Feature Detection

Table of Contents

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Introduction

In this lab we explore the process of detecting features or keypoints in an image at a particular scale. We will develop an algorithm for the detection of well-localized features using Gaussians and Gaussian derivatives. We also exploit the use of thresholds in order to create repeatability when analyzing images taken from differing angles.

Filtering for Detection

We want to consider only well-localized features in the image that are unique. We begin by creating our Gaussian filters, one with a variance of 1 which will be used to compute the partial derivtives of the image, and the other with a variance of 1.5^2 to average our feature responses by smoothing. We begin with the familiar cameraman image as shown below, and compute its partial derivatives via separable filters by convolving the Gaussian and its derivative across first the rows and then the columns of the image. Then we square the partials in each direction and blur them with the larger Gaussian kernel to average the image. Finally, we calculate the product of the partials (IxIy) and blur this as well.

Original Cameraman Image

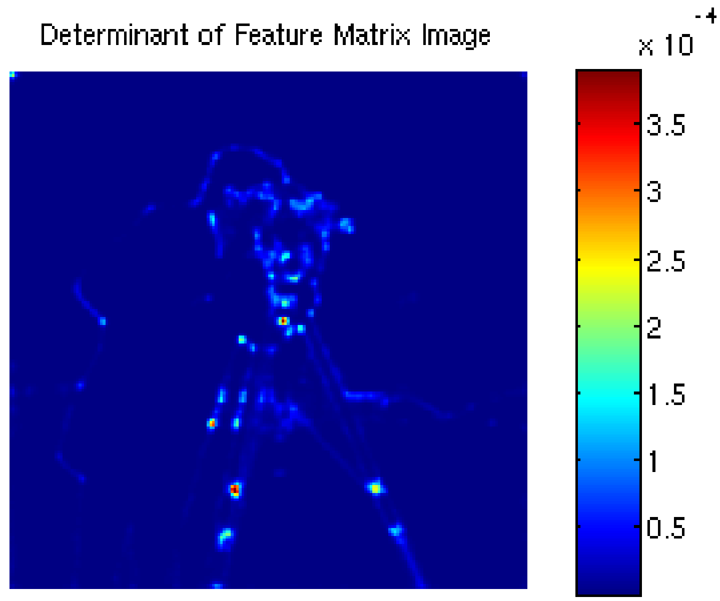
Arranging the squared partials and the directional derivative, we get the following conceptual matrix A, where Ix represents the partial derivative across the rows and Iy the derivative across the columns.

Theoretical Matrix of