Lecture 12: Scale Invariant Features (SIFT)
Where are the good features, and how do we match them?
Photometric Transformations
Geometric Transformations

objects will appear at different scales, translation and rotation

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
Let's assume for the moment we can figure out where the good features (patches) are ... how do we **match** them?
Intensity Image

Just use the pixel values of the patch

\[
\begin{pmatrix}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9 \\
\end{pmatrix}
\rightarrow
\begin{pmatrix}
1 & 2 & 3 & 4 & 5 \\
6 & 7 & 8 & 9 \\
\end{pmatrix}
\]

vector of intensity values

Perfectly fine if geometry and appearance is unchanged

(a.k.a. template matching)

What are the problems?

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
Just use the pixel values of the patch

Perfectly fine if geometry and appearance is unchanged
(a.k.a. template matching)

What are the problems?

How can you be less sensitive to absolute intensity values?
Image **Gradients / Edges**

Use pixel differences

![Illustration of pixel differences](image)

Vector of x derivatives

Feature is invariant to absolute intensity values

**What are the problems?**
Image **Gradients / Edges**

Use pixel differences

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
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<tbody>
<tr>
<td>4</td>
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$(- + + - - +)$

Feature is invariant to absolute intensity values

What are the problems?

How can you be less sensitive to deformations?

**Slide Credit:** Ioannis (Yannis) Gkioulekas (CMU)
**Where does SIFT fit in?**

<table>
<thead>
<tr>
<th>Representation</th>
<th>Result is...</th>
<th>Approach</th>
<th>Technique</th>
</tr>
</thead>
<tbody>
<tr>
<td>intensity</td>
<td>dense (2D)</td>
<td>template matching</td>
<td>(normalized) correlation, SSD</td>
</tr>
<tr>
<td>edge</td>
<td>relatively sparse (1D)</td>
<td>derivatives</td>
<td>$\nabla^2 G$, Canny</td>
</tr>
<tr>
<td>“corner”</td>
<td>sparse (0D)</td>
<td>locally distinct features</td>
<td>Harris, SIFT</td>
</tr>
</tbody>
</table>
Object **Recognition** with Invariant Features

**Task:** Identify objects or scenes and determine their pose and model parameters

**Applications:**
- Industrial automation and inspection
- Mobile robots, toys, user interfaces
- Location recognition
- Digital camera panoramas
- 3D scene modeling, augmented reality
David Lowe’s Invariant Local Features

Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters.
Advantages of Invariant Local Features

**Locality**: features are local, so robust to occlusion and clutter (no prior segmentation)

**Distinctiveness**: individual features can be matched to a large database of objects

**Quantity**: many features can be generated for even small objects

**Efficiency**: close to real-time performance
Scale Invariant Feature Transform (SIFT)

SIFT describes both a detector and descriptor

1. Multi-scale extrema detection
2. Keypoint localization
3. Orientation assignment
4. Keypoint descriptor

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
1. Multi-scale Extrema Detection

First octave

Second octave

Half the size

Gaussian

Difference of Gaussian (DoG)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
1. Multi-scale Extrema Detection

Gaussian

Laplacian
1. Multi-scale Extrema Detection

Detect maxima and minima of Difference of Gaussian in scale space

\[ \sigma = 2^{1/s} \]

Selected if larger than all 26 neighbors

Difference of Gaussian (DoG)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
1. Multi-scale Extrema Detection — Sampling Frequency

More points are found as sampling frequency increases, but accuracy of matching decreases after 3 scales/octave
2. Keypoint Localization

— After keypoints are detected, we remove those that have **low contrast** or are **poorly localized** along an edge
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— After keypoints are detected, we remove those that have low contrast or are poorly localized along an edge

How do we decide whether a keypoint is poorly localized, say along an edge, vs. well-localized?
2. Keypoint Localization

— After keypoints are detected, we remove those that have low contrast or are poorly localized along an edge.

How do we decide whether a keypoint is poorly localized, say along an edge, vs. well-localized?

\[
C = \begin{bmatrix}
\sum_{p \in P} I_x I_x & \sum_{p \in P} I_x I_y \\
\sum_{p \in P} I_y I_x & \sum_{p \in P} I_y I_y
\end{bmatrix}
\]
2. Keypoint Localization

— After keypoints are detected, we remove those that have low contrast or are poorly localized along an edge.

How do we decide whether a keypoint is poorly localized, say along an edge, vs. well-localized?

— Lowe suggests computing the ratio of the eigenvalues of $C$ (recall Harris corners) and checking if it is greater than a threshold.

— Aside: The ratio can be computed efficiently in fewer than 20 floating point operations, using a trick involving the trace and determinant of $C$ - no need to explicitly compute the eigenvalues.
2. Keypoint Localization

Example:

(a) 233 × 189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principal curvatures
3. Orientation Assignment

- Create **histogram** of local gradient directions computed at selected scale

- Assign **canonical orientation** at peak of smoothed histogram

- Each key specifies stable 2D coordinates \((x, y, \text{scale}, \text{orientation})\)