Lecture 8: Geometric Modeling and Visualization

Finite Elements from Imaging I & II: Active Contouring, Segmentation, Reconstruction

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The Context: Structure Determination via Cryo-EM





- \rightarrow Cryo-EM images
- \rightarrow Reconstructed density maps
- \rightarrow Structure Segmentation
- → Sub-Atomic Modeling
- \rightarrow Functional Analysis
- \rightarrow Visualization



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Dr. Wah Chiu, NCMI, BCM(Houston);

Problem Description

Rice Dwarf Virus



segmented outer capsid layer with icosahedral symmetry segmented asymmetric subunits

segmented monomer (protein)



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Algorithm Overview

- Three steps:
 - Detection of critical points
 - (Anisotropic vector diffusion)
 - Detection of icosahedral symmetry

(Five-fold symmetry detection)

- Segmentation of asymmetric subunits

(A variant of the fast marching method)



Detecting Critical Points

- Three types
 - maximal, minimal, saddle







density map

initial gradient vector field

diffused vector field



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Detecting Critical Points (contd.)

- Gradient vector diffusion:
 - smoothing the vector fields
 - diffusion to the flat regions
 - Isotropic diffusion

$$\begin{cases} \frac{\partial u}{\partial t} = \mu \cdot \nabla^2 u\\ \frac{\partial v}{\partial t} = \mu \cdot \nabla^2 v \end{cases}$$

where

(u, v) are gradient vector.

Anisotropic diffusion

$$\begin{cases} \frac{\partial u}{\partial t} = \mu \cdot div(g(\alpha)\nabla u) \\ \frac{\partial v}{\partial t} = \mu \cdot div(g(\alpha)\nabla v) \end{cases}$$

where $g(\alpha)$ is a decreasing function α is the angle between the central pixel and its surrounding pixels.



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Detecting Critical Points (contd.)



Detecting Critical Points (contd.)



- We consider only the maximal critical points
- Used for two purposes:
 - Speed up the symmetry detection
 - Seed points in the fast marching method



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Symmetry Detection

• Icosahedral symmetry overview (Caspar & Klug 1962; Baker et al. 1999)



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• Asymmetric subunits in an icosahedra





Example: RDV

- Two-fold vertices
- Three-fold vertices
- Five-fold vertices

Task: detect all 12 five-fold symmetry axes !



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• Detect five-fold symmetry axes



$$f(\vec{r}) = f(R_{(\theta,\varphi,2\pi/5)} \cdot \vec{r}) \text{ for } \forall \vec{r}$$
$$R_{(\theta,\varphi,\alpha)} \text{ is the rotation around } l_{\theta,\varphi} \text{ by a}$$

amount of α

$$R_{(\theta,\varphi,\alpha)} = A^{-1} \cdot B^{-1} \cdot \begin{pmatrix} \cos(\alpha) & -\sin(\alpha) & 0\\ \sin(\alpha) & \cos(\alpha) & 0\\ 0 & 0 & 1 \end{pmatrix} \cdot B \cdot A$$



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• Detect five-fold symmetry axes





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• Direct correlation

$$C(\theta,\varphi) = \sum_{\vec{r} \in V} f(\vec{r}) f(R_{(\theta,\varphi,2\pi/5)} \cdot \vec{r})$$

Total time: O(MN)

M: total number of angular bins

N: total number of voxels (e.g., 512³)

- Solutions: reduce *M*
 - Principal axis evaluation
 - Hierarchical sampling
- One solution: reduce N



 \sim 46,000 angular bins



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- Algorithm: *detect 5-fold rotation symmetry*
 - Compute the scoring function
 - For every angular bin B_j , compute θ_j, φ_j { For every critical points C_i {

$$\vec{r}_{k}(C_{i}, B_{j}) = R_{(\theta_{j}, \varphi_{j}, 2k\pi/5)} \cdot C_{i}, \quad k = 0, 1, 2, 3, 4$$
$$Dev(C_{i}, B_{j}) = \frac{1}{5} \sum_{k=0}^{4} (f(\vec{r}_{k}) - \bar{f}) \}$$

$$SF(B_j) = \frac{1}{p} \sum_{i=0}^{p} Dev(C_i, B_j)$$

- Locate the symmetry axes
 - The 12 peaks
- Refine the symmetry axes
 - In order to generate a perfect icosahedra

(rotate the axes by 0^0 , 63.43⁰, 116.57⁰, 180⁰)



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Inverted and normalized SF(Bj)



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• Performance evaluation: *RDV outer layer*





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Asymmetric Subunit Segmentation

• A simple case



Infinite number of partitionings

which one is the best?



