Lecture 3: Geometric and Signal 3D Processing (and some Visualization)

Chandrajit Bajaj

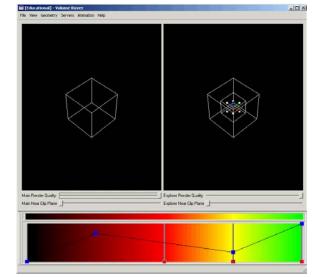


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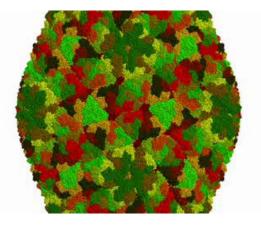
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Algorithms & Tools

- Structure elucidation: filtering, contrast enhancement, segmentation, skeletonization, subunit identification
- > Structure Modeling: finite element meshing, spline representations(Aspline,RBF representations) for structural fitting & complementary docking
- Visualization: multi-dimensional transfer functions, surface and volume texture rendering, wavelet compression, hierarchical representations, cluster based parallelism



VolRover





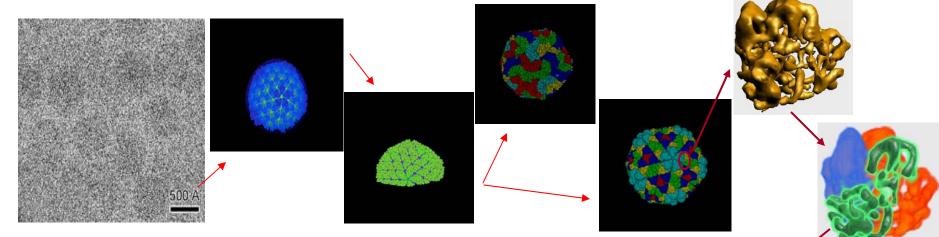


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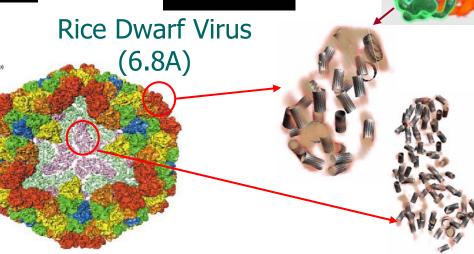
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Sub-nanometer Structure Elucidation from 3D Cryo-EM



Cryo-EM \rightarrow FFT based 3D Reconstruction \rightarrow Anisotropic and Vector Diffusion Filtering \rightarrow Structure Segmentation \rightarrow Quasi-Atomic Modeling \rightarrow Visualization



**Sponsored by NSF-ITR, NIH

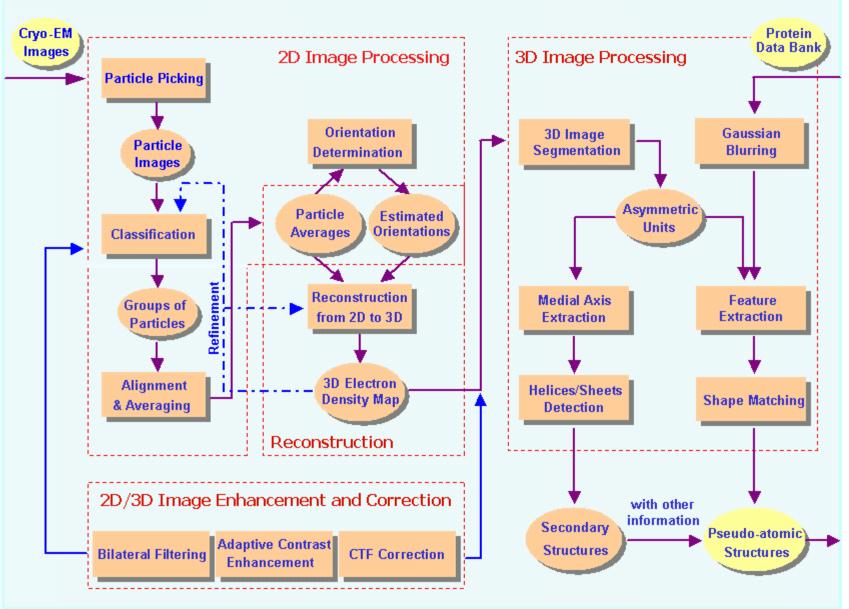


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A Structure Determination Pipeline for single particle cryo-EM

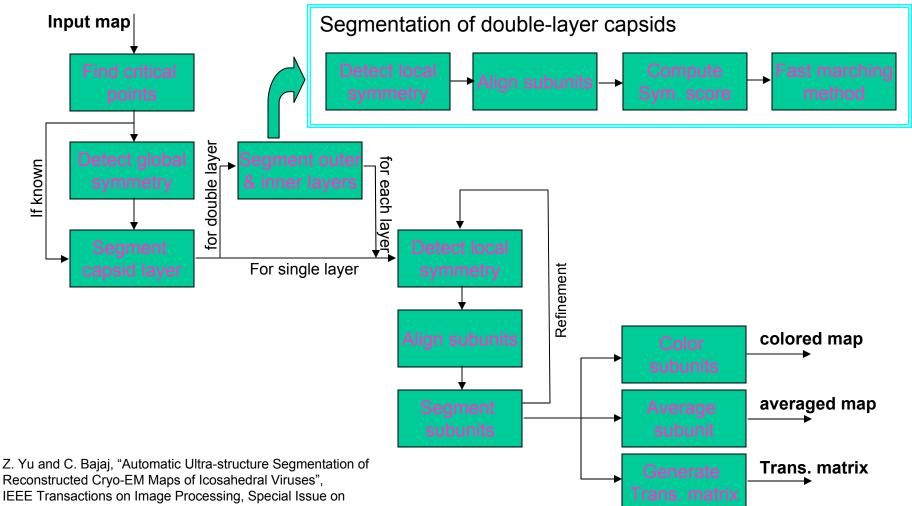


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Structure Elucidation for Icosahedral Viruses



