Corner Detection

• Basic idea: Find points where two edges meet—i.e., high gradient in two directions
• Categories image windows based on gradient statistics
  - **Constant**: Little or no brightness change
  - **Edge**: Strong brightness change in single direction
  - **Corner**: Strong brightness changes in orthogonal directions
Corner Detection: Weighted Gradient Covariance

- Intuitively, in corner windows both $I_x$ and $I_y$ should be high
  - Can’t just set a threshold on them directly, because we want rotational invariance

- Covariance of gradient components over a window quantifies distribution of gradient directions

$$C = \left( \begin{array}{cc} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{array} \right)$$

- The lengths of the major and minor ellipse axes are encoded by the eigenvalues $\lambda_1$, $\lambda_2$ of $C$
- Corners are thus where $\min(\lambda_1, \lambda_2)$ is over a threshold

Example: Gradient Covariances

Corners are where both eigenvalues are big
Two-step corner detection

- Step 1. Cornerness assignment
- Step 2. Candidate selection

Scale Invariant Corners

1. Enforce invariance to scale: Compute Gaussian difference max, for many different scales; non-maximum suppression, find local maxima: keypoint candidates
Finding “Keypoints” (Corners)

Idea: Find Corners, but scale invariance

Approach:
• Run linear filter (Diff of Gaussians)
• At different resolutions of image pyramid

Difference of Gaussians
Build Scale-Space Pyramid

- All scales must be examined to identify scale-invariant features
- An efficient function is to compute the Difference of Gaussian (DOG) pyramid

Keypoint Localization

- Detect maxima and minima of difference-of-Gaussian in scale space
Keypoints

Example of keypoint detection

(a) 233x189 image
(b) 832 DOG extrema
Example of keypoint detection

Threshold on value at DOG peak and on ratio of principle curvatures (Harris approach)

(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures

Select canonical orientation

• 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, scale, orientation)
Imbalance Oriented Selection

- Imbalance is characterized by the first-order local intensity information, i.e., first-order derivatives.

Redundant Pixels
Characterization of Imbalance

- The index of maximum difference is used to characterize imbalance
Index = 2

Index = 3
Index = 4

Index = 5
Index = 6

Index = 7
Non-maximum vs. imbalance

Non-maximum suppression
Imbalance oriented selection

Diverse Imbalanced Points

The most diverse imbalanced points
Diverse Imbalanced Points

Index of maximum difference

Rank of imbalance diversity $\frac{n}{2} - o$

$n=$number of directions

$o=$number of imbalanced points of different index of maximum difference in a neighborhood

Keypoints

Diverse Imbalanced Points
Repeatability evaluation

$\varepsilon$: Repeatability rates

Repeatability across Rotations

Rotation angle $\theta = -45:10:45$