CMSC 491/691: Computer Vision **Spring 2024**

Lecture 5: 2024-02-12 Features I

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5.1 Feature Overview

We define a good feature as a part of an image fitting one of the following categories: Important, Unusual, or Unique

Features have usage in object search, image stitching, object detection, object counting, and pattern recognition.

5.2 Invariant Local Features

Ideal features are invariant to transformations. The two types of transformation we are interested in are: **Geometric** which includes rotation, translation, and scaling and **Photometric** which includes brightness, exposure, and shadows

5.3 Local Feature Components

To find local features in two transformed images we must follow 3 steps:

1. Detection: Identify interest points
2. Description: Extract feature descriptor vectors
3. Matching: Determine correspondence between descriptors in two views.

5.4 Corners

To understand corners we define 3 types of areas. Flat means there is no change over the defined area, edge means that there is no change along a specific direction (the edge direction), and corner means that there is a significant change in all directions.

5.5 Harris Corner Detector

The Harris Corner Detector algorithm uses a sliding window over an image to see how the pixels change in order to detect edges. In this algorithm a high error is considered a good feature. These errors are detected using the change across window transformations as a sum of squared differences. It is notably slow to compute and the algorithm runs as follows.

Algorithm 1: Harris Corner Detector Algorithm

1. Compute image gradients over a small region
2. Subtract mean from each image gradient
3. Compute covariance matrix
4. Compute eigenvalues and eigenvectors
5. Use threshold on eigenvalues and eigenvectors

5.5.1 Interpreting Eigenvalues

We interpret eigenvalues to determine the type of feature we have found.

For edges:

$$\lambda_1 > \lambda_2 \quad \text{or} \quad \lambda_2 > \lambda_1 \tag{5.1}$$

For flat surfaces:

$$\lambda_1 \approx \lambda_2 \approx 0 \tag{5.2}$$

For corners:

$$\lambda_1 \approx \lambda_2 \approx \lambda_{max} \tag{5.3}$$

5.5.2 Corner Goodness Checks

When we find a corner we need a way to determine if it is a good corner. Two such formulas for this determination are as follows:

$$R = max(\lambda_1, \lambda_2) \text{ or } R = \lambda_1\lambda_2 - k(\lambda_1 + \lambda_2)^2 \tag{5.4}$$

In the second expression k is a constant able to be optimized by the user.

5.6 Invariance and Covariance

Definition 5.1 (Invariance) *When the image is transformed corner locations do not change.*

Definition 5.2 (Covariance) *Features will be detected in the locations corresponding to the actual transformation.*

Ideally we want corners to be invariant to photometric transformations and covariant to geometric transformations. Unfortunately, corners are invariant to scaling. To fix this we utilize multi-scaling methods. One such approach is applying a Laplacian filter to every pixel and utilizing the a cross-scale maximum to determine the corner locations.