Cellular/Molecular Imaging, 14(9), pp. 1324-1337, 2005.



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Structure Elucidation 1(A)

- Adaptive contrast enhancement
- Bilateral filtering

$$h(x,\xi) = e^{-\frac{(x-\xi)^2}{2\sigma_d^2}} \cdot e^{-\frac{(f(x)-f(\xi))^2}{2\sigma_r^2}}$$

- where σ_d and σ_r are parameters and f(.) is the image intensity value.
- Anisotropic diffusion filtering

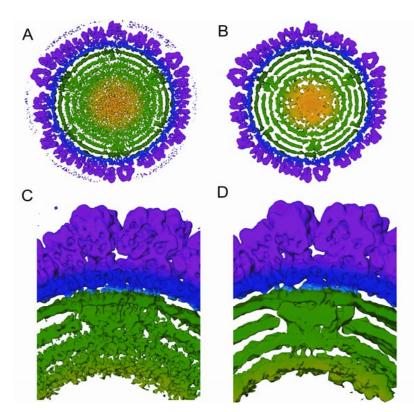
$$\partial_t \phi - \operatorname{div}(a(|\nabla \phi_\sigma|) \nabla \phi) = 0$$

where **a** stands for the diffusion tensor determined by local curvature estimation.

• Anisotropic gradient vector diffusion

C. Bajaj, G. Xu, ACM Transactions on Graphics, (2003),22(1), 4 - 32.

- Z. Yu & C. Bajaj, Proc. Int'l Conf. Image Processing, 2002. pp. 1001-1004.
- Z. Yu & C. Bajaj, Proc. Int'l Conf. Computer Vision and Pattern Recognition, 2004. 415-420.



W. Jiang, M. Baker, Q. Wu, C. Bajaj, W. Chiu, Journal of Structural Biology, 144, 5,(2003),114-122

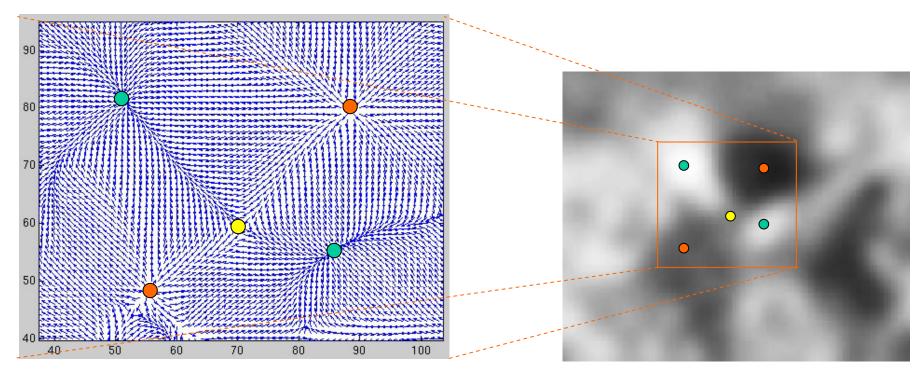


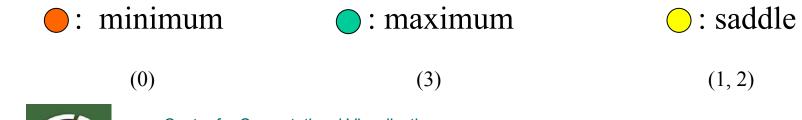
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Compute Critical Points Using AGVD







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Anisotropic Gradient Vector Diffusion (AGVD)

Isotropic Diffusion (Xu et al., 1998)

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

Where:

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

f is the original image to be diffused;

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

Anisotropic Diffusion (Yu & Bajaj ICPR'02) $\begin{cases} \frac{\partial u}{\partial t} = \mu \nabla (g(\alpha) \cdot \nabla u) - (u - f_x)(f_x^2 + f_y^2) \\ \frac{\partial v}{\partial t} = \mu \nabla (g(\alpha) \cdot \nabla v) - (v - f_y)(f_x^2 + f_y^2) \end{cases}$

Where

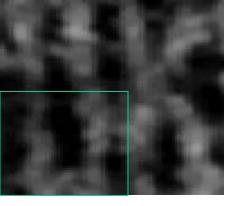
(u(t), v(t)) stands for vector field; μ is a constant; $(f_x, f_y) = (u(0), v(0))$. *f* is the original image to be diffused; g(.) is the angle between two vectors



