Extracting Structure from 3D Images

Joseph Schlecht
Dept. of Computer Science
University of Arizona

Computer Vision and ... Fungus

- Collaboration with mycologist Barry Pryor (UA) to analyze images of fungus
- Genus *Alternaria*
  - ~50 distinct species
  - Infects human and plant tissue
  - Microscopic
- Images of fungus obtained from microscope
  - Sequence of images created by varying focal length of microscope
  - 3D Microscopy

http://www.botany.utoronto.ca
3D Microscopy

- Transmitted light microscope
- Very shallow depth of field
  - Ratio of focal length to aperture very large


3D Microscopy

- View of fungus is imaged while focal length varied
- Results in a stack of images
  - Volumetric image data $I(x,y,z)$
- Image at depth $d$ contains
  - In-focus portions of fungus within DOF
  - Blurry portions of fungus outside DOF at depths $\neq d$
**Analysis Goals**

- Automatically extract *Alternaria* structure
  - Visualization
  - Morphological quantification
  - Species classification
  - Link extracted structure to DNA

**Approaches**

- Initial approach focused on edge detection
  - Useful for visualization
- Probabilistic modeling approach
  - Good model will capture essence of the fungus
  - Enables pursuit of all analysis goals

**Surface Detection**

- 3D Edge detector
  - Extension of standard 2D Canny algorithm
- Convolve image stack with gradient of 3D Gaussian kernel
  - \( \nabla I(x,y,z) = I(x,y,z) \ast \ast \ast \nabla G_o(x,y,z) \)
  - Results in 3D gradient vector at each pixel
- Surface points defined by
  - All \( v \) in \( \nabla I(x,y,z) \) with \( |v| > t \)
2D Edge Detection

Resulting Gradient
**Gradient Magnitude**

If gradient magnitude larger than threshold, mark it as an edge point.

**Thick Edges**

Results in thick edges, depending on $\sigma$.

Use non-maximal suppression.

Choose max value along gradient.
**Edge Following**

- Follow edges in direction perpendicular to maximal gradient vector
- Re-apply non-maximal suppression
- Stop when maximal gradient magnitude drops below threshold
  - Hysteresis

**Surface Detection**

- Results in thick, bulky surfaces depending on $\sigma$
- Non-maximal suppression
  - For each $v$ in $\nabla f(x,y,z)$ with $|v| > t$
    - Follow direction of $v$ until $|u| < |v| > |w|$
    - Where $u, w$ are neighbors in same/opposite direction of $v$
    - Mark $v$ as surface point
- Follow maximum surface points (hysteresis)
  - For each neighbor $u$ orthogonal to direction of $v$
    - If $|u| > t'$, apply non-maximal suppression to $u$ using $t' < t$
- Construct 3D surface from detected points
  - Location of $v$ in $\nabla f(x,y,z)$ gives position of surface point
  - Use direction of $v$ to define surface orientation of a small surface patch
Modeling Alternaria

- Surface detection useful for visualization
  - Difficult to accomplish other goals
- Instead model Alternaria as a geometric structure
  - Fit parameters to data using statistical inference
- Could model it as a set of connected ellipsoids and cylinders
  - Good model simplifies structure but is also explanatory
- Initial model
  - Set of independent ellipsoids, [al-Awadhi 2003]
  - $\theta_i = (x, y, z, a, b, c, \varphi, \theta, \psi, \lambda)$

Model

- Use Bayesian inference to estimate parameters
  - $p(\theta | I) = c \cdot L(I | \theta) \cdot \pi(\theta)$
- From model parameters $\theta$, define $J$ as the (true) image scene
- Use $J$ to construct data likelihood
  - $L(I | \theta) = \prod_k G(I_k ; \mu_k, \sigma_k^2)$
  - where $\mu_k = J_k$, $\sigma_k^2 \propto J_k$
**Model**

- Model prior
  
  \[ \pi(\theta) = G(n; \mu_n, \sigma_n) \prod_{i=1}^{n} f_i(x_i, y_i, z_i) f_i(\alpha_i, \beta_i, \gamma_i) f_p(\lambda_i) \]

- Initially used near uniform distributions for \( f \)

- Improved by detecting near uniform estimates of ellipsoid parameters in data \( f \)
  
  - Apply Hough transform to (approximately) find ellipsoids
  
  - Vote for ellipsoids that fit the data
  
  - More votes == more likely

- Define probability distribution over ellipsoid parameters

- Uses output from surface detection

**Sampler**

- Posterior distribution over parameters very complex

- Created an MCMC sampler to find most likely \( \theta \)
  
  - Iteratively generates more likely samples from posterior
  
  - Used Metropolis-Hastings algorithm
    
    - Each iteration, generate a proposal and accept or reject
    
    - \[ \alpha(\theta') = \min \left[ 1, \frac{q(\theta') p(\theta' | I)}{q(\theta) p(\theta | I)} \right] \]

- Proposal types
  
  - shift, resize, rotate, intensity
  
  - birth, death, split, merge

- Proposals from Hough transform (as in \( \pi \))
  
  - Data-driven MCMC
Results

- Validation of model on synthetic data
  - 10 ellipsoids
  - 80 images
  - 300x300
Results

- Sampler is expensive for volumetric image data
- Run it on increasing resolutions of the image data
Results

- Results from *Alternaria* data
  - 102 images
  - 700x700
Future Work

- Improve model prior to enforce connectedness between ellipsoids
  - Create conditionals for each ellipsoid
    \[ \pi(\theta) = G(n; \mu_\alpha, \sigma_\alpha) \prod_{\rho=1}^n \pi_i(\theta_i | \theta_{i-1}, \ldots, \theta_1) \]
- Questions?