Lecture 5: blobs and feature descriptors

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• **webpage:**  [http://cbl.eng.cam.ac.uk/Public/Turner/Teaching](http://cbl.eng.cam.ac.uk/Public/Turner/Teaching)

• **office hours** – for questions about the course
Recap of last lecture: Corner detection

at a corner
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center small (equal magnitude) displacements

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eigenvectors/values tell us about fastest/slowest changing directions

\[ C_n(x) \approx \frac{\bar{n}^T \langle \nabla I(x) \nabla I(x)^T \rangle \bar{n}}{|\bar{n}|^2} \]
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\[ \lambda_1 \leq \frac{\bar{n}^T \langle \nabla I(x) \nabla I(x)^T \rangle \bar{n}}{\bar{n}^T \bar{n}} \leq \lambda_2 \]
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eigenvectors/values tell us about fastest/slowest changing directions

\[
C_n(x) \approx \frac{\tilde{n}^T \langle \nabla I(x) \nabla I(x)^T \rangle \tilde{n}}{|\tilde{n}|^2} = \frac{\tilde{n}^T \langle \nabla I(x) \nabla I(x)^T \rangle \tilde{n}}{\tilde{n}^T \tilde{n}}
\]

slowest change \( \lambda_1 \leq \frac{\tilde{n}^T \langle \nabla I(x) \nabla I(x)^T \rangle \tilde{n}}{\tilde{n}^T \tilde{n}} \leq \lambda_2 \) fastest change

\[
n = \frac{\tilde{n}}{|\tilde{n}|}
\]
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fastest change

corners have two high eigenvalues
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eigenvectors/values tell us about fastest/slowest changing directions

$$C_n(x) \approx \frac{n^T \langle \nabla I(x) \nabla I(x)^T \rangle n}{|n|^2} = \frac{n^T \langle \nabla I(x) \nabla I(x)^T \rangle n}{n^T n}$$

slowest change $$\lambda_1 \leq \frac{n^T \langle \nabla I(x) \nabla I(x)^T \rangle n}{n^T n} \leq \lambda_2$$ fastest change
corners have two high eigenvalues: $$\lambda_1 \lambda_2 - \kappa(\lambda_1 + \lambda_2)^2 > \text{threshold}$$
Today

- Properties of Harris corners: need scale invariant features
- All regions classified as edges
- Corner scale change
- All regions classified as edges
- Corner

- How do we match features: descriptors
Blob detection

Polka Dots

Detected Blobs
Blob detection

Polka Dots * Laplacian of a Gaussian convolved image = Detected Blobs

sigma = 20
Blob detection

Polka Dots

* 

Detected Blobs

image

Laplacian

of a Gaussian

convolved

image

sigma = 20

blob
Blob detection

Polka Dots \* Laplacian of a Gaussian \= Detected Blobs

image

Laplacian of a Gaussian

convolved image

\( \text{sigma} = 20 \)
Blob detection

Polka Dots * = Detected Blobs

Laplacian of a Gaussian convolved image

sigma = 20

image
Laplacian of a Gaussian
convolved image

---

blob
Marr edge
Scale

Original

Level 0

Level 1

Level 2

Level 3

Level 4

\(\sigma = 5\)

\(\sigma = 10\)

\(\sigma = 20\)

\(\sigma = 40\)

\(\sigma = 80\)
Scale

• ideally: consider the (continuous) scale space of the image

\[ L(x, y, t) = G(x, y, t) \otimes I(x, y) \]

\[ G(x, y, t) = \frac{1}{2\pi t} \exp \left( -\frac{1}{2t} (x^2 + y^2) \right) \quad \text{where} \quad t = \sigma^2 \]
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- practically: can only consider finite number of scales
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• practically: can only consider finite number of scales

repeatedly blur using a narrow Gaussian
Scale

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where \( t = \sigma^2 \)

- practically: can only consider finite number of scales

repeatedly blur using a narrow Gaussian

subsample
Gaussian quiz \[ g_\sigma(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \]

