University of Idaho
Department of Computer Science
Coeur d'Alene

Lecture #18

Object Detection II

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Review

1. Features
2. Object Detection
   - Histograms
   - Image Moments
   - Hough Transforms
   - Optical Flow, Sparse & Dense
   - Harris Corners

Shi-Tomasi Corner Detection

- Remember...
  - Harris Corners
  - Corners maximize gradient in all directions
- Modification: $min(\lambda_1, \lambda_2)$ rather than using Harris scoring equation $(\lambda_1\lambda_2 - k(\lambda_1 + \lambda_2)^2)$) [1]

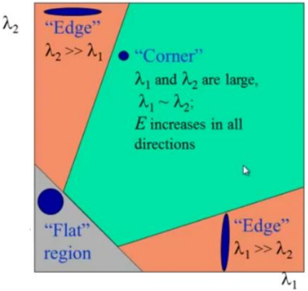


Figure: Harris Space

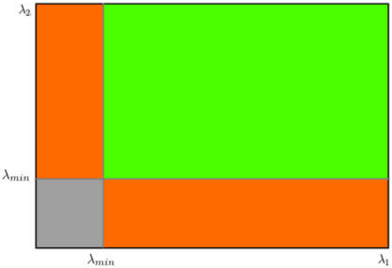


Figure: Shi-Tomasi Space

Shi-Tomasi Corner Detection in OpenCV

```
# Uses Shi-Tomasi function
corners = cv.goodFeaturesToTrack(
      image,                     # 8-bit/fp-32, single channel
      maxCorners,                # max corners returned
      qualityLevel,              # min quality, [0,1] for corner
      minDistance,               # min dist between corners
      mask = noArray(),          # region of interest
      blockSize = 3,             # size of pixel neighborhood
      useHarrisDetector=false,   # use Harris corner detector
      k=0.04)                    # free param for Harris
```

Keypoints

Keypoints

Points that are interesting in an image.

Components:

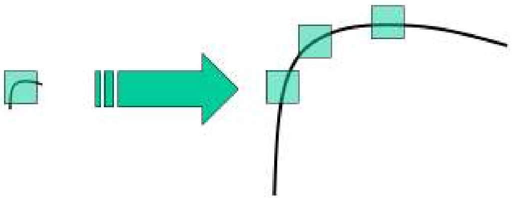
1. (x, y) coordinate
2. diameter
3. orientation
4. strength
5. octave
6. object ID

Algorithms That Use Keypoints

1. SIFT
2. BRISK
3. SURF
4. FAST
5. BRIEF
6. ORB

SIFT

- Scale Invariant Transform [2]
- Harris Corners are rotation invariant, not scale invariant
- This is a problem for corners



SIFT

1. Scale-space Extrema Detection
2. Keypoint Localization
3. Orientation Assignment
4. Keypoint Descriptor
5. Keypoint Matching

SIFT

1. Scale-space Extrema Detection
   - *Search image at various scales for corners, local maxima and potential keypoint*
2. Keypoint Localization

3. Orientation Assignment

4. Keypoint Descriptor

5. Keypoint Matching

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1. Scale-space Extrema Detection
   - *Search image at various scales for corners, local maxima and potential keypoint*
2. Keypoint Localization
   - *Taylor series expansion to increase extrema location accuracy*

3. Orientation Assignment

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   - *If intensity at extrema is less than threshold(0.33), reject*
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3. Orientation Assignment
   - *Create orientation histogram using pixel neighborhood*

4. Keypoint Descriptor

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3. Orientation Assignment
   - *Create orientation histogram using pixel neighborhood*
   - *Weight results to calculate outcome*
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5. Keypoint Matching

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   - *Create orientation histogram using pixel neighborhood*
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   - *Create keypoint descriptor*
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   - *If intensity at extrema is less than threshold(0.33), reject*
3. Orientation Assignment
   - *Create orientation histogram using pixel neighborhood*
   - *Weight results to calculate outcome*
4. Keypoint Descriptor
   - *Create keypoint descriptor*
   - Take 16×16 neighborhood
5. Keypoint Matching

