Fundamental limits on shape estimation Alfred Hero University of Michigan - Ann Arbor http://www.eecs.umich.edu/~hero/hero.html Students: Jia Li and Robinson Piramuthu

# Outline

- $\blacktriangleright$  Resolution–limited imaging problem
- ► Parametric shape model
- ➡ Minimum achievable estimator variance: the CR bound
- $\blacktriangleright$  Bound sensitivity and extremal shapes
- $\blacktriangleright$  Numerical comparisons

## **Resolution Limited Imaging Problem**





An arbitrary two–level image containing boundary curve  $r_{\tilde{\theta}}$ 

## Notation:

- $I_{\tilde{\theta}}(x,y) = True image$ 
  - $\tilde{\theta}$  = Parameterization of boundary of object
  - $I_{R_{\tilde{\theta}}}$  = Indicator function for the object  $R_{\tilde{\theta}}$
  - $C_{\rm INT}$  = Uniform intensity of interior of  $R_{\tilde{\theta}}$

 $C_{\rm BG}$  = Uniform intensity of background

$$\mathbf{I}_{\tilde{\boldsymbol{\theta}}}(x,y) = C_{\mathrm{INT}} \cdot \mathbf{I}_{R_{\tilde{\boldsymbol{\theta}}}}(x,y) + C_{\mathrm{BG}} \cdot (1 - \mathbf{I}_{R_{\tilde{\boldsymbol{\theta}}}}(x,y)).$$







Examples: B-splines, Fourier descriptors, Bezier curves, ...



#### Finite dimensional parameterization: B-splines

- Polar parameterization by periodic B–splines with a fixed number K of knots.
- ✤ Notation:

$$\boldsymbol{\theta} = \text{B-spline coefficients}$$

$$B_i(\phi) = i\text{-th B-spline basis at angle } \phi$$

$$r_{\boldsymbol{\theta}}(\phi) = \sum_{i=1}^{K} \theta_i B_i(\phi) = \boldsymbol{B}^T(\phi) \boldsymbol{\theta} \text{ (radial samples).}$$



The periodic cubic B– spline basis functions for an equiangularly spaced set of 9 knots on domain  $[-\pi, \pi]$ .

## CR Bound

• Cramèr–Rao lower bound:

For any unbiased estimator  $\hat{\boldsymbol{\theta}}$  of parameter vector  $\boldsymbol{\theta}$ :

$$\operatorname{cov}_{\boldsymbol{\theta}}\left(\hat{\boldsymbol{\theta}}\right) \geq F_{\boldsymbol{\theta}}^{-1}$$

where  $F_{\theta}$  is Fisher information matrix

$$F_{\boldsymbol{\theta}} = E_{\boldsymbol{\theta}} \left[ -\nabla^2 \log f(\boldsymbol{Y}_M | \boldsymbol{\theta}) \right]$$

$$\boldsymbol{F}_{\boldsymbol{\theta}} = C_{\text{CN}} \iint_{-\pi}^{\pi} \exp\left[-\frac{\|\vec{r}_{\boldsymbol{\theta}}(\phi) - \vec{r}_{\boldsymbol{\theta}}(\gamma)\|^{2}}{4\sigma_{s}^{2}}\right] r_{\boldsymbol{\theta}}(\phi) r_{\boldsymbol{\theta}}(\gamma) \boldsymbol{B}(\phi) \boldsymbol{B}^{T}(\gamma) d\phi d\gamma$$
(1)

where

$$C_{\rm CN} = \frac{\left(C_{\rm INT} - C_{\rm BG}\right)^2}{4\pi\sigma_n^2\sigma_s^2} = \frac{\left(contrast\right)^2}{4\pi\sigma_n^2\sigma_s^2}$$

# Asymptotic Fisher Information for 2–D

• Define:

$$h_{\boldsymbol{\theta}}(\psi) = \frac{r_{\boldsymbol{\theta}}^2}{\sqrt{r_{\boldsymbol{\theta}}^2(\psi) + \left[r_{\boldsymbol{\theta}}'(\psi)\right]^2}}$$

and

$$\sigma_m = \max_{\phi} \left\{ \frac{\sqrt{2}\sigma_s}{\left| \left| \vec{r'_{\theta}}(\phi) \right| \right|} \right\}$$

• Then:

$$\boldsymbol{F}_{\boldsymbol{\theta}} = \frac{(contrast)^2}{2\sqrt{\pi}\sigma_s\sigma_n^2} \cdot \int_{-\pi}^{\pi} h_{\boldsymbol{\theta}}(\psi) \ \boldsymbol{B}(\psi) \boldsymbol{B}^T(\psi) d\psi + o(\sigma_m)$$



Figure 1: Relation between tangent line and  $h_{\theta}(\psi)$ .