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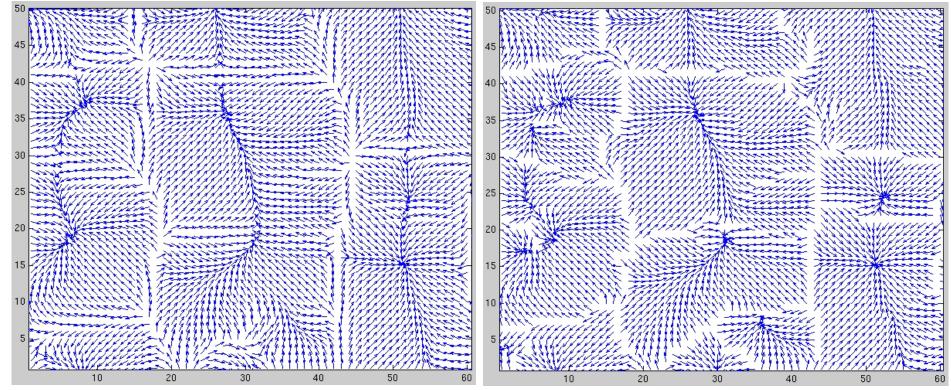
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GVD v.s. AGVD

Isotropic diffusion

Anisotropic diffusion





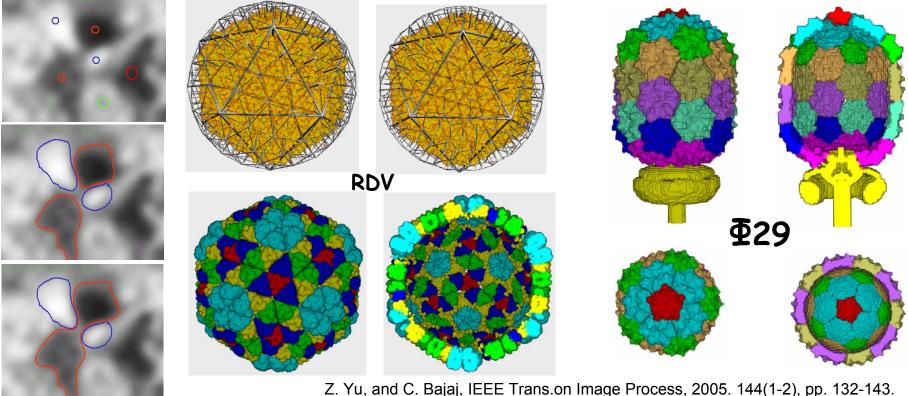
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Structure Elucidation 1(B)

- Multi-seed Fast Marching Method
 - Classify map critical points as seeds based on local symmetry.
 - Each seed initializes a contour, with its group's membership.
 - Contours march simultaneously. Contours with same membership are merged, while contours with different membership stop each other.

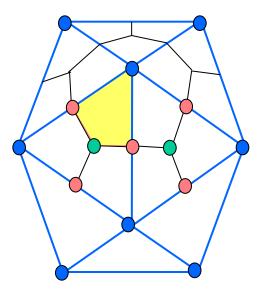


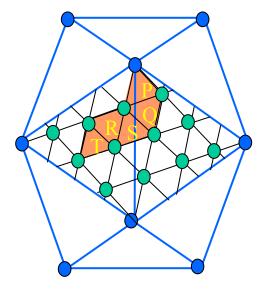


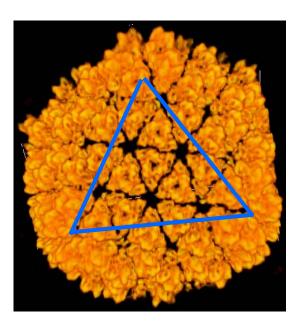
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Global and Local Symmetry

• Automatic structure unit identification in a 3D Map







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

Example: RDV



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Symmetry Detection: Correlation Search

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

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

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

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

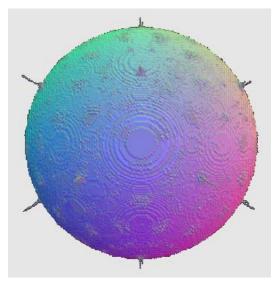
- Locate the symmetry axes
 - The 12 peaks
- Refine the symmetry axes
 - In order to locate a perfect icosahedron

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

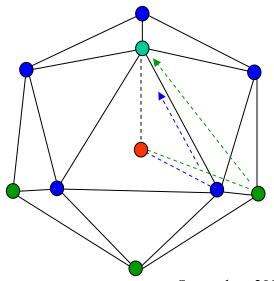


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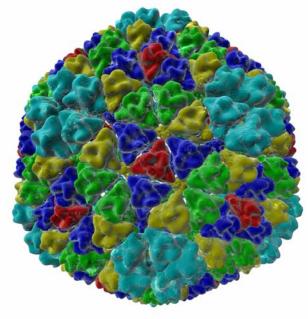
Inverted and normalized SF(Bj)



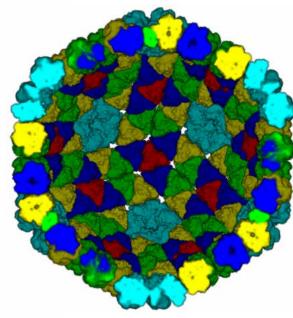
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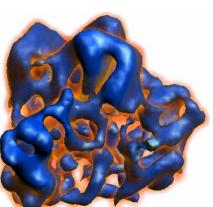
Structure Elucidation Results: RDV (Bakeoff)