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• The criterion for partitioning a symmetric image



A related problem: data clustering

Criterion: distance !



Classifying critical points

Task: distance !



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• Marching distance

 $MD_f(A,B) = Min\{ \int_{A \to B} e^{\|\nabla f(\vec{r})\|} ds \} \text{ along all paths from } A \text{ to } B$

$$MD_{f}(A,B) = Min\{\sum_{r=A}^{B} e^{\|\nabla f(\vec{r})\|} - \frac{e^{\|\nabla f(A)\|} + e^{\|\nabla f(B)\|}}{2}\}$$

(discrete form)

Closely related to the fast marching method !





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• The fast marching method Start from a seed and propagate by certain speed $\|\nabla T(\vec{r})\| \cdot F(\vec{r}) = 1$

where *F* is the speed function, which can be defined as:

$$F(\vec{r}) = e^{-\alpha \|\nabla F(\vec{r})\|} \qquad \alpha > 0$$

The map *T* gives the *marching distances* from the seed to all the other points





• The multi-seeded fast marching method Start from seeds and propagate independently by: $\|\nabla T(\vec{r})\| \cdot F(\vec{r}) = 1$

where *F* is the speed function, which can be defined as:

$$F(\vec{r}) = e^{-\alpha \|\nabla F(\vec{r})\|} \qquad \alpha > 0$$

The map *T* gives the *marching distances* from the seed to all the other points







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- The solution
 - Use multiple seed points for each subunit
- The overall algorithm
 - Detect the critical points
 - Classify the critical points
 - Use the multi-seeded fast marching method
 - Merge for contours of the same group
 - Stop for contours of different groups







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• Segmentation of capsid layers



selection of seeds (manually)

segmented capsid layer

Bacteriophage P22



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- Asymmetric subunit of icosahedral maps
 - 12 vertices, 60 subunits



index = 1;
for (i = 1; i < 5; i + +) {

$$Q = R_{2i\pi/5}^0(P)$$
;
assign index to Q;
index + +; }
for (j = 1; j < 11; j + +) {
 $P' = R_{0 \rightarrow j}(P)$;
for (i = 0; i < 5; i + +) {
 $Q = R_{(2i+1)\pi/5}^j(P')$;
assign index to Q;
index + +; }
 $P' = R_{0 \rightarrow 11}(P)$;
for (i = 0; i < 5; i + +) {
 $Q = R_{2i\pi/5}^{11}(P')$;
assign index to Q;
index + +; }

Start from index 0

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November 2007



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- Asymmetric subunit of icosahedral maps
 - 12 vertices, 60 subunits



$$\begin{split} & if \, (j == 0) \\ & B_0 = R^0_{-2i\pi/5}(B); \\ & else \, if \, (j < 11) \, \{ \\ & B' = R^j_{-(2i+1)\pi/5}(B); \\ & B_0 = R_{j \to 0}(B'); \} \\ & else \, if \, (j == 11) \, \{ \\ & B' = R^{11}_{-2i\pi/5}(B); \\ & B_0 = R_{11 \to 0}(B'); \} \end{split}$$

Start from any index



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Results: Rice Dwarf Virus (6.8Å) (Zhou et al 2001)





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Results: Rice Dwarf Virus (6.8Å) (Zhou et al 2001)





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Results: Bacteriophage P22 (9.5Å) (Jiang et al 2003)



segmented capsid layer

segmented asymmetric subunits (five-fold & three-fold)



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Results: Semliki Forest Virus (9.0Å) (Mancini et al 2000)



segmented capsid layer

segmented asymmetric subunits (five-fold & three-fold)



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Results: Synthetic Map PDB ID = 1HB9, San Martin et al 2001



synthetic capsid layer

asymmetric subunits (our method)

true segmentation



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Results: Synthetic Map PDB ID = 1HB9, San Martin et al 2001



crystal structure of subunit

blurred map

one subunit of our result



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Gradient Vector Diffusion (GVD)

• Partial Differential Equation (Xu and Prince, 1998)

$$\begin{cases} \frac{\partial u}{\partial t} = \mu \nabla^2 u - (u - f_x)(f_x^2 + f_y^2) \\ \frac{\partial v}{\partial t} = \mu \nabla^2 v - (v - f_y)(f_x^2 + f_y^2) \end{cases}$$

where (u(t), v(t)) stands for the evolving vector field; μ is a constant;

f is the original image to be diffused;

 $(f_x, f_y) = (u(0), v(0)).$

• Polar-representation version of GVD (Yu and Bajaj, ICPR02)





utricle

saccule

medical and biological importance of hearing

- 1 child in 1000 is born deaf
- **30 million Americans suffer from severe hearing problems** (~10% of population)
- large bandwidth
- high fidelity
- high sensitivity
- outstanding amplification
- high speed of detection
 - high dynamic range

semicircular canals

tectorial

membrane

basilar membrane oputation

nputation

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tectorial membrane

basilar

membrane



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hair bundle - hearing organelle of the hair cell

- direct mechanotransduction 1-2 channels/stereocilium
- adaptation machinery

via non-conventional myosin 1c

- amplification

spontaneous bundle oscillation, driven by myosin-motor proteins





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transduction & adaptation

- mechanical stretching of tip links opens mechanosensitive channel
- membrane depolarisation by $\mathrm{K}^{+},$ fast channel reclosure by Ca^{2+}

- slipping of adaptation machinery by conformational changes of myosin motor domain upon Ca²⁺ binding to calmodulin/IQ domain





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Detergent Extraction & PLT dehydration

- membranes partially dissolve
- raft-like structures remain
- actin filaments are well preserved
- extracellular links remain intact



200 nm

enter for stitute o partme

functional states of myosin 1c
-> rigor versus ATP
antibody labeling

enter for Computationa stitute of Computationa epartment of Compute

Imaging of a cell organelle







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structural organization of the adaptation machinery

- electronic "dissection" of the motor complex -





Side Plaque

20 nm



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2nd TIPLINK



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TipLink-Cilia





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Compute Critical Points Using GVD



•: minimum







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How GVD Helps Image Segmentation ?

- Fast Marching Method
 - Initial seed points
 - Stopping criterion
- Use GVD to locate seed points
 - Compute min/max critical points using GVD (discard saddle critical points)
 - All such critical points are used as seeds
 - Advantages: automatic, close to centers of homogenous regions, robust to noise due to vector diffusion.



Stopping Criteria Using Multiple-Contour

• Multiple-Contour

- Group the critical points (for example, two groups as follows:
 max. critical points is feature & min. critical points is background)
- Each seed initializes one contour, coupled with its group's I.D.
- Contours march simultaneously. Contours with same I.D. are merged while contours with different I.D. stop on their common boundaries









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Segmentation of TipLink (B206a)





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How GVD Helps Image Skeletonization ?

• Use GVD to locate critical points

Include minimum/maximum/saddle critical points

- Prune the Morse graph for more meaningful skeletons
- Advantages:
 - Robust to noise due to vector diffusion.
 - Critical points are on the "skeletons" of features even for "flat" regions.



Skeletons of ActinBundle (B280a)





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Reading

- 1. Z. Yu, C. Bajaj Computational Approaches for Automatic Structural Analysis of Large Bio-molecular Complexes *IEEE/ACM Transactions on Computational Biology and Bioinformatics, June 2007*
- 2. C. Bajaj, G. Xu, Q. Zhang **Bio-Molecule Surfaces Construction Via a Higher-Order Level Set Method** *Proceedings of the 14th CAD/CG International Conference, 2007, Beijing, China*
- 3. G. Xu, Q. Pan, C. Bajaj **Discrete Surface Modelling Using Partial Differential Equations** *Computer Aided Geometric Design, Volume 23/2, pp 125-145, 2006.*
- 4. Z. Yu, C. Bajaj Automatic Ultrastructure Segmentation of Reconstructed CryoEM Maps of Icosahedral Viruses IEEE Transactions on Image Processing: Special Issue on Molecular and Cellular Bioimaging, 2005 Sep;14(9):1324-37
- 5. C. Bajaj, Z. Yu, M. Auer Volumetric Feature Extraction and Visualization of Tomographic Molecular Imaging *Journal of Structural Biology, Volume 144, Issues* 1-2, October 2003, Pages 132-143
- 6. Z. Yu, C. Bajaj **A Fast and Adaptive Algorithm for Image Contrast Enhancement** *Proceedings of 2004 IEEE International Conference on Image Processing (ICIP'04), Volume 2, Oct. 24-27 2004, Pages 1001-1004, Singapore.*
- 7. Z. Yu, C. Bajaj A Segmentation-Free Approach for Skeletonization of Gray-Scale Images via Anisotropic Vector Diffusion Proceedings of 2004 IEEE International Conference on Computer Vision and Pattern Recognition (CVPR'04), Volume 1, Pages 415-420, Washington, DC.
- 8. C. Bajaj, J. Chen, R. Holt, A. Netravali **Energy Formulations of A-Splines** *Computer Aided Geometric Design*, *16:1(1999)*, *39-59.*

