

Stochastic analysis of (sub-pixel) geometric image processing using B-splines

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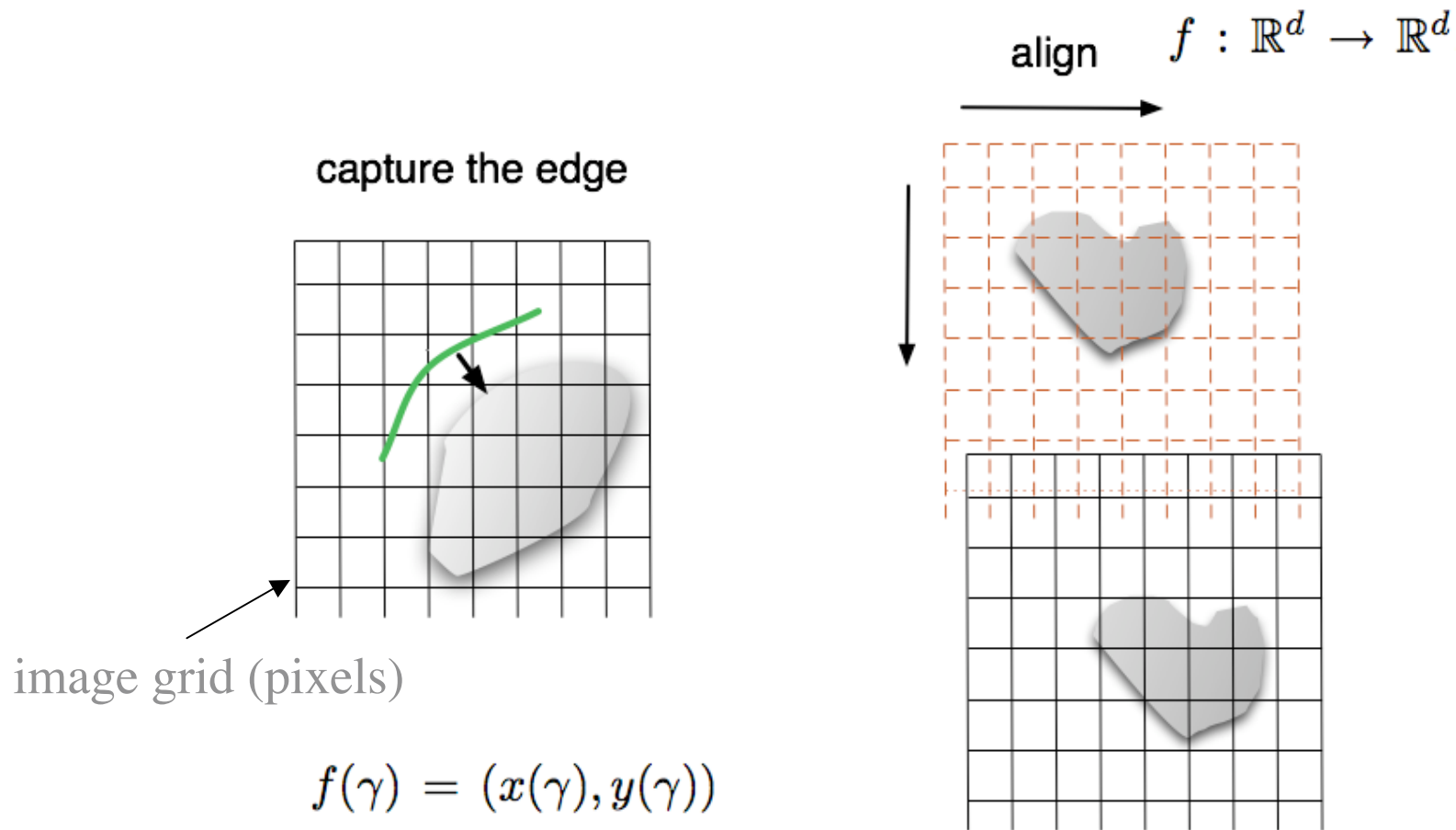
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Sub-pixel geometric image processing



Variational energy minimization framework

$$\arg \min_f \Psi(s_1(\mathbf{x}), s_2(\mathbf{x}), \dots, f) = \underbrace{\Psi_{data}(s_1(\mathbf{x}), s_2(\mathbf{x}), \dots, f)}_{\text{Image force term}} + \Psi_{constraint}(f)$$