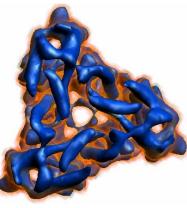
surface rendering (outside)



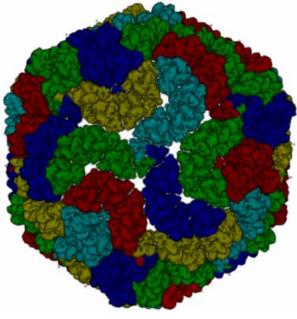
volume rendering (inside)



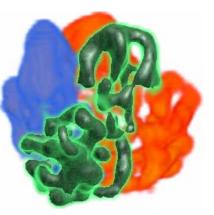
averaged trimer (side)



averaged trimer (bottom) Center for Computational Visualization Institute of Computational and Engineering Sciences **Department of Computer Sciences**



volume rendering (asymmetric unit)

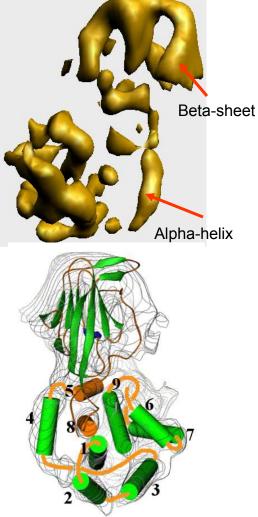


segmented monomers

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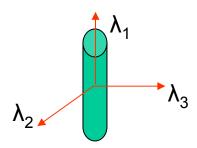
Structure Elucidation 1(C): Secondary Structure Identification

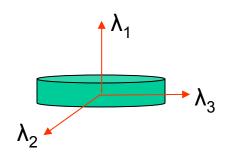




 $G_{\sigma} * \begin{pmatrix} I_x^2 & I_x I_y & I_x I_z \\ I_x I_y & I_y^2 & I_y I_z \\ I_x I_z & I_y I_z & I_z^2 \end{pmatrix}$

The eigenvectors of the local structure tensor give the principal directions of the local features:





Line structure (alpha-helix)

 $\lambda_2 \approx \lambda_3 >> \lambda_1 \approx 0$

plane structure (beta-sheet)

 $\lambda_1 >> \lambda_2 \approx \lambda_3 \approx 0$

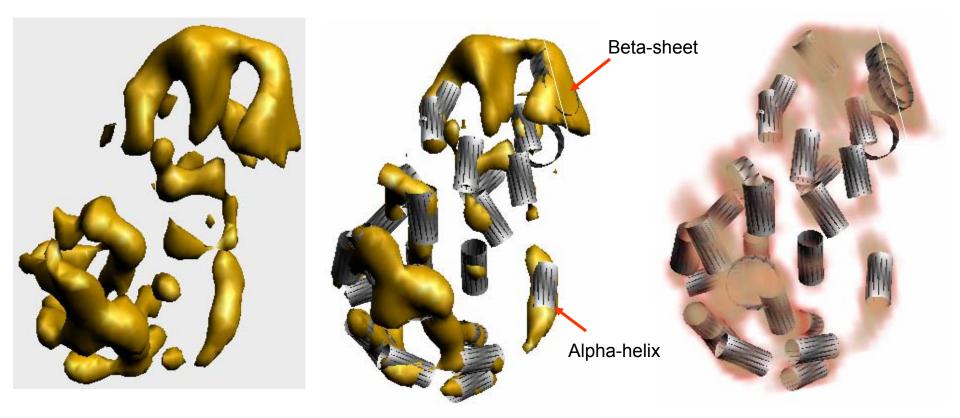


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Monomeric Unit of Outer Capsid of RDV

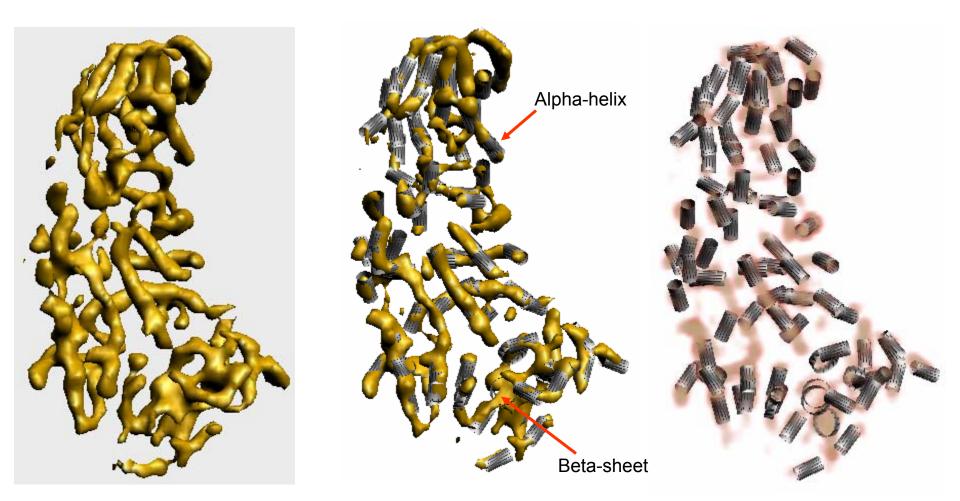




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Monomeric Unit of Inner Capsid of RDV

