- Object Recognition
- 3D modeling (drones correspondence)
- Image alignment/stitching (Chapter 9)
- Camera pose

Why?

Back to Lecture 10 - Guiding Features

Lecture 15
Region

Edges, corners, straight lines, can help... (keypoint or interest point features)

What?
of the same order

Auto-correlation to eliminate

\[ \int [(\nabla x)^0 I - (n \nabla + i \gamma x) I] (\nabla x)^m \underbrace{ \sum }_{\text{EAC}} = (n \nabla)^0 \]

Stability of the feature

Residues

\[ \text{(c)} \]

Grises

\[ \text{(q)} \]

Comercs

\[ \text{(a)} \]

Aperture Problem (observing the world through a straw)
\[ x \approx 1 \] (Enlarged, Zoomed)

Better criterion when

\[ \text{Compute } \frac{d^2 f(x)}{dx^2}(c) > 0 \]

\[ 0 \]

\[ x < 0 \]

\[ x_0 - 0.06(x_0 + x_1)^2 \]

\[ \text{Compute } \frac{d^2 f(x)}{dx^2}(c) > 0 \]

\[ x > x_0 \]

\[ \text{Compute eigenvalues of } G \]

\[ 0 \]

\[ g \]

\[ \text{Algorithm} \]

\[ g = \Delta T \]

\[ \text{Harris} \]

\[ \text{Lukas & Kanade} \]
Contrast Selection in Neurons of the Neocortex

Finding Local Maxima in Interest Function

Analytic Non-Maximal Suppression

Solution: (Support, see link, until 05)

4) Extract MRF Keypoints

Value is significant

Maximum and whose

which are local

Contrast in Neurons of the Neocortex

Finding Local Maxima in Interest Function

Analytic Non-Maximal Suppression

Contrast

Contrast in Neurons of the Neocortex

Finding Local Maxima in Interest Function

Analytic Non-Maximal Suppression

Contrast in Neurons of the Neocortex

Finding Local Maxima in Interest Function

Analytic Non-Maximal Suppression

Contrast in Neurons of the Neocortex

Finding Local Maxima in Interest Function

Analytic Non-Maximal Suppression
Scene Invariance

Covariances w.r.t. best Gaussian derivatives or Hessian

-$t$ image (small, many, thousands)

Location of the transform

Relatively within $\pm 15$ pixels of the cone's surface
Stable features in location & scale

Lindeberg 93/98 → extrema points in LOG functions

 Lowe 04 → Difference of Gaussian (DOG)

$3D = 2D$ space + 1D scale

---

Gaussian filters w/ different G's (1σ, 2σ, 3σ...)

Preserves the information "between" the frequencies of the two filters (2 G's)

Max of 2G neighbors
For $k = 1: 5$

$\mathbb{C}(\mathbb{R}^2, \mathbb{R}^2)$

$\mathbb{G}(\mathbb{R}^2, \mathbb{R}^2)$

$\mathbb{G}_F(K) = \text{Gaussian Filter } (S \in \mathbb{C}(\mathbb{R}^2, \mathbb{R}^2), K)$

For $k = 1: 5$

* Scale - $K$ in Gaussian Filter

* Resolution/Downsampling

\[ H = \mathbb{C}(\mathbb{R}^2, \mathbb{R}^2) \]

\[ \det(H) | \frac{1}{\sqrt{2\pi \sigma}} > 10 \]

\[ H = \mathbb{H}(x, y) \]

\[ \mathbb{C}(\mathbb{R}^2, \mathbb{R}^2) \]

\[ \mathbb{G}_F(K) - \mathbb{G}(K) \]
- Shepard's window
- Speakers
- Read
- Information
- Understanding
- Downward orientation
- Poor discrimination
- Metaphor of mulitple Us
- Descriptive, Good orientation
- Scale vs. Features
- Resemble the same
- Important Information
Peaks within 80% of global maximum

36 bins (discrete angles)

Image gradients

Histogram of Orientations

(can be noisy + low SNR)

Gaussian filter
derivatives

average gradient = horizontal / vertical derivatives
From Deva Ramanan's slide: Como Slides

Histograms of oriented gradients
$x \rightarrow x'_{1/2}$

$A^{-1/2}x'_{1/2} \rightarrow x_z$

$R_{x_{1/2}}$

$A^{-1/2}x_{1/2} \rightarrow x_0$

Affine Invariance