- registration (alignment): $f : \mathbb{R}^d \rightarrow \mathbb{R}^d$
- edge detection: $f(\gamma) = (x(\gamma), y(\gamma))$

Image registration

$$\Psi_{data}(s_1(\mathbf{x}), s_2(\mathbf{x}), \dots, f) = \int_{\mathbb{R}^d} \Upsilon(\mathbf{x}, f) d\mathbf{x}$$

$$\Upsilon(\mathbf{x}, f) = \frac{1}{2} (s_1(\mathbf{x} + \mathbf{v}(\mathbf{x})) - s_2(\mathbf{x}))^2$$

$$f(\mathbf{x}) = \mathbf{x} + \mathbf{v}(\mathbf{x})$$

Discretize first variation

$$(s_1(\mathbf{i} + \mathbf{v}(\mathbf{i})) - s_2(\mathbf{i})) \nabla s_1|_{\mathbf{i} + \mathbf{v}(\mathbf{i})} = 0$$

$$\Psi_{data}(s_1(\mathbf{x}), s_2(\mathbf{x}), \dots, f) \simeq \sum_{\mathbf{i} \in \mathbb{Z}^d} (s_1(\mathbf{i}) - s_2(\mathbf{i} + \mathbf{v}(\mathbf{i})))^2$$

Differentiate sum

- Sampled digital images: $\mathbf{S}_1 = s_1(\mathbf{i}), \mathbf{i} \in \mathbb{Z}^d$
 $\mathbf{S}_2 = s_2(\mathbf{i}), \mathbf{i} \in \mathbb{Z}^d$

- Spatial transformation:

$$\mathbf{FS} = \hat{s}(f(\mathbf{q})) = \sum_{\mathbf{i} \in \mathbb{Z}^d} s(\mathbf{i}) \eta(f(\mathbf{q}) - \mathbf{i}), \text{ with } f : \mathbb{R}^d \rightarrow \mathbb{R}^d$$

- Image registration minimization problem:

$$\min_f \|\mathbf{FS}_1 - \mathbf{S}_2\|^2$$

Edge detection

$$\Psi_{data}(s(\mathbf{x}), f) = \int_0^1 P(f, \gamma) d\gamma$$

$$P(f, \gamma) = |\nabla s(f(\gamma))|^2$$

$$f(i\tau) = \mathbf{X}_i, i = 0, \dots, L-1$$

Discretize first variation

$$\nabla P|_{\mathbf{x}_i} = 0$$

$$\Psi_{data}(s(\mathbf{x}), f) = -\tau \sum_{i=0}^{L-1} |\nabla s(f(i\tau))|^2, \tau = \frac{1}{L}$$

Differentiate sum

- Edge (contour) function:

$$f(\gamma) = (x(\gamma), y(\gamma))$$

- Edge detection minimization problem:

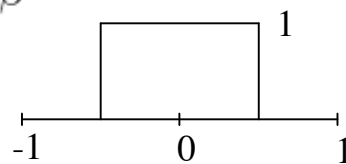
$$\min_f -\tau \sum_{i=0}^{L-1} |\nabla s(f(i\tau))|^2, \quad \tau = \frac{1}{L}$$

Derivatives computed based on
interpolation/approximation

Image interpolation

- B-splines:

$$\beta^n = \beta^{n-1} * \beta^0$$

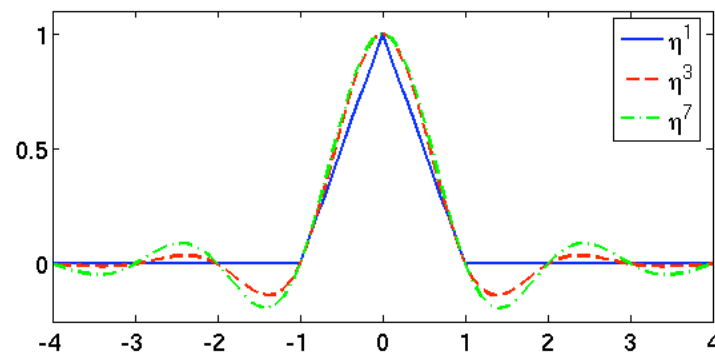
$\beta^0(\mathbf{x}) \longrightarrow$ 

- Image interpolation:

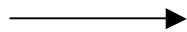
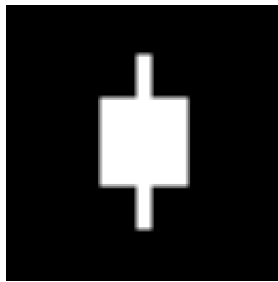
$$\hat{s}(\mathbf{x}) = \sum_{\mathbf{i} \in \mathbb{Z}^d} s(\mathbf{i}) \eta^n(\mathbf{x} - \mathbf{i})$$