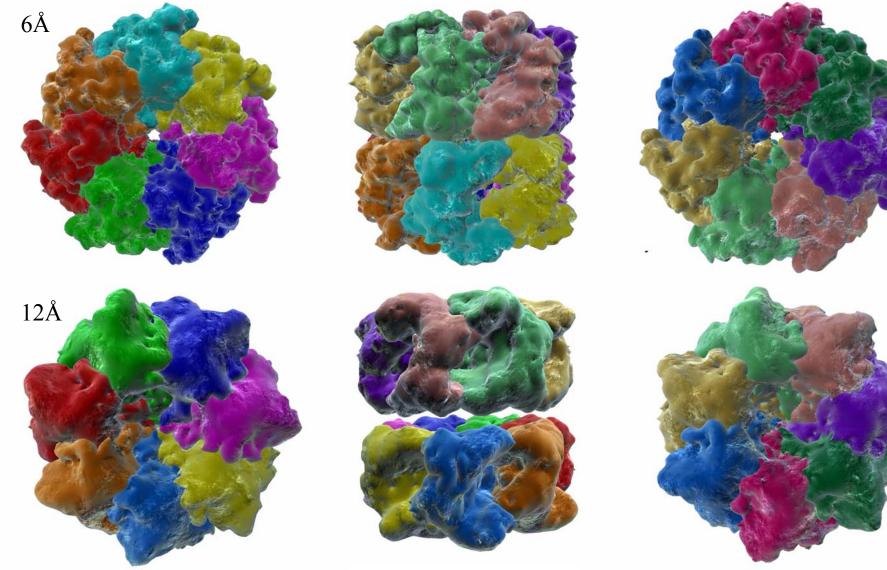




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Structure Elucidation Results: GroEL

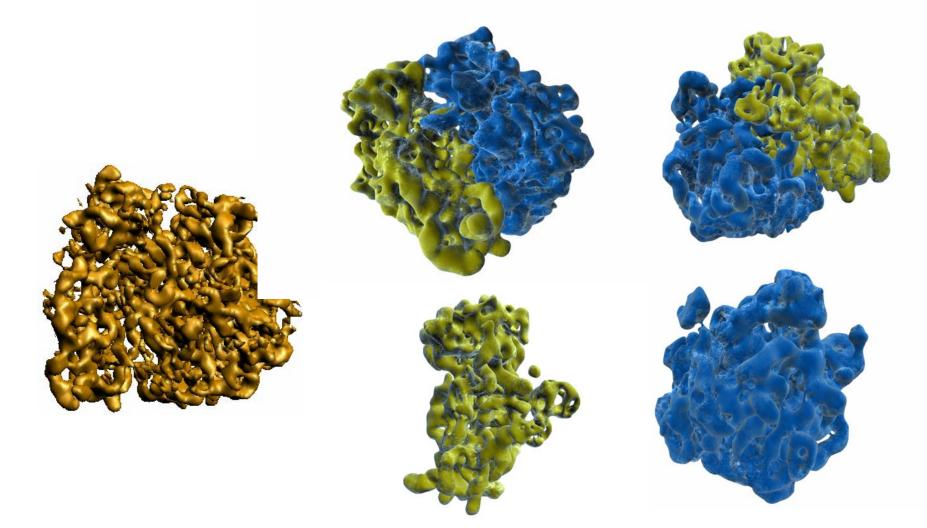




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Data courtesy: Dr. Wah ChiuUniversity of Texas at AustinSeptember 2007

Segmentation Results: Ribosome (Bakeoff)



70S ribosome from E. coli complex. 70S-tRNAfMet-MF-tRNAPhe. Data courtesy: EBI & J.Frank

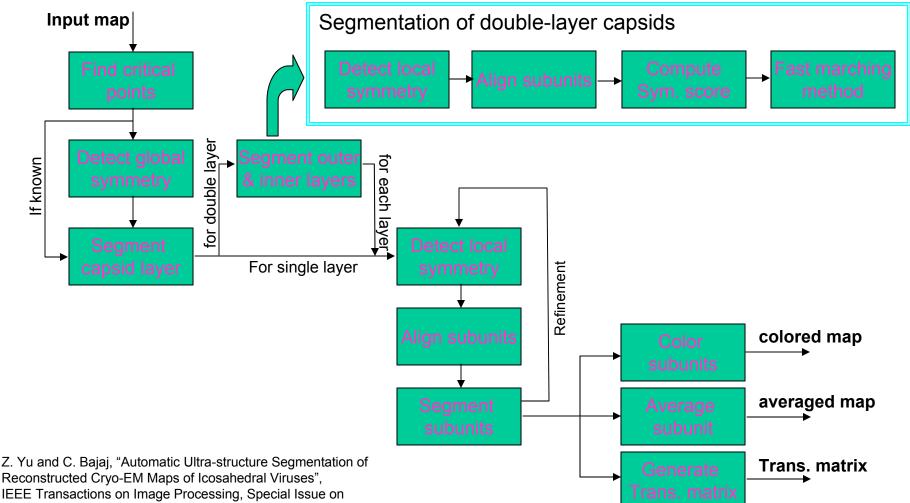


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Structure Elucidation for Symmetric Capsid Viruses



Cellular/Molecular Imaging, 14(9), pp. 1324-1337, 2005.

