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★ Harris vs Shi-Tomasi Corner Detection

→ Shi-Tomasi is almost similar to Harris corner detection, apart from the way the score (R) is ~~comy~~ calculated.

→ This gives a better result than harris.

→ In this method, we find the top N corners, which might be useful in case we don't want to detect each and every corner.

→ In Shi-Tomasi, R is calculated in the following way:

$$R = \min(\lambda_1, \lambda_2)$$

If R is > threshold it's considered a corner.

Scale Space

It is a formal theory for handling image structures at different scale, by representing an image as a one-parameter family of smoothed images, the scale-space representation, parameterized by the size of the smoothing kernel used for suppressing fine scale structures.

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The main type of scale space is the linear (Gaussian) scale space, which has wide applicability as well as the attractive property of being possible to derive from a small set of scale-space axioms.

Scale Selection

* SIFT: Scale Invariant Feature Transform

→ Addresses the problem of matching features with changing scale and rotation.

→ one of best approaches and known to be very successful.

→ Approach:

- create a scale space of images
  - ↳ construct a set of progressively Gaussian blurred images.
  - ↳ Take differences to get a "difference of Gaussian" pyramid (similar to Laplacian of Gaussian)
- Find local extrema in this scale space. choose keypoints from the extrema.
- For each keypoint, in a 16x16 window, find histograms of gradient directions

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- → from a picture, Laplacian of Gaussian at sigma = 2 would give
  very dark parts as maxima
  very bright parts as minima

→ LoG filter extrema locates "blob" as: → maxima = dark blobs on light background.
→ minima = light blobs on dark background.

→ Scale of blob (size; radius in pixels) is Determined by the sigma param of LoG filter.

Key point localization

→ Detect maxima & minima of difference-of-gaussian in scale space.

→ fit quadratic to surrounding values for ~~sup~~ subpixels and sub-scale interpolation

→ Taylor expansion around point.

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x$$

→ Offset of extremum (use finite differences for derivatives): $\hat{x} = -\frac{\partial^2 D^{-1}}{\partial x^2} \cdot \frac{\partial D}{\partial x}$

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Select canonical Orientation

To extract the features of each keypoint.

- → 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)

SIFT vector formation

- → Threshold image gradients are sampled over 16x16 array of locations in scale space.
- → Create array of orientation histograms
- → 8 orientations x4x4 histogram array = 128 dimensions

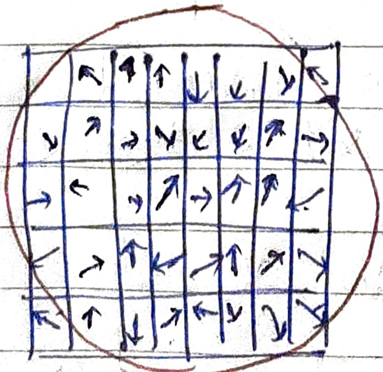
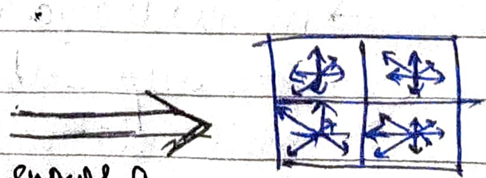


Image gradients

8x8



shows a 2x2 descriptor array computed from an 8x8 set of samples

Keypoint Descriptor