- Cardinal splines:

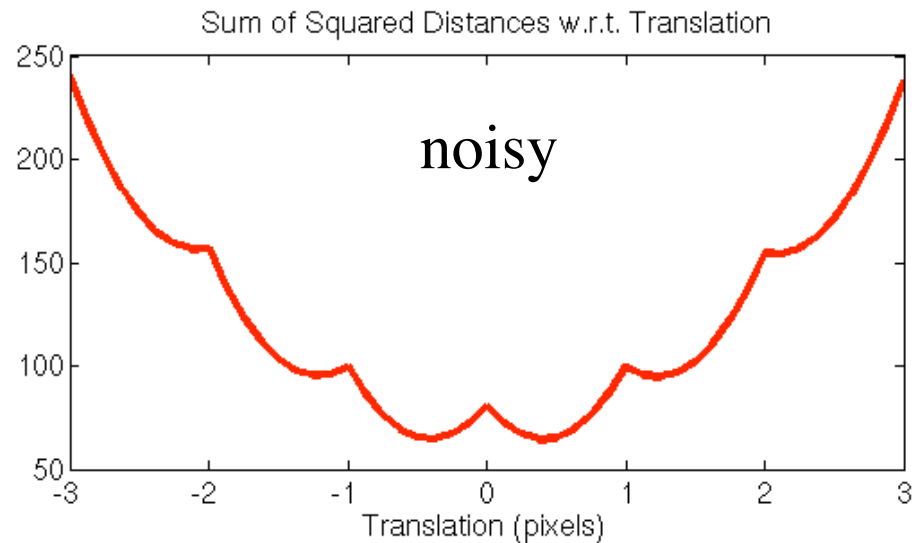
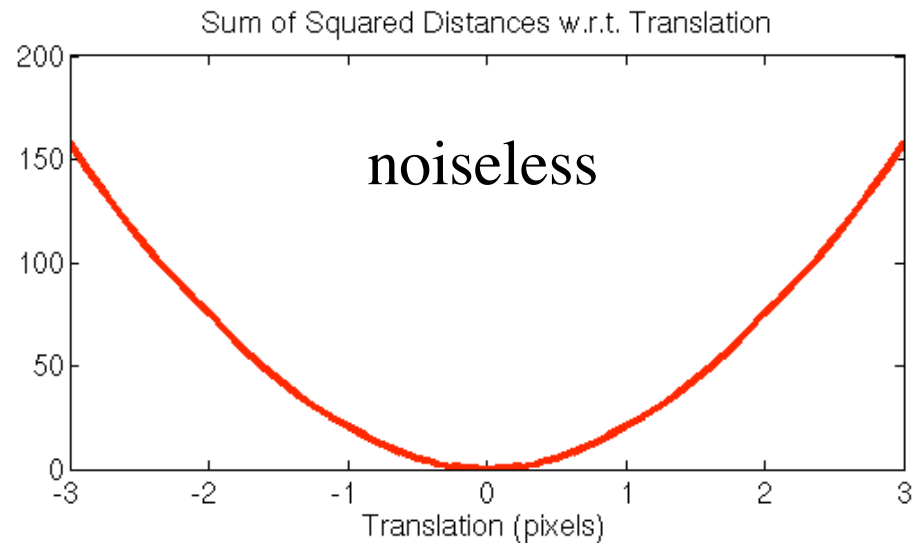
$$\eta^n(\mathbf{x}) = \sum_{\mathbf{k} \in \mathbb{Z}^d} (\beta^n)^{-1}(\mathbf{k}) \beta^n(\mathbf{x} - \mathbf{k})$$