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   - *Create orientation histogram using pixel neighborhood*
   - *Weight results to calculate outcome*
4. Keypoint Descriptor
   - *Create keypoint descriptor*
   - Take 16×16 neighborhood
   - Subdivided in to 4×4 sub-blocks
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   - *If intensity at extrema is less than threshold(0.33), reject*
3. Orientation Assignment
   - *Create orientation histogram using pixel neighborhood*
   - *Weight results to calculate outcome*
4. Keypoint Descriptor
   - *Create keypoint descriptor*
   - Take 16×16 neighborhood
   - Subdivided in to 4×4 sub-blocks
   - *8 bin orientation histograms created*

5. Keypoint Matching

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   - *Search image at various scales for corners, local maxima and potential keypoint*
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   - *Taylor series expansion to increase extrema location accuracy*
   - *If intensity at extrema is less than threshold(0.33), reject*
3. Orientation Assignment
   - *Create orientation histogram using pixel neighborhood*
   - *Weight results to calculate outcome*
4. Keypoint Descriptor
   - *Create keypoint descriptor*
   - Take 16×16 neighborhood
   - Subdivided in to 4×4 sub-blocks
   - *8 bin orientation histograms created*
   - 128 bin values $\rightarrow$ vector to form keypoint descriptor
5. Keypoint Matching

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   - *Create orientation histogram using pixel neighborhood*
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   - *Create keypoint descriptor*
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   - Subdivided in to 4×4 sub-blocks
   - *8 bin orientation histograms created*
   - 128 bin values $\rightarrow$ vector to form keypoint descriptor
5. Keypoint Matching
   - *Keypoints matched through nearest neighbors*

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   - *Create orientation histogram using pixel neighborhood*
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   - *Create keypoint descriptor*
   - Take 16×16 neighborhood
   - Subdivided in to 4×4 sub-blocks
   - *8 bin orientation histograms created*
   - 128 bin values $\rightarrow$ vector to form keypoint descriptor
5. Keypoint Matching
   - *Keypoints matched through nearest neighbors*
   - *Takes ratio of closest and second closest match, rejects based on threshold*

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    - *Create orientation histogram using pixel neighborhood*
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4. Keypoint Descriptor
    - *Create keypoint descriptor*
    - Take 16×16 neighborhood
    - Subdivided in to 4×4 sub-blocks
    - *8 bin orientation histograms created*
    - 128 bin values → vector to form keypoint descriptor
5. Keypoint Matching
    - *Keypoints matched through nearest neighbors*
    - *Takes ratio of closest and second closest match, rejects based on threshold*
    - Paper claims approx. 90% of false matches discarded, while only discarding 5% of correct matches

SIFT

Notes...

- SIFT is a patented algorithm
- Thus, some OpenCV versions dropped support
- OpenCV 4.10 contains SIFT in main packages

SIFT in OpenCV

```
# create sift object
sift = cv.SIFT_create()
# pass input image, mask
kp = sift.detect(img, None)
# draw output
img = cv.drawKeypoints(still[1], kp, outImage=None)
```

BRISK

- Open source alternative to SIFT [3]
- Uses concentric rings around a center point
- Multi-scale and non-maximum suppression
- Based on AGAST detector

BRISK in OpenCV

```
# create BRISK object
brisk = cv.BRISK_create()
# gather keypoints
kp = brisk.detect(img, None)
# draw keypoints
img = cv.drawKeypoints(still[1], kp, outImage=None)
```

SURF

- Speeded-Up Robust Features [4]
- Faster than SIFT (3x)
- Approximates Laplacian of Gaussian with a Box Filter
- Good for:
  1. blurring changes
  2. rotation changes
- Not great with:
  1. viewpoint changes
  2. illumination changes

SURF

Notes. . .