# Fisher Information Matrix for 3–D

$$\begin{aligned} \boldsymbol{F}_{\boldsymbol{\theta}} &= C_{\mathrm{CN}} \cdot \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \int_{-\pi}^{\pi} \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \int_{-\pi}^{\pi} \exp\left(\frac{\|\vec{r}_{\boldsymbol{\theta}}(\alpha_{1},\beta_{1}) - \vec{r}_{\boldsymbol{\theta}}(\alpha_{2},\beta_{2})\|^{2}}{-4\sigma_{s}^{2}}\right) \\ r_{\boldsymbol{\theta}}^{2}(\alpha_{1},\beta_{1}) r_{\boldsymbol{\theta}}^{2}(\alpha_{1},\beta_{2}) \cdot \boldsymbol{B}(\alpha_{1},\beta_{1}); \boldsymbol{B}^{T}(\alpha_{2},\beta_{2}) \cos\alpha_{1}\cos\alpha_{2} d\alpha_{1} d\beta_{1} d\alpha_{2} d\beta_{2} \\ \text{where} \end{aligned}$$

$$C_{\rm CN} := \frac{(C_{\rm INT} - C_{\rm BG})^2}{8\pi^{3/2}\sigma_s^3\sigma_n^2} = \frac{\rm contrast^2}{8\pi^{3/2}\sigma_s^3\sigma_n^2}.$$

# Asymptotic Fisher Information for 3–D

• Define:

$$h_{\boldsymbol{\theta}}(\alpha,\beta) = \frac{\boldsymbol{r}_{\boldsymbol{\theta}}^{3}(\alpha,\beta)}{\sqrt{\left[\boldsymbol{r}_{\boldsymbol{\theta}}^{10}(\alpha,\beta)\right]^{2} + \left[\boldsymbol{r}_{\boldsymbol{\theta}}^{01}(\alpha,\beta)\right]^{2} + \boldsymbol{r}_{\boldsymbol{\theta}}^{2}(\alpha,\beta)}}$$

• Then:

$$\boldsymbol{F}_{\boldsymbol{\theta}} = 4\pi C_{\rm CN} \sigma_s^2 \int_{\alpha = -\frac{\pi}{2}}^{\frac{\pi}{2}} \int_{\beta = -\pi}^{\pi} h_{\boldsymbol{\theta}}(\alpha, \beta) \boldsymbol{B}(\alpha, \beta) \boldsymbol{B}^T(\alpha, \beta) \cos^2 \alpha \, d\alpha \, d\beta$$

 $+o(\sigma_m)$ 



Figure 2: Unit tangent and normal vectors for a spherical surface through P. Here, O is the center of the sphere as well as the center-of-description.



### **Optimum Center of Description: example**



Figure 4: Sensitivity of CR bound to shift in center-of-description of a test shape.

#### Worst-Case 2–D Shape Analysis via FIM

• Consider minimization of

trace{
$$F_{\theta}$$
} =  $C \int_{\phi=-\pi}^{\pi} h_{\theta}(\phi) f_B(\phi) d\phi$ 

(2)

where  $C = \frac{(contrast)^2}{2\sqrt{\pi}\sigma_s\sigma_n^2}$  and

$$f_B(\phi) = \boldsymbol{B}^T(\phi)\boldsymbol{B}(\phi) = \sum_{i=1}^K B_i^2(\phi).$$

• under fixed perimeter constraint

$$P = \int_{\phi=-\pi}^{\pi} \sqrt{[r_{\theta}(\phi)]^2 + [r'_{\theta}(\phi)]^2} d\phi = 1.$$
 (3)



Figure 5: Collection of worst shapes on quadratic B-splines basis.