An interesting experiment



translate w.r.t. itself



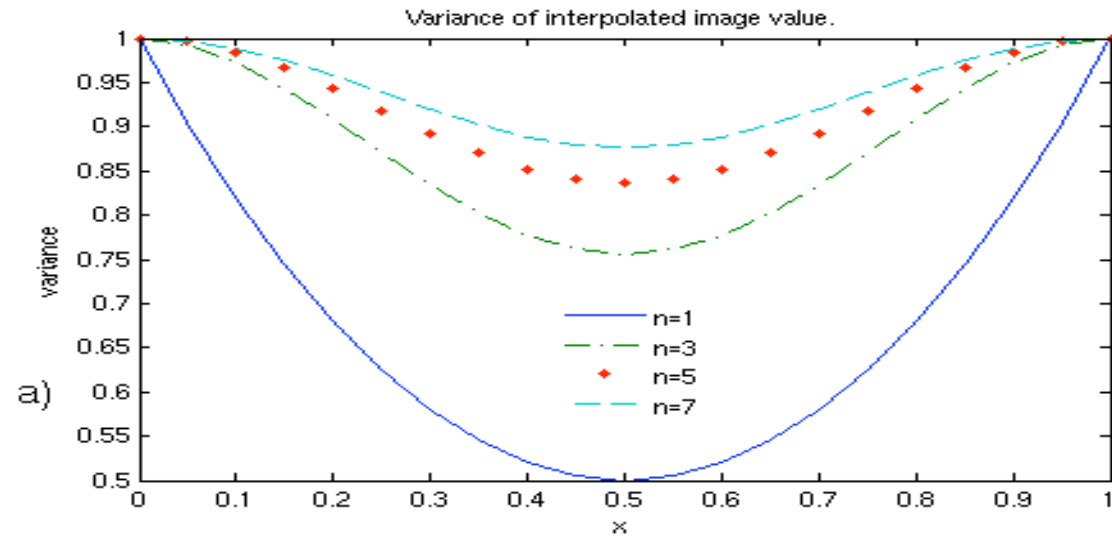
Stochastic image model

- Additive noise: $s(\mathbf{i}) = w_s(\mathbf{i}) + e(\mathbf{i})$
- Image covariance:
$$\begin{aligned} R_s(\mathbf{i}, \mathbf{j}) &= \mathbb{E}\{(s(\mathbf{i}) - \bar{s}(\mathbf{i}))(s(\mathbf{j}) - \bar{s}(\mathbf{j}))\} \\ &= \text{Cov}\{e(\mathbf{i}), e(\mathbf{j})\} = R_e(\mathbf{i}, \mathbf{j}) \end{aligned}$$
- Interpolated covariance (white noise):

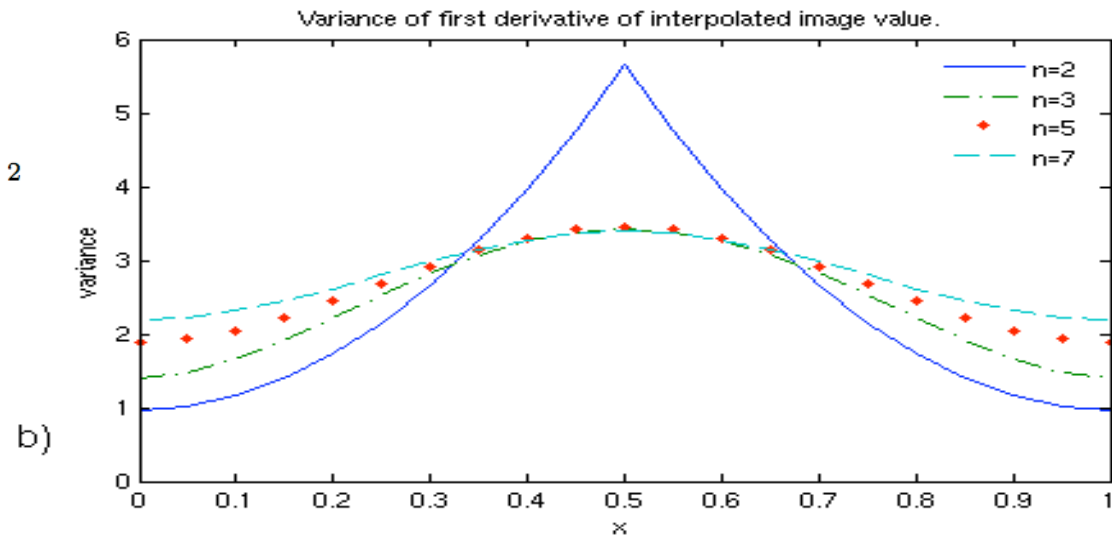
$$R_{\hat{s}}(\mathbf{x}, \mathbf{x}) = \sigma^2 \sum_{\mathbf{q} \in \mathbb{Z}^d} [\eta^n(\mathbf{x} - \mathbf{q})]^2$$

$$R_{\hat{s}^k}(\mathbf{x}, \mathbf{x}) = \sigma^2 \sum_{\mathbf{q} \in \mathbb{Z}^d} \left[\frac{d\eta^n}{dx_k}(\mathbf{x} - \mathbf{q}) \right]^2 \quad \hat{s}^k = \frac{d\hat{s}(\mathbf{x})}{dx_k}$$

