Homework 4 Questions

Instructions

- 4 questions.
- Write code where appropriate.
- Feel free to include images or equations.
- **Please use only the space provided and keep the page breaks.** Please do not make new pages, nor remove pages. The document is a template to help grading.
- If you really need extra space, please use new pages at the end of the document and refer us to it in your answers.

Questions

Q1: Imagine we were tasked with designing a feature point which could match all of the following three pairs of images. Which real world phenomena and camera effects might cause us problems? Use the OpenCV function $cornerHarris$ to investigate.

RISHLibrary — Chase — LaddObservatory

A1: Your answer here.

* Figure in the last page

1. Blurring Effect

   As in First two images in Figure1, blurred image might loose its corner if detection window is too small.

2. Noisy Objects

   As in image 3,4,5,6, Noisy objects such as trees, humans might affect the maximum magnitude of each features, which will change the threshold value.

3. Color Temperature

   Right two images are same background, but color temperature are different. Intensity of light or different kind of camera might caused this phenomenom, and as a result, it might affect the magnitude of each corner.

Q2: In designing our feature point, what characteristics might we wish it to have? Describe the fundamental trade-off between feature point invariance and discriminative power. How should we design for this trade-off?

A2: Your answer here.

When we concentrate on feature point invariance only, which means the distance to the nearest feature point, we might loose the discriminative power if those features are general and repetitive among the image.

As a result, we consider the nearest two features, NNDR, so that we can also concentrate on the uniqueness of the feature, which are actually important when discriminating.

Q3: In the Harris corner detector, what do the eigenvalues of the 'M' second moment matrix represent? Discuss both how they relate to image intensity and how we can interpret them geometrically.

A3: Your answer here.

Eigenvalues of M represent the gradient of direction that has the biggest intensity changes and the gradient of direction that is perpendicular to the prior direction.

If two eigenvalues are both big, those window of image are most likely to be a corner. And when the second eigenvalue is small compared to the first one, those window of image are likely to be an edge. And if the both eigenvalues are small, those window of image are likely to be a flat.

Q4: Explain the difference between the Euclidean distance and the cosine similarity metrics between descriptors. What might their geometric interpretations reveal about when each should be used? Given a distance metric, what is a good method for feature descriptor matching and why?

A4: Your answer here.

The biggest difference between the Euclidean distance and the cosine similarity is that whether the two features are normalized or not. Which means, Euclidean distance between two normalized features has no difference with cosine similarity.

As a result, two different methods will show difference in comparing corners that have the same shape, but different intensity. Cosine similarity will regard these corners as same features, but Euclidean distance will not.

Therefore, Euclidean distance may be advantageous when matching corners of two images taken in a sophisticated environment, but cosine distance may be better in general cases where the environment is not controlled.

A1 Continued: Your answer continued here.

Figure 1: Corner Detections from different images