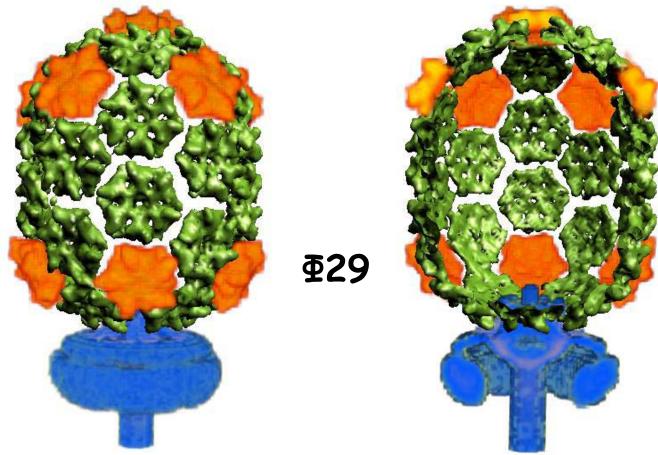


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Subunit alignment (1): averaging



The above two pictures (left: outer; right: inner) show the averaged capsid layer, calculated from one 5-fold subunit (orange) and one 6-fold subunit (green). The tail structure (blue) is augmented after the averaging.



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Data courtesy: Tim Baker

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• Cross-correlation

	#0	#1	#2	#3
#0	1	0.95	0.95	0.34
#1	0.95	1	0.96	0.31
#2	0.95	0.96	1	0.31
#3	0.35	0.31	0.32	1

	#4	#5	#6	#7	#8	#9
#4	1	0.79	0.95	0.94	0.87	0.88
#5	0.79	1	0.79	0.78	0.77	0.79
#6	0.95	0.79	1	0.96	0.88	0.88
#7	0.94	0.78	0.96	1	0.89	0.88
#8	0.87	0.77	0.88	0.89	1	0.94
#9	0.88	0.79	0.88	0.88	0.94	1

1.2 0.99 0.96 0.96 ^{0.99} 0.97 0.98 0.96 **29** 1 0.87 0.81 0.81 auto-correlation 0.8 0.6 0.4 0.2 0 #0 #1 #2 #3 #4 #5 #6 #7 #8 #9

Symmetry score

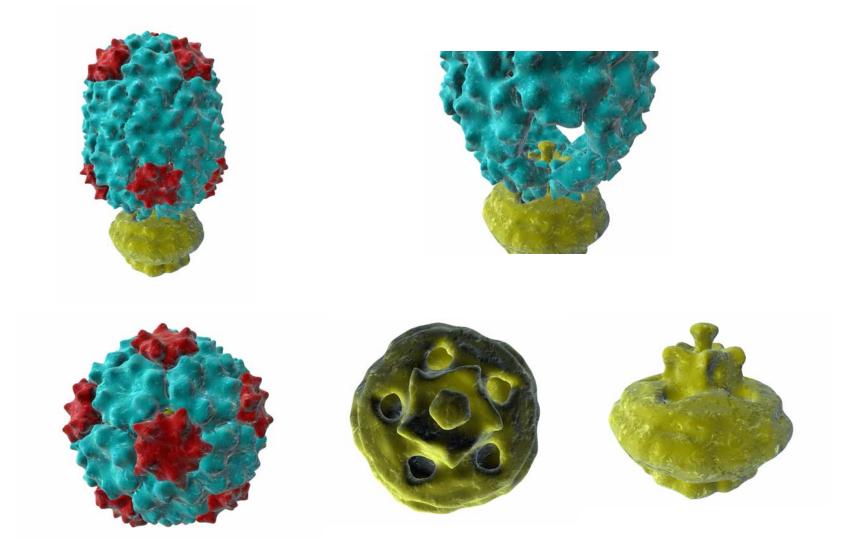


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8-

segmented subunit Center for Computational Visualization Institute of Computational and Engineering Sciences Department of Computer Sciences

Structure Elucidation Results: **Ф29**

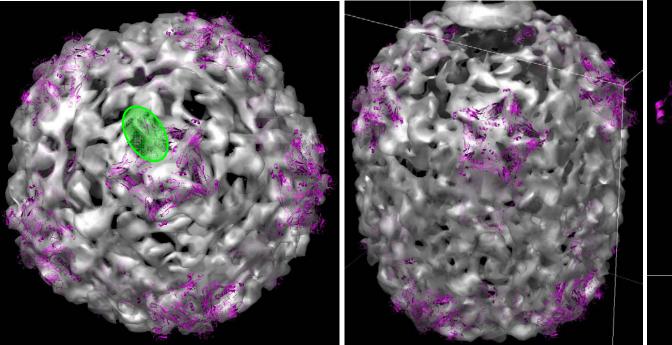




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Data courtesy: Tim Baker University of Texas at Austin

Subunit alignment (2): Fitting

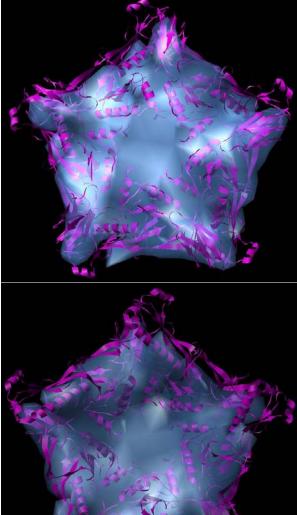


The PDB structure of one monomer is matched & fit into the cryo-EM map (as shaded in green in the left figure). Then all the quasisymmetric 5-fold subunits are computationally fit with the PDB structure using the transform matrices obtained in subunit alignment. Similar procedure can be applied to all 6-fold subunits.