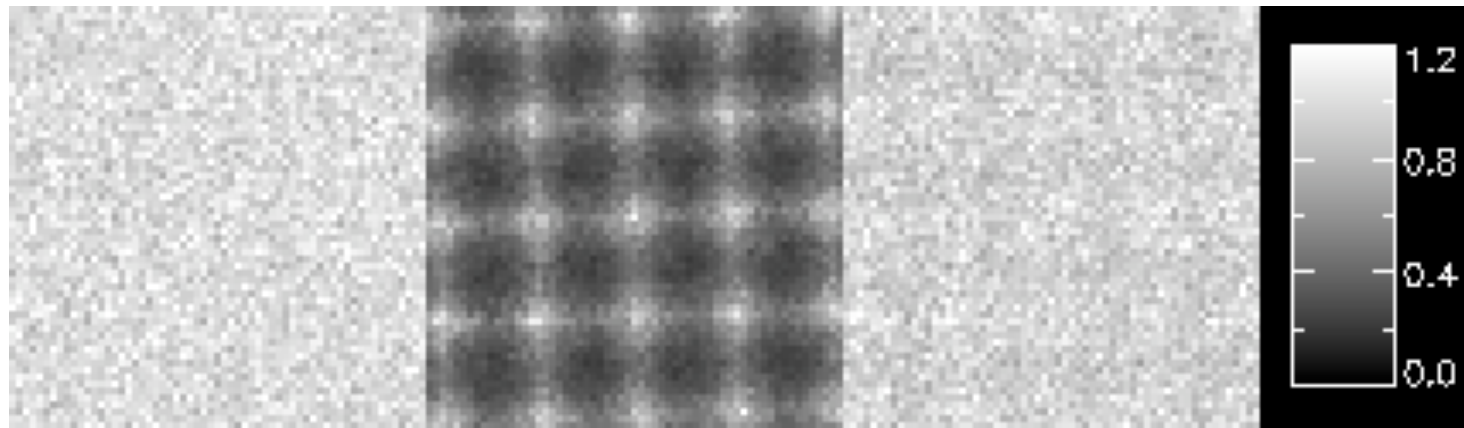
$$R_{\hat{s}}(\mathbf{x}, \mathbf{x}) = \sigma^2 \sum_{\mathbf{q} \in \mathbb{Z}^d} [\eta^n(\mathbf{x} - \mathbf{q})]^2$$



$$R_{\hat{s}^k}(\mathbf{x}, \mathbf{x}) = \sigma^2 \sum_{\mathbf{q} \in \mathbb{Z}^d} \left[\frac{d\eta^n}{dx_k}(\mathbf{x} - \mathbf{q}) \right]^2$$



Simulation



Linear interpolation Sinc interpolation

Deconstructing 2 norms

- Image registration:

$$\|\mathbf{F}_v \mathbf{s} - \mathbf{t}\|^2 = \|\mathbf{F}_v \tilde{\mathbf{w}}_s - \tilde{\mathbf{w}}_t\|^2 + \|\mathbf{e}_t\|^2 + \boxed{\|\mathbf{F}_v \mathbf{e}_s\|^2} + \mathcal{G}$$

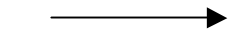
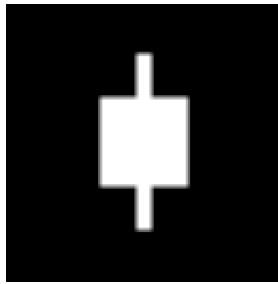
- Edge detection:

$$\sum_{i=0}^{L-1} |\nabla s(f(i\tau))|^2 = - \sum_{i=0}^{L-1} \|\nabla \hat{w}_s(f(i\tau))\|^2 - \boxed{\|\nabla \hat{e}(f(i\tau))\|^2} + \mathcal{Q}$$

$$\frac{1}{N^d} \|\mathbf{F}_v \mathbf{e}_s\|^2 \approx R_{\hat{s}} \longrightarrow \text{image sample variance (uniform translation)}$$

$$\frac{1}{L} \sum_{i=0}^{L-1} \|\nabla \hat{e}(f(i\tau))\|^2 \approx R_{\hat{s}^k} \longrightarrow \text{derivative sample variance (st. line)}$$

