Machine learning and vision laboratory

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Amirreza Velae 400102222 github repository

Pre-Lab 6

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Optional Question

Soloution

We aim to prove the following approximation:

$$LOG(\sigma) \approx \frac{1}{(K-1)\sigma^2} [G(x, y; K\sigma) - G(x, y; \sigma)]$$

Proof:

$$\begin{split} \operatorname{LOG}(\sigma) &= \nabla^2 G(x,y;\sigma) \\ &= \frac{\partial^2}{\partial x^2} G(x,y;\sigma) + \frac{\partial^2}{\partial y^2} G(x,y;\sigma) \\ &\propto \frac{\partial}{\partial \sigma^2} G(x,y;\sigma) \\ &\approx \frac{G(x,y;K\sigma) - G(x,y;\sigma)}{K^2 \sigma^2 - \sigma^2} \\ &= \frac{G(x,y;K\sigma) - G(x,y;\sigma)}{\sigma^2 (K^2 - 1)} \\ &\approx \frac{1}{(K-1)\sigma^2} \big[G(x,y;K\sigma) - G(x,y;\sigma) \big] \end{split}$$

Where in last equation, we used that for K close to 1, $K^2 - 1 \approx 2(K - 1)$, thus:

$$LOG(\sigma) \approx \frac{1}{(K-1)\sigma^2} [G(x, y; K\sigma) - G(x, y; \sigma)].$$

SIFT method

How does the SIFT method maintain its robustness against rotation?

Soloution

SIFT method maintains its robustness against rotation by using the following steps:

- Scale-space Extrema Detection: Detect local extrema in the scale-space by convolving the image with a Gaussian kernel at multiple scales.
- **Keypoint Localization**: Localize keypoints by fitting a 3D quadratic function to the scale-space extrema.
- Orientation Assignment: Assign an orientation to keypoints based on the gradient magnitude and direction to ensure rotation invariance.
- **Descriptor Generation**: Generate descriptors using gradient information in the keypoint's neighborhood for matching across images.

K-means clustering

Explain the k-means clustering method. Are clusters dependent on the initial values of cluster centroids? How can k-means be used to perform clustering that does not depend on the initial values of cluster centroids?

Soloution

K-means clustering is an unsupervised algorithm that partitions data into K clusters by iteratively assigning data points to the nearest centroid and updating centroids as the mean of assigned points. It minimizes the sum of squared distances between data points and centroids.

Clusters are partially dependent on the initial values of centroids, as k-means can converge to a local minimum. Poor initialization may lead to suboptimal clustering results. To reduce dependency on initial centroids:

- **K-means++ Initialization**: Select initial centroids to maximize the distance between them, leading to better convergence.
- Multiple Runs: Run k-means multiple times with different initializations and select the best result based on the cost function.
- Cluster Refinement: Use techniques like hierarchical clustering to refine initial centroids before applying k-means.