =2*





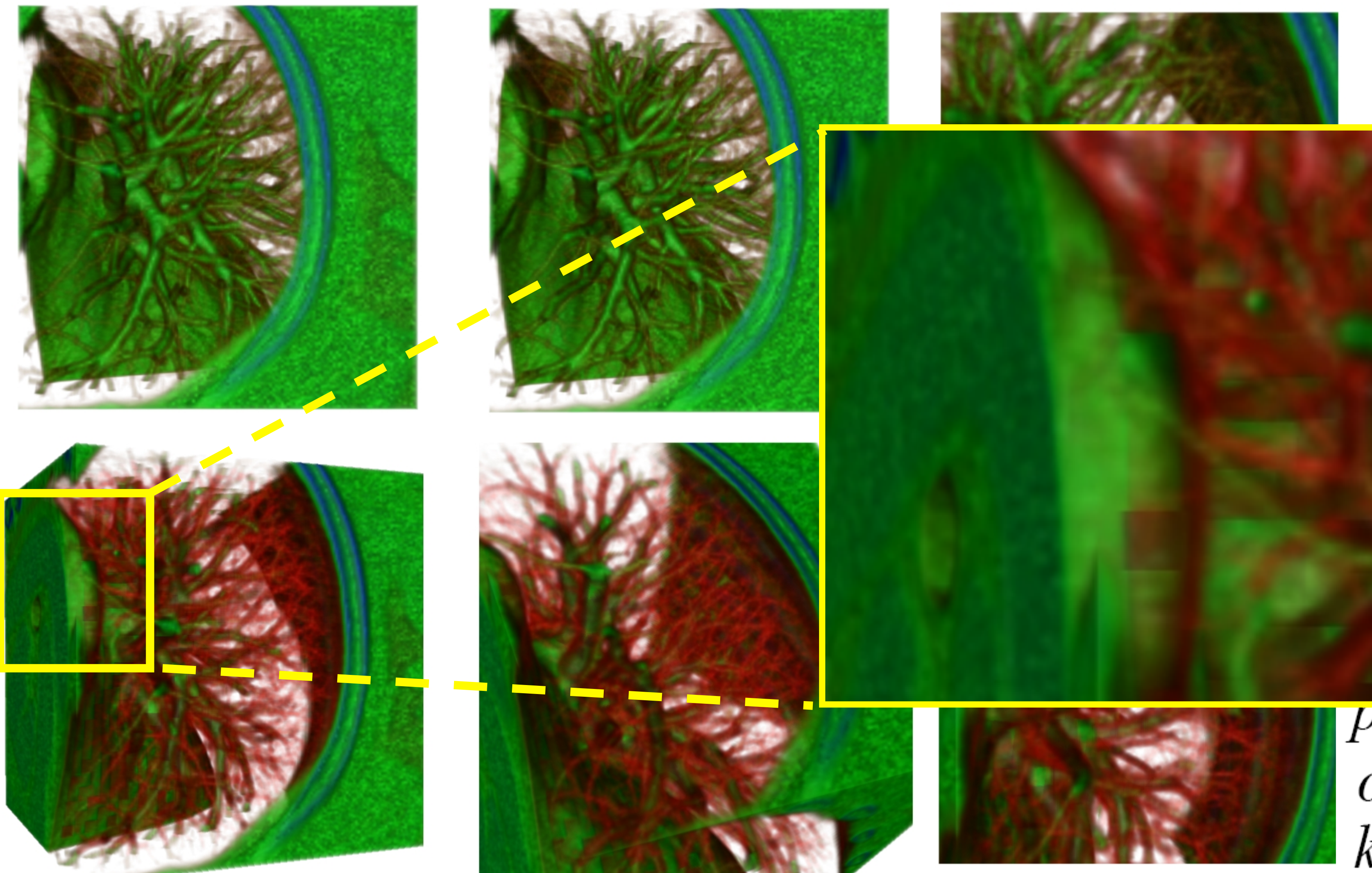
Performance

Volume Size	$p=4, o=2$	$p=2, o=2$	$p=1, o=2$
64x64x32	0.15s	0.61s	4.09s
$k=3$	0.01s	0.10s	0.74s
$k=4$	0.02s	0.12s	0.82s
64x64x64	0.30s	1.21s	8.33s
$k=3$	0.04s	0.18s	1.32s
$k=4$	0.05s	0.20s	1.50s
128x128x64	0.86s	4.57s	32.43s
$k=3$	0.08s	0.76s	6.25s
$k=4$	0.11s	0.[illegible]	[illegible]
128x128x128	1.33s	8.[illegible]	[illegible]
$k=3$	0.14s	1.[illegible]	[illegible]
$k=4$	0.20s	1.[illegible]	[illegible]
256x256x128	5.25s	32[illegible]	[illegible]
$k=3$	0.62s	6.[illegible]	[illegible]
$k=4$	0.76s	6.[illegible]	[illegible]