- SURF also patented, thus not included in OpenCV
- may be able to install in extra module

FAST

- Features from Accelerated Segment Test [5]
- Proposed to accelerate corner detection
- by Edward Rosten & Tom Drummond

FAST

From [5]

1. For given image, select pixel p with intensity I_p
2. Apply threshold value t
3. Consider circle of 16 pixels surrounding p
4. p is a corner pixel if n contiguous pixels in the circle are brighter than $I_p + t$ or darker than $I_p - t$
5. **Enhancement:** A high-speed test is applied → check a few pixels to determine existence of corner

Weaknesses of High-Speed Test

- For $n < 12$, may not reject properly
- Efficiency varies based on order in which they are checked & the distribution of corner types
- Multiple features adjacent to each other are detected (solve with non-maxima suppression)

FAST in OpenCV

```
# create FAST object
fast = cv.FastFeatureDetector_create()
# detect keypoints
kp  = fast.detect(img, None)
# draw keypoints
img = cv.drawKeypoints(still[1], kp, outImage=None)
```

Blob Detection

Binary **L**arge **Ob**ject

“A blob is a group of connected pixels that share some common property” [6]

1. Thresholding
2. Grouping
3. Merging
4. Center & Radius Calculation

Blob Detection

Binary **L**arge **Obj**ect

“A blob is a group of connected pixels that share some common property” [6]

1. Thresholding
   - Make multiple binary images using different thresholding methods
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Blob Detection

Binary **L**arge **Obj**ect

“A blob is a group of connected pixels that share some common property” [6]

1. Thresholding
   - Make multiple binary images using different thresholding methods
2. Grouping
   - Create curves from continuous points(same color/intensity) in binary images
3. Merging
4. Center & Radius Calculation

Blob Detection

Binary Large Object

"A blob is a group of connected pixels that share some common property" [6]

1. Thresholding
   - Make multiple binary images using different thresholding methods
2. Grouping
   - Create curves from continuous points(same color/intensity) in binary images
3. Merging
   - Compute centers of binary blobs, if distance less than threshold, merge
4. Center & Radius Calculation

Blob Detection

Binary **L**arge **Ob**ject

“A blob is a group of connected pixels that share some common property” [6]

1. Thresholding
   - Make multiple binary images using different thresholding methods
2. Grouping
   - Create curves from continuous points(same color/intensity) in binary images
3. Merging
   - Compute centers of binary blobs, if distance less than threshold, merge
4. Center & Radius Calculation
   - Calculate center and radius of each blob

Blob Detection in OpenCV

```python
# create blob detector object
blob = cv.SimpleBlobDetector_create()
# detect keypoints
kp = blob.detect(img, None)
# draw keypoints
img = cv.drawKeypoints(
    still[1],
    kp,
    outImage=None,
    color=(0, 0, 255),
    flags=cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
```

Descriptors

- Keypoints ☞ areas of interest
- Descriptors ☞ describe keypoints
- Not calculated by all algorithms seen up to this point
  - `<obj>.detect(...)` gives keypoints
  - `<obj>.compute(...)` gives descriptors
  - `<obj>.detectAndCompute(...)` for both

BRIEF

- Binary Robust Independent Elementary Features [7]
- Uses less memory than SIFT & SURF
- Finds location pairs and compares pixel intensity
- Finds binary strings without finding initial descriptors
- Must be provided features
- BRIEF paper recommends CenSurE (STAR in OpenCV)

ORB

- Oriented FAST and Rotated BRIEF [8]
- FAST → finds keypoints
- Harris to find top *N* points
- Pyramid to check various scales
- Calculates orientation
- BRIEF → descriptors with modifications

ORB in OpenCV

```
# create ORB
orb = cv.ORB_create()
# detect
kp = orb.detect(img, None)
# draw output
img = cv.drawKeypoints(
      still[1],
      kp,
      outImage=None,
      color=(0, 255, 0),
      flags=0)
```

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