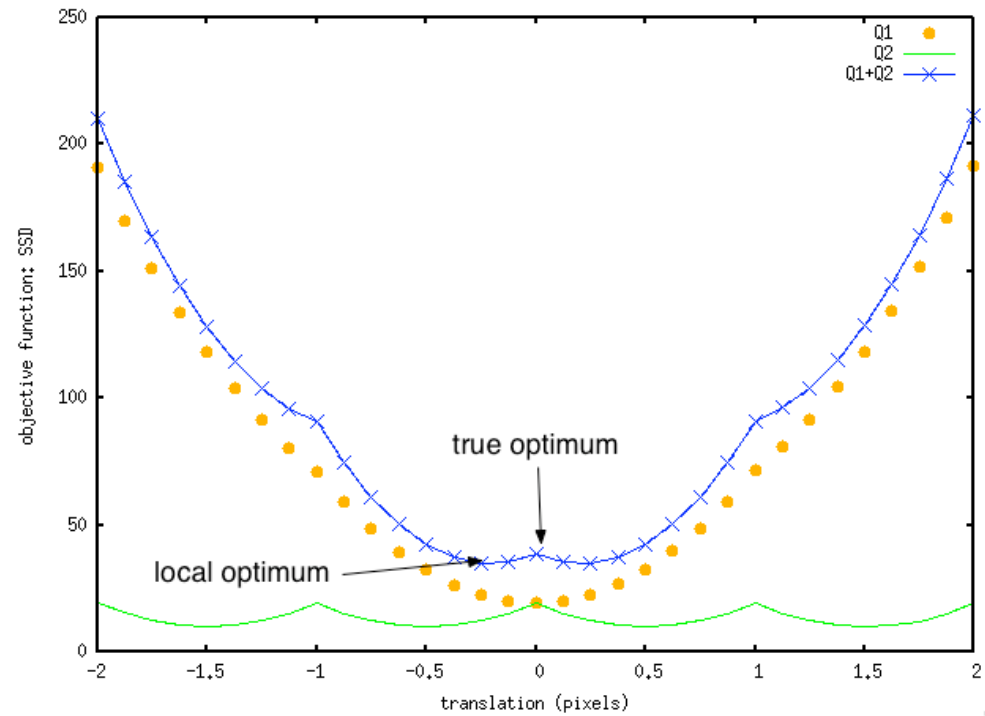
Back to intriguing experiment



$$\|\mathbf{F}_v \mathbf{s} - \mathbf{t}\|^2 = Q_1 + Q_2$$

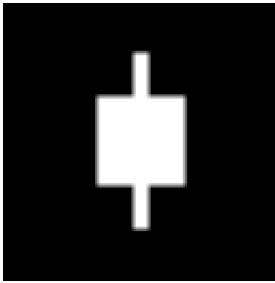
$$Q_1 = \|\mathbf{F}_v \tilde{\mathbf{w}}_s - \tilde{\mathbf{w}}_t\|^2 + \|\mathbf{e}_t\|^2$$