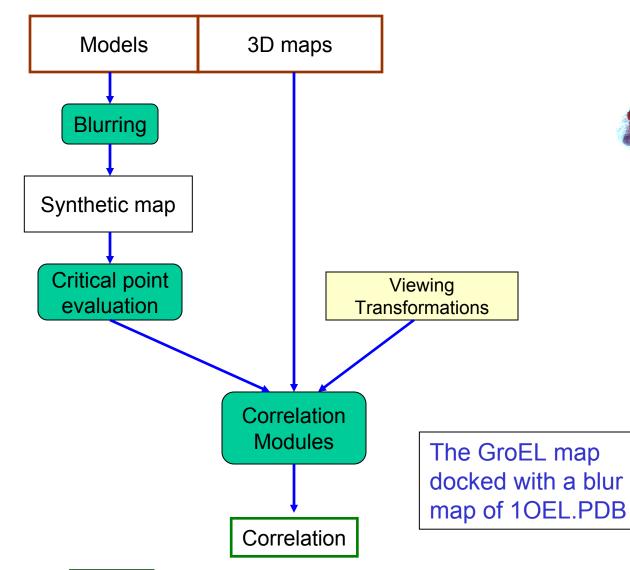
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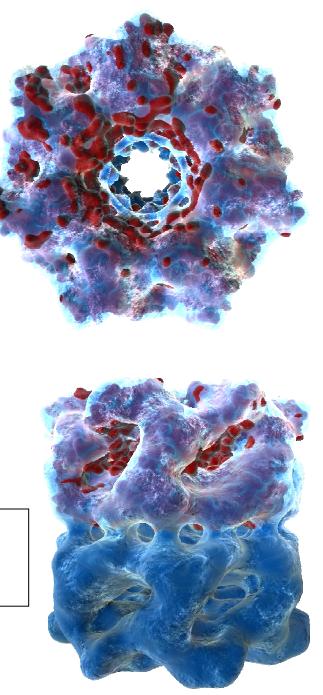
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"Interactive" Fitting





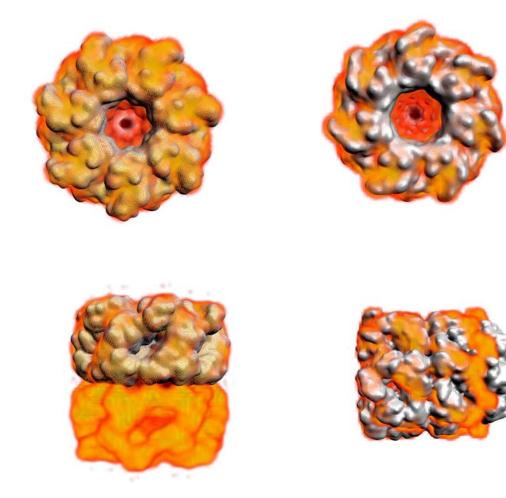


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Gro-EL: X-ray structures docked in Cryo-EM

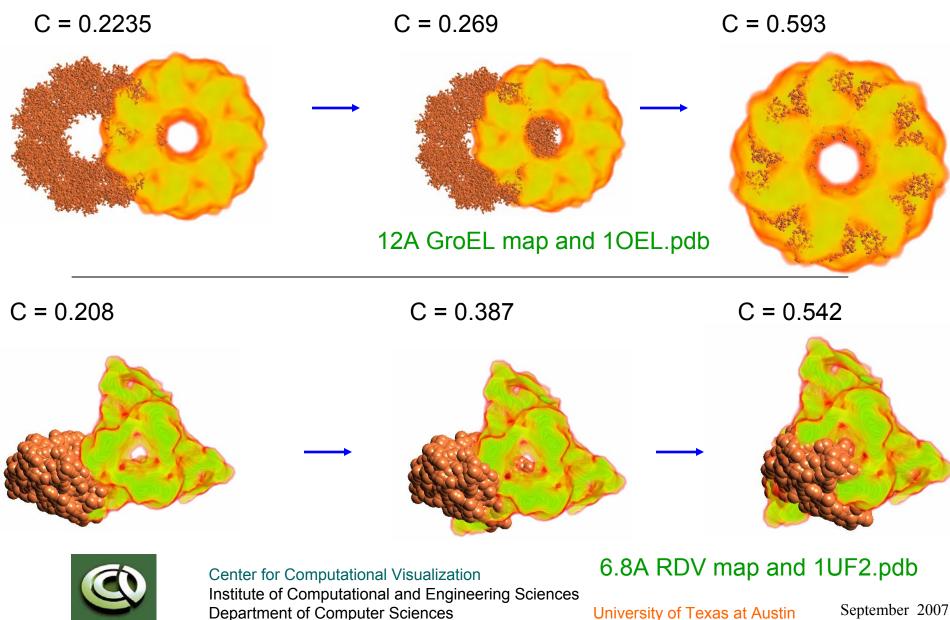




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Interactive Correlation Analysis