### Worst-Case Nearly Circular 2–D Shapes

• circularity measure:

$$\gamma = \frac{4\pi A}{P^2} = \frac{4\pi \int_{\phi=-\pi}^{\pi} \boldsymbol{r}_{\boldsymbol{\theta}}^2(\phi) d\phi}{\left(\int_{\phi=-\pi}^{\pi} \sqrt{[\boldsymbol{r}_{\boldsymbol{\theta}}(\phi)]^2 + [\boldsymbol{r}_{\boldsymbol{\theta}}'(\phi)]^2} d\phi\right)^2}$$

where  $\gamma \in [0,1]$ 

• Lagrangian for: max trace  $\{F_{\theta}\}$  s.t.  $\gamma \ge 1 - \epsilon, P = 1$ 

$$L(\boldsymbol{\theta}) = a_f^T \boldsymbol{\theta} - \frac{1}{2} \boldsymbol{\theta}^T D_f \boldsymbol{\theta} + \lambda_1 \boldsymbol{\theta}^T Q \boldsymbol{\theta} + \lambda_2 (a^T \boldsymbol{\theta} + \frac{1}{2} \boldsymbol{\theta}^T D \boldsymbol{\theta})$$



Figure 6: Worst-shapes local to a circle for finite dimensional case with quadratic B-splines and equally spaced knots.

#### Worst-Case Nearly Spherical 3–D Shapes

• sphericity measure  $\gamma \in [0, 1]$ :

$$\begin{split} \gamma &= \frac{36\pi S^3}{V^2} = \\ \frac{36\pi \left(\int \sqrt{[\boldsymbol{r}_{\boldsymbol{\theta}}(\alpha,\beta)]^2 + [\boldsymbol{r}_{\boldsymbol{\theta}}^{10}(\alpha,\beta)]^2 + [\boldsymbol{r}_{\boldsymbol{\theta}}^{01}(\alpha,\beta)]^2} \ \boldsymbol{r}_{\boldsymbol{\theta}}(\alpha,\beta) \cos(\alpha) d\alpha d\beta\right)^3}{\left(\int_{-\pi/2}^{\pi/2} \int_{-\pi}^{\pi} \boldsymbol{r}_{\boldsymbol{\theta}}^3(\alpha,\beta) \cos(\alpha) d\alpha d\beta\right)^2} \end{split}$$

• Lagrangian for max trace  $\{F_{\theta}\}$  s.t.  $\gamma \ge 1 - \epsilon, P = 1$ 

$$L(\boldsymbol{\theta}) = \boldsymbol{\theta}^T [Q_f - \frac{1}{2}D_f] \boldsymbol{\theta} + \lambda_1 (\boldsymbol{\theta}^T Q \boldsymbol{\theta} - a^T \boldsymbol{\theta}) + \lambda_2 (\frac{1}{2} \boldsymbol{\theta}^T [D + Q] \boldsymbol{\theta} + a^T \boldsymbol{\theta}$$







Worst shape for 4 knots (equal for azimuth and elevation basis)

(a)  $3 \times 3$  Knots

(b)  $4 \times 4$  Knots

Figure 7: Worst-shapes local to a sphere.



#### Worst shape for 8 knots (equal for azimuth and elevation basis)



Worst shape for 12 knots (equal for azimuth and elevation basis)

(a)  $8 \times 8$  Knots



Figure 8: Worst-shapes local to a sphere.

# Edge Filtering Technique

- Transform observed data from cartesian coordinates to spherical coordinates.
- Apply edge filter ( [-1,...,-1,1,...,1]) along each angle and extract edge.
- Apply a 2 x 2 median filter to this extracted surface of radial values.

Drawbacks:

- $\blacktriangleright$  Bias due to system PSF.
- ➡ Sensitive to noise.

# Edge Filtering Technique (contd.)







## Empirical Bias as a Function of $\sigma_s$



# Empirical Bias as a Function of $\sigma_n$



### Empirical Standard Deviation as a Function of $\sigma_s$



### Empirical Standard Deviation as a Function of $\sigma_n$



# **Conclusions**

- CR bound permits study of sensitivity of minimum achievable boundary estimation error
- **2** Approach has been applied to
  - MRI-aided PET: Fisher information = confidence of side info
  - Analysis of lung nodule quantification in ECT
  - PET/CT/MRI image registration studies
  - Assessment of ML, active contour, and edge filtering methods of shape estimation

**3** Method restricted to star shaped objects