$$Q_2 = \|\mathbf{F}_v \mathbf{e}_s\|^2$$



Rotation too

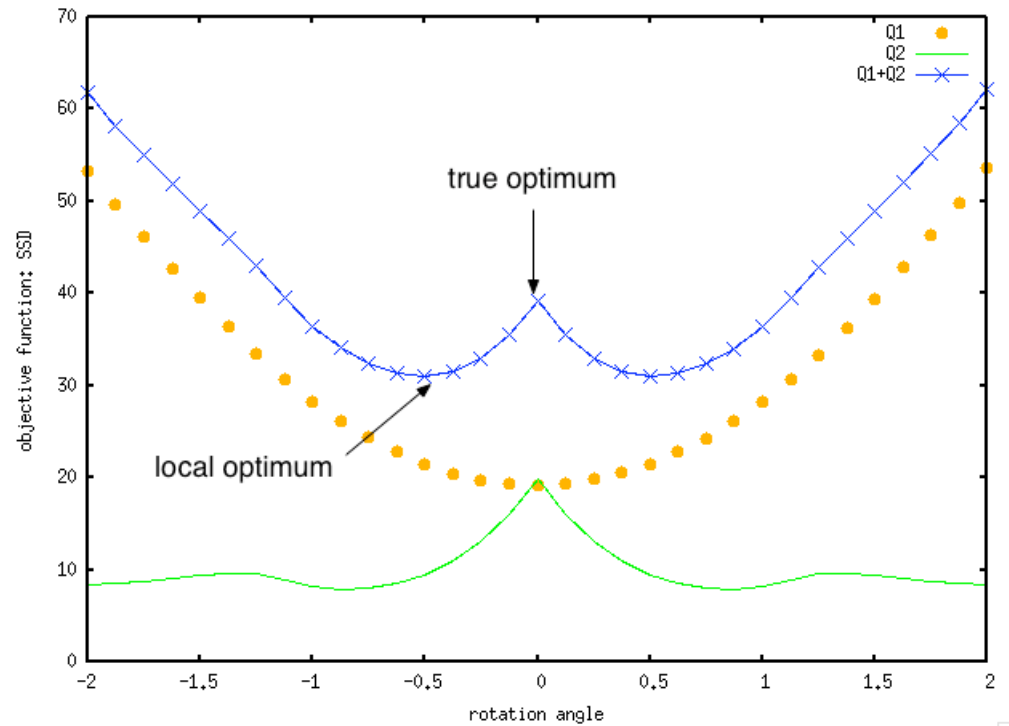
rotate



$$\|\mathbf{F}_v \mathbf{s} - \mathbf{t}\|^2 = Q_1 + Q_2$$

$$Q_1 = \|\mathbf{F}_v \tilde{\mathbf{w}}_s - \tilde{\mathbf{w}}_t\|^2 + \|\mathbf{e}_t\|^2$$

$$Q_2 = \|\mathbf{F}_v \mathbf{e}_s\|^2$$



Other similarity measures (cost functions)

- Cross correlation:

$$\Psi(\hat{s}(f(\mathbf{q})), t(\mathbf{q}), f) = \frac{(\mathbf{F}_v \mathbf{s})^T \mathbf{t}}{\|\mathbf{F}_v \mathbf{s}\| \|\mathbf{t}\|}$$

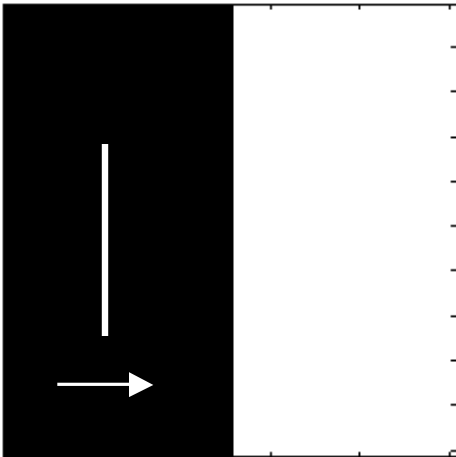
$$\sqrt{\|\mathbf{F}_v \mathbf{s}\|^2} = \sqrt{\|\mathbf{F}_v \tilde{\mathbf{w}}_s\|^2 + \|\mathbf{F}_v \mathbf{e}_s\|^2}$$

- Mutual Information (Gaussian assumption):

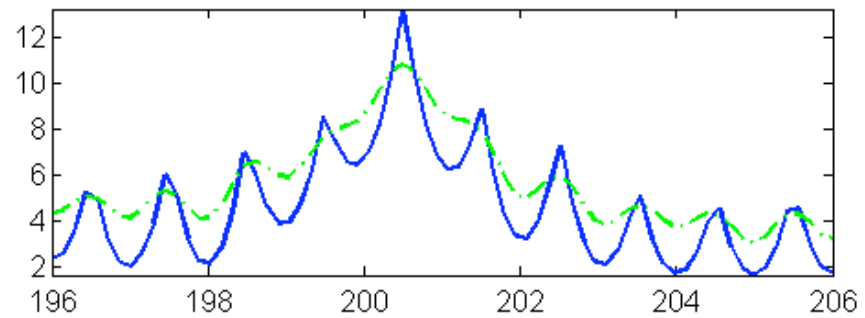
$$\Psi(\hat{s}(f(\mathbf{q})), t(\mathbf{q}), f) = -\frac{1}{2} \log(1 - \rho^2)$$