1) Derivative of a Gaussian \[ = b \]
\[
\frac{d}{dx} g_\sigma(x) = -\frac{x}{\sigma^2} g_\sigma(x)
\]

2) Second derivative of a Gaussian \[ = c \]
\[
\frac{d^2}{dx^2} g_\sigma(x) = \frac{1}{\sigma^2} \left( \frac{x^2}{\sigma^2} - 1 \right) g_\sigma(x)
\]

3) Multiplication of two Gaussians \[ = a \]
\[
g_{\sigma_1}(x)g_{\sigma_2}(x) = g_{\sigma_3}(x)
\]
\[
\sigma_3^{-2} = \sigma_1^{-2} + \sigma_2^{-2}
\]

4) Fourier Transform of a Gaussian \[ = a \]
\[
\int \exp(ikx) g_\sigma(x) dx \propto g_{\sigma'}(k)
\]
\[
\sigma' = \frac{1}{\sigma}
\]

5) Convolution of 2 Gaussians \[ = a \]
\[
\int g_{\sigma_1}(x-x')g_{\sigma_2}(x')dx = g_{\sigma_3}(x)
\]
\[
\sigma_3^2 = \sigma_1^2 + \sigma_2^2
\]
Extracting interest points from scale space

- finding the ideal scale: maximum of the scale space function
- use interpolation to find the precise location

E.g. for blob detection
Efficient blob detection

- repeated blurring/down-sampling accelerates scale space
- Laplacian if a Gaussian can be approximated by a difference of Gaussians
  
  E.g. for blob detection
Efficient blob detection: example
Matching interest points: Descriptors

- Main idea: use properties of image around interest point to match
Idea 1: Raw Patch Descriptor

Original Patch and Intensity Values

Brightness Decreased, \( CC = 0.26272039707803 \)

Contrast increased, \( CC = 0.380413705374859 \)

Various changes, \( CC = 0.297579822063629 \)
Idea 1: Raw Patch Descriptor

Sensitive to brightness/contrast/general lighting changes
Idea 2: Normalised Patch Descriptor

Original Patch and Intensity Values

Brightness Decreased, $CC = 0.999988956295594$

Contrast increased, $CC = 0.969868160814465$

Various changes, $CC = 0.985010389868036$
Idea 2: Normalised Patch Descriptor

Original Patch and Intensity Values

Brightness Decreased, CC = 0.999988956295594

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Various changes, CC = 0.985010389868036

Sensitive to changes in viewpoint
Idea 3: Intensity Edges

- gradient at each ‘pixel’ is computed
  - robust to contrast and brightness changes
- directions binned into histogram
  - adds robustness to orientation changes
Scale Invariant Feature Transform (SIFT) Keypoints

- Detect blobs
  - using DoG scale space plus interpolation (*scale invariance*)

- Find orientation of keypoint (*rotation invariance*)
  - find gradients with region of keypoint
  - histogram weighted by magnitude
  - find maximum of histogram
Scale Invariant Feature Transform (SIFT) Descriptor
Scale Invariant Feature Transform (SIFT) Descriptor

- $N \times N$ patch (e.g. $N=16$) extracted at scale and orientation of interest points (scale and orientation invariance)

- split patch into $c$ cells

- gradient at each ‘pixel’ (within cell) is computed

- directions binned into histogram
  - weighted by gradient magnitude and Gaussian window (robust to occlusion)
  - typically $d=8$ bins

- normalise and threshold (robust to lighting changes)
Scale Invariant Feature Transform Demo
Texture and filter banks
Texture and filter banks

Bar

Brightness

Edge

Blob

Bar Filter Response

Edge Filter Response

Intensity Filter Response

Blob Filter Response
Texture and filter banks

Original patch

Filter Bank Response

Brightness change

No change

Contrast change

Small Change

Various changes

Medium Change
Texture, filter banks and the brain
Texture, filter banks and the brain
Texture, filter banks and the brain
Texture, filter banks and the brain