1. Worst case scenario
2. Textures can be pre-computed
3. Textures can be extracted for a small intensity range

Application Domain: Medical Volumetric Data

Results – Lung Dataset

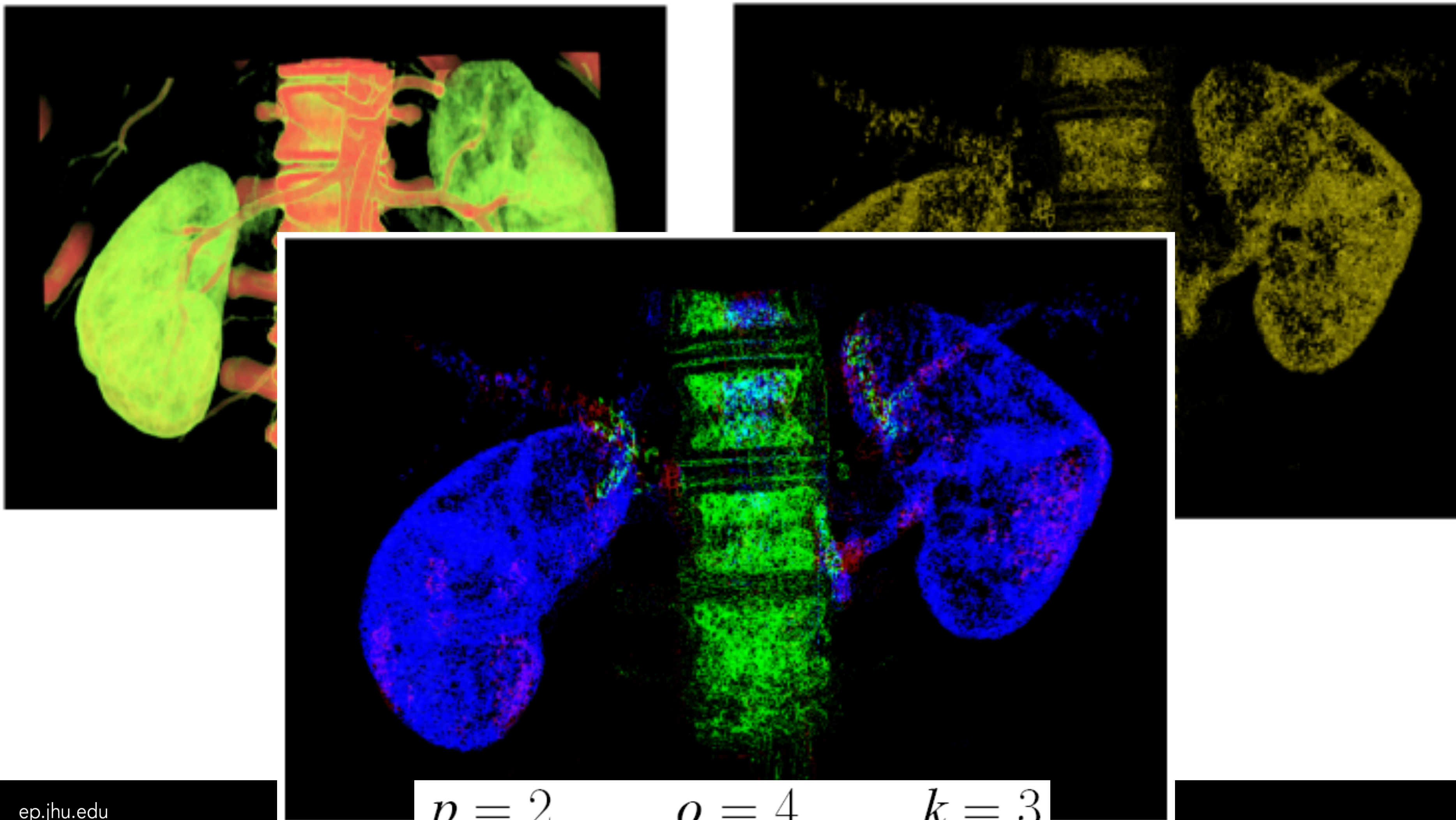


$p = 2$

$o = 2$

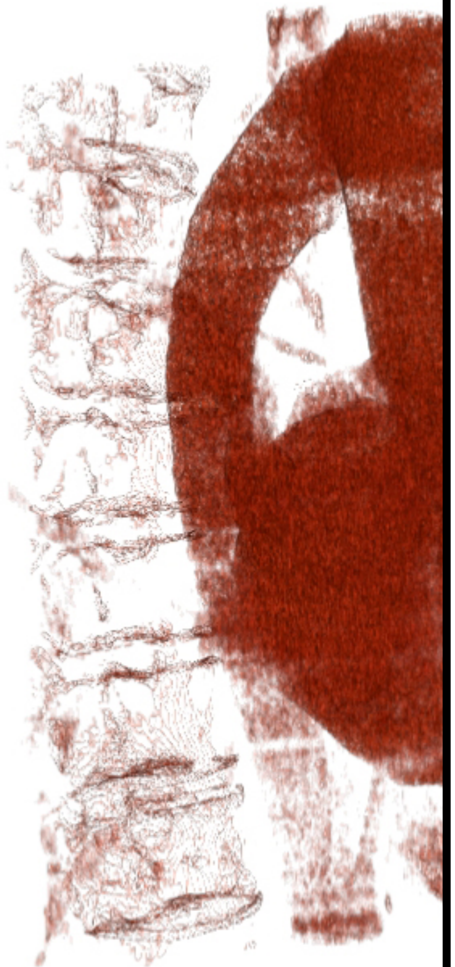
$k = 3$

Results

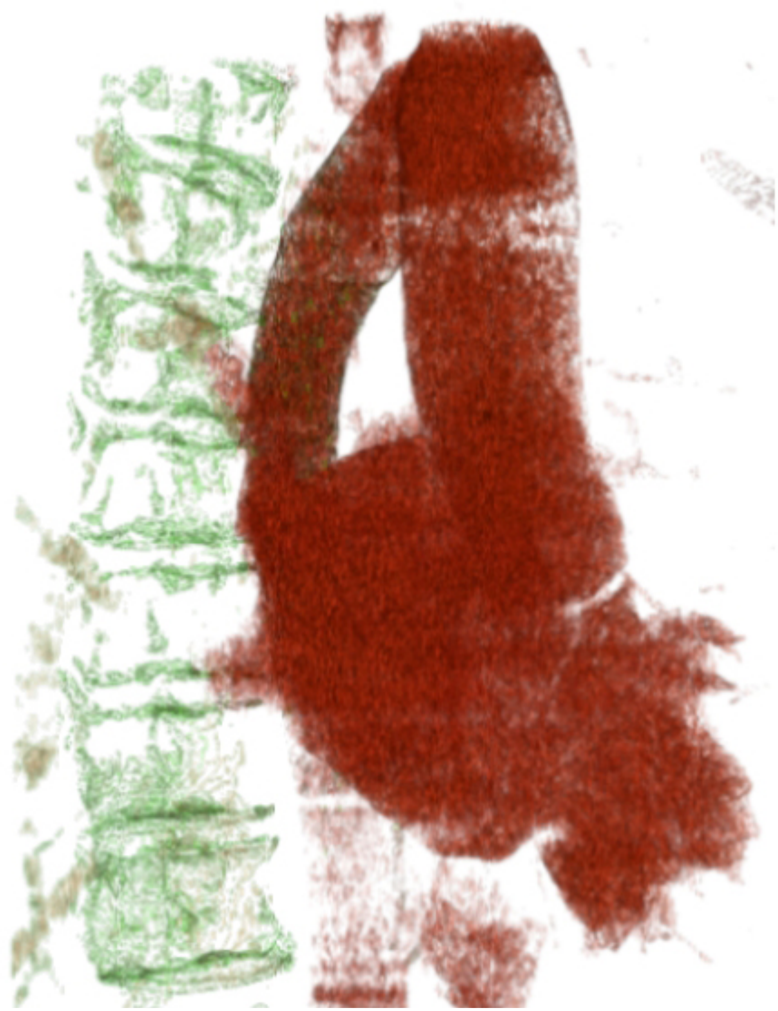