↓
correlation coefficient

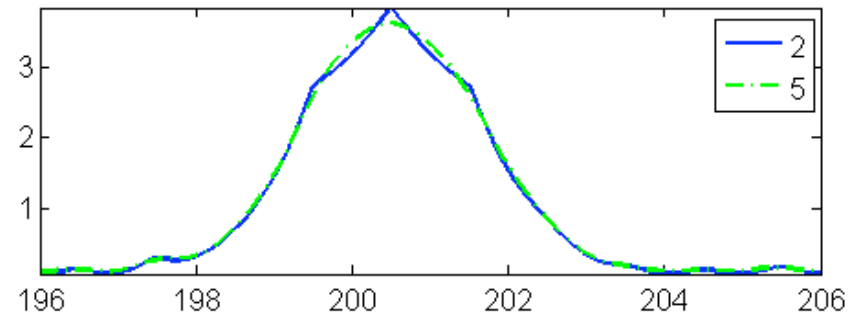
Edge detection



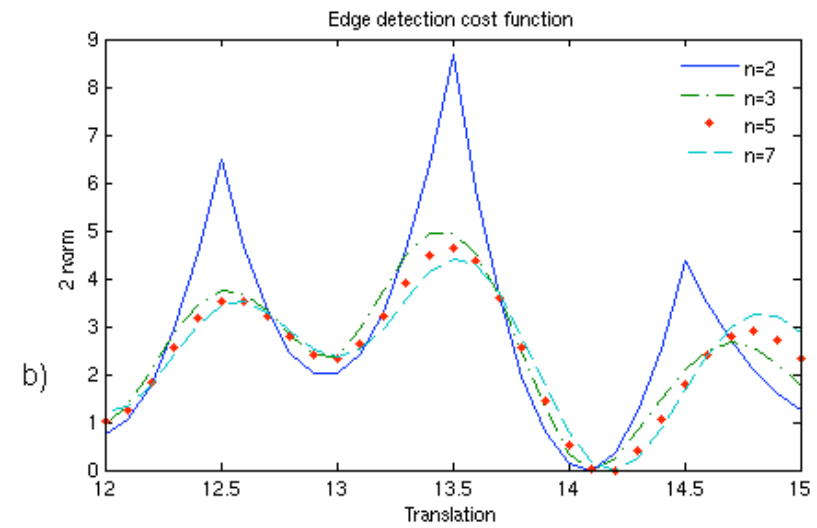
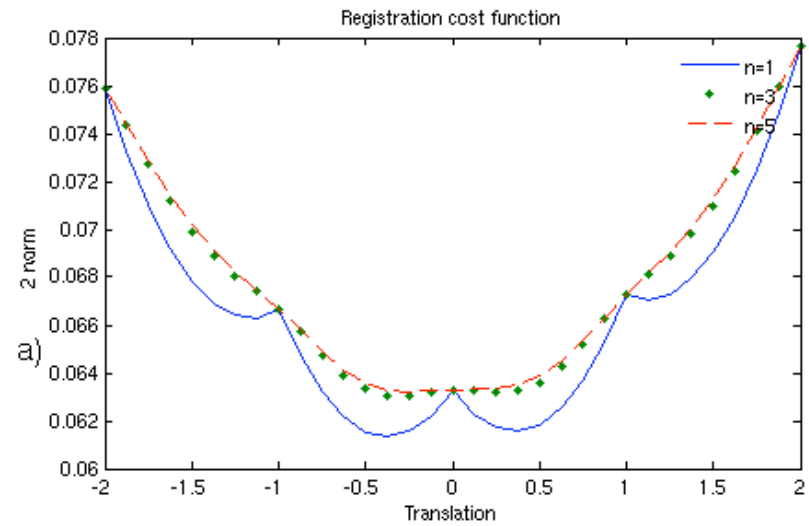
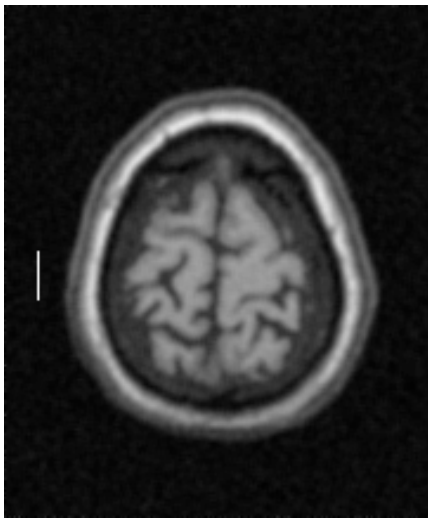
Gradient magnitude: noisy phantom



Gradient magnitude: noisy phantom blurre



Real data:



Summary & Conclusions

- Trying to obtain information about geometry to sub-pixel accuracy from discrete images is problematic: local optima artifacts.
- Provided a stochastic description for artifacts in terms of the variance/covariance of B-spline interpolated images.
- Solutions: blurring, higher degree (sinc) interpolation.