Advanced Robot Perception: Lecture 2
Lecture Notes

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1 Feature Descriptors

Today we will talk about more robuts features. These features are described by a pixel, and use only the information just around them.

These features are "old school" since it has been overtaken by AI. They are however still relevant. There is no need to train these feature extraction algorithms.

Descriptors are more advanced when using e.g. edges rather than just pixel values.

Bad features have very little change in pixel values around them. Medium features are edges, which are somewhat directional Best features are corners, which have very few potential matches other than the excact match.

1.1 Harris corners

Issue: We use eigenvalues to consider the quality of a corner, but they are rotation invariant.

Issue: Brightness invariance. If you threshold the corners, then some cornes may move outside the threshold.

1.2 Histogram of Oriented Corners (HOG)

1. Find gradients

2. Compute orientation of gradients in cell

3. Create histograms, or orientation vectors (which are also histograms), which, which show the heatmap of how many edges are oriented in a certain direction with a specific resolution, based on the resolution of the histogram.

4. Normalize histograms. Use the L2-norm

5. Collect HOG's over the detection window.

6. Run a classifier (SVM).

Benefits:

- Light invariant

- Scale invariant

Issues: Not rotation invariant.

1.3 Scale Invariant Feature Transform (SIFT)

- Use Difference of Gaussians (DoG) - Subtract gausian blurred images from eac other and do that in different octaves and σ's.

- Compute gradient directions and magnitudes

- Rotate the dominant features to the same direction. This entails rotation invariance.

1.4 Deep Features

Deep learning

2 Feature selection

Find transformation between two images.
Look for homography. The typical approach is least squares to detect the same features, however there are outliers.
RANSAC solves this issue.

2.1 RANSAC

- Select random subset of the original selection of data, e.g. corners.

- A model is fitted to the subset

- Try the model, and count inliers while keeping track of the model with the most inliers.

- Untill you are satisfied or run out of time.

Benefits: Works great to find inliers (horizontal lines, two images side by side), and it is great when there is a lot of noise.

3 Dimensionality reduction

Goal: Reduce data, while maintaining as much information as possible.

3.1 Principle Component Analysis (PCA)

Based on the Covariance matrix. $\boxed{\text{Covariance matrix is Symmetric.}}$

$$\Sigma = \begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix} \tag{1}$$

Transform the covariance matrix into a diagonal matrix using the eigenvectors, and extract the singular values/eigenvalues.

$$\Sigma = \begin{bmatrix} 1.05 & 0 \\ 0 & 0.8 \end{bmatrix} \tag{2}$$

Then just choose the amount of principle components that you want.

Note Important that the data is standardized before doing PCA. (within the same range, e.g. -1:1, but it can be other ranges.

PCA is unsupervised.

3.2 Linear Descriminant Analysis (LDA)

Find the projection of data such that the ration of between-class scatter s_b and within-class scatter s_w