$p = 2$ $o = 4$ $k = 3$

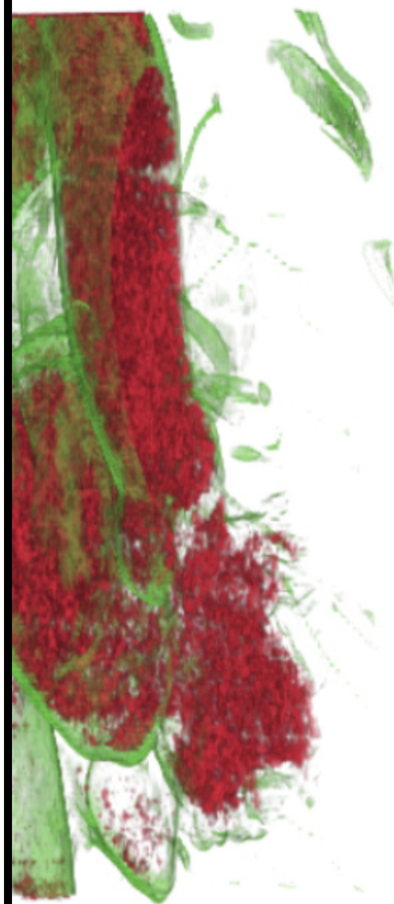
Results



1D TF

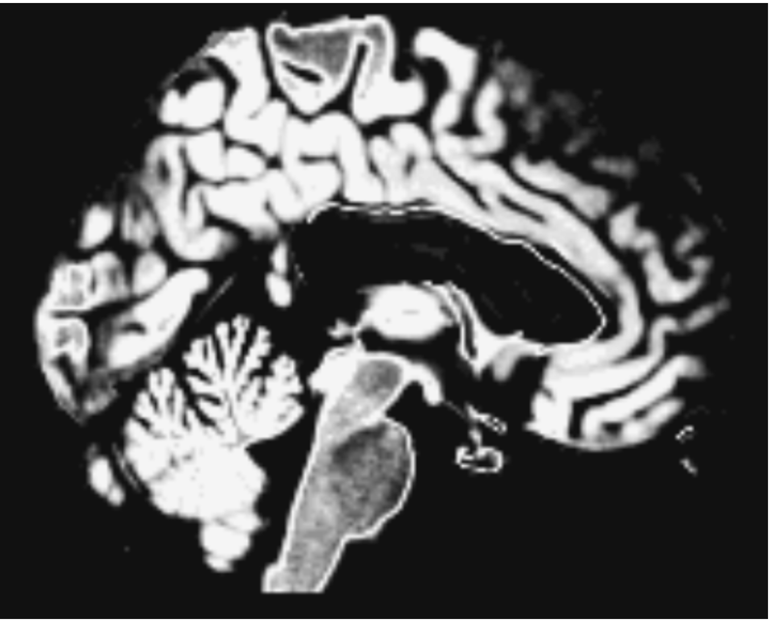


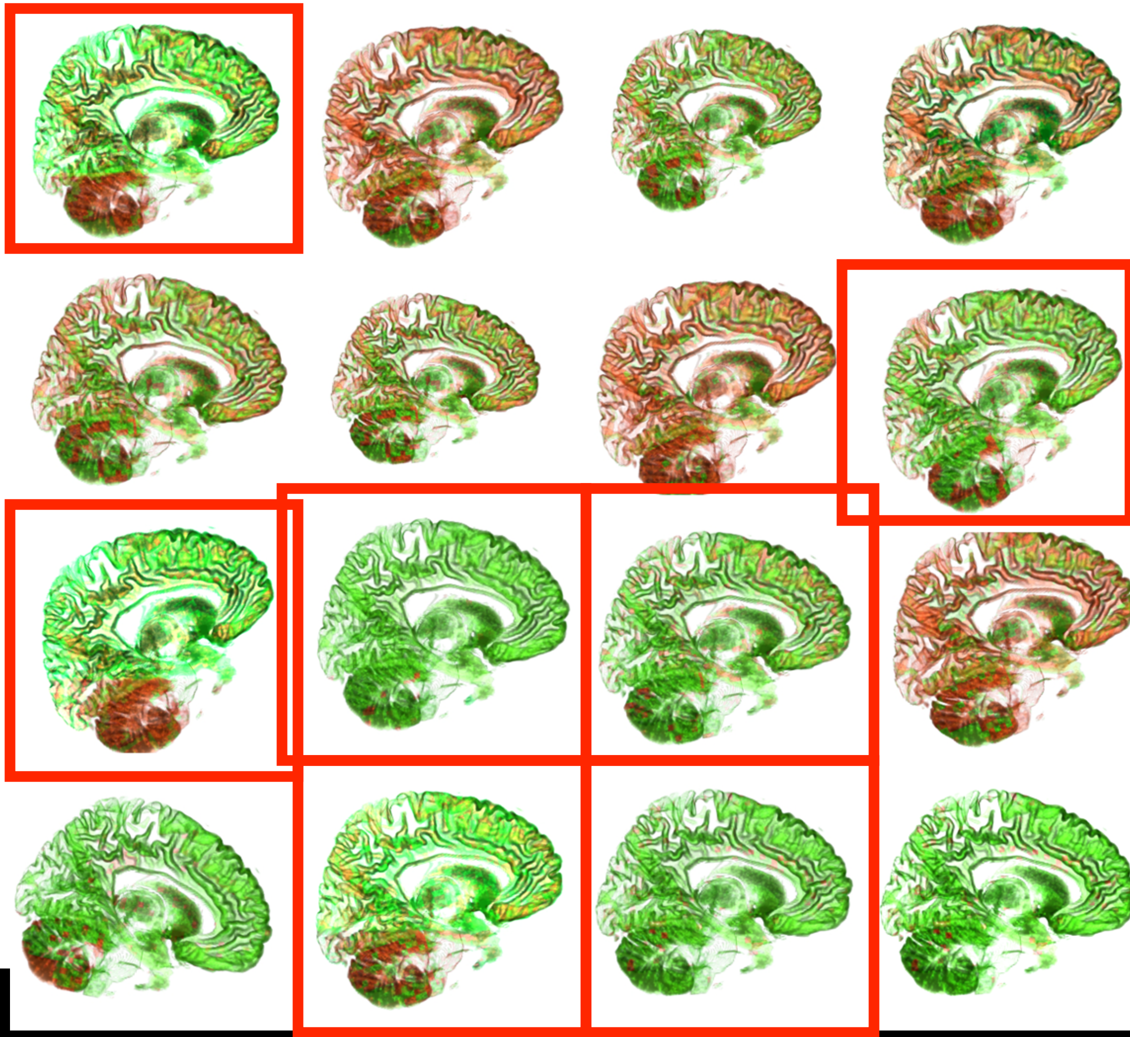
$p = 2$ $o = 4$ $k = 3$