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Approximate Correlation Analysis

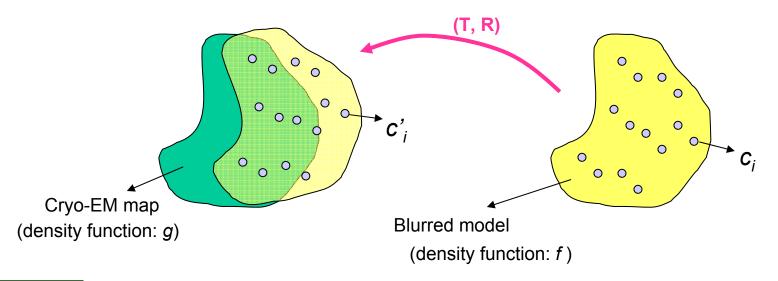
$$score = 1 - \frac{\sum_{i=1}^{N} |f(c_i) - g(c'_i)|}{\sum_{i=1}^{N} \max(f(c_i), g(c'_i))}$$

Where *f* is the normalized density function of the blurred crystal structure;

g is the normalized density function of the cryo-EM map;

 c_i , i=1,2,...N, are the critical points of the blurred crystal structure;

 c'_i , i=1,2,...N, are the transformations of the critical points.





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Blurring I

• For a molecule with M atoms, we can define a 3D electron density map as

$$f_{elec_dens}(\vec{\mathbf{x}}) = \sum_{i=1}^{M} G_i(\vec{\mathbf{x}}) \quad \mathbf{x} \in \mathbf{R}^3$$

• For quadratic decay kernels, $A_i = e^d$:

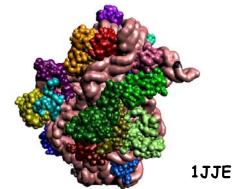
$$f_{elec_dens}(\mathbf{x}) = \sum_{i=1}^{M} A_i e^{-\frac{d}{r^2} \mathbf{x}^2} \delta(c_i)$$

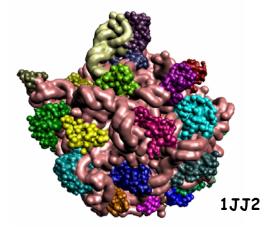
• For linear decay kernels, $A_i = e^{dri}$:

$$f_{elec_dens}(\mathbf{x}) = \sum_{i=1}^{M} A_i e^{-d|\mathbf{x}|} \delta(c_i)$$



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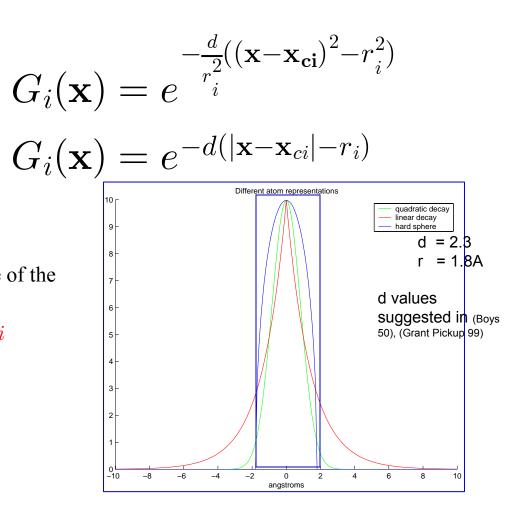




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Atomic Shape Parameters

- Isotropic Quadratic Kernel
- Isotropic Linear Kernel
 - ➢ where
 - The decay d controls the shape of the Gaussian function.
 - \succ The van der Waals radius is r_i
 - > The center of the atom is \mathbf{x}_{c} .
- Anisotropic Kernels





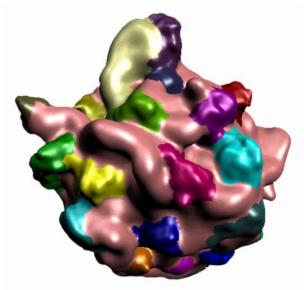
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Blurring II

- For quadratic decay kernels, $A_i = e^d$: $f_{elec_dens}(\mathbf{x}) = \sum_{i=1}^M A_i e^{-\frac{d}{r^2}\mathbf{x}^2} \delta(c_i)$
- For linear decay kernels, $A_i = e^{dri}$: $f_{elec_dens}(\mathbf{x}) = \sum_{i=1}^{M} A_i e^{-d|\mathbf{x}|} \delta(c_i)$



• For above kernels G:

$$f_{elec_dens}(\mathbf{x}) = G \otimes \sum_{i=1}^{M} A_i \delta(c_i)$$



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Institute of Computational and Engineering Sciences Department of Computer Sciences $\sum_{i=1}^{M} A_i \delta(\overrightarrow{x} - \overrightarrow{x_i}) \qquad \mathbf{G}$

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