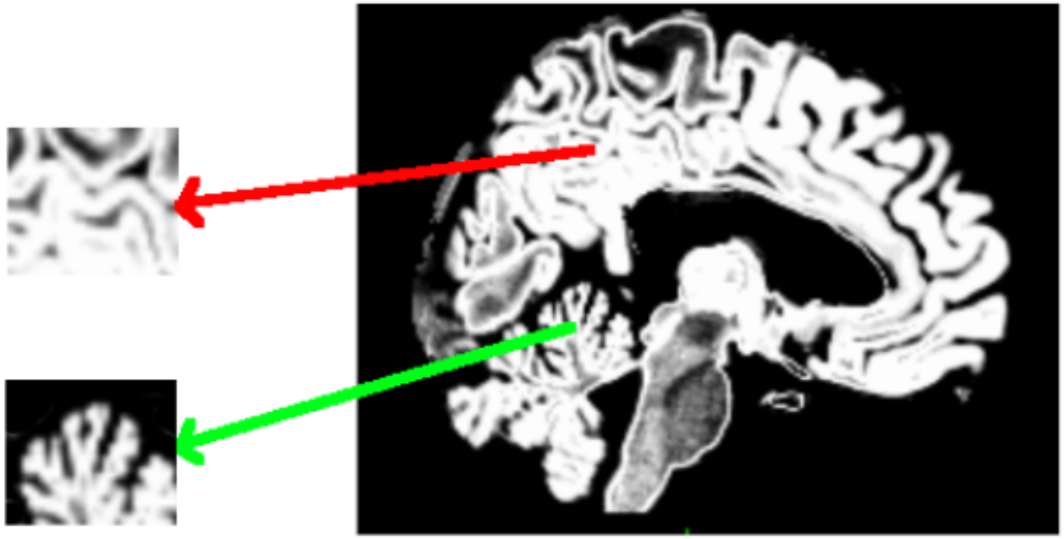
ti-D TF

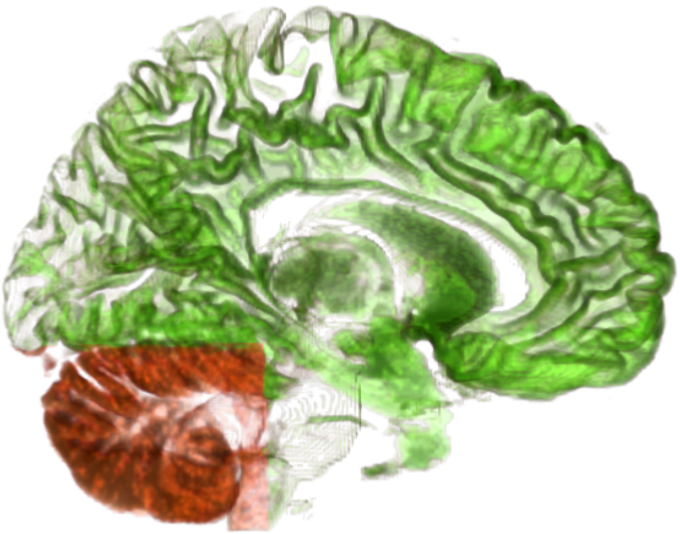
Results





Weighted Textures





[1] Peng et al, "Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy" [2005]

Conclusion

- Texture analysis opens new ways to design transfer functions
- Proven to be effective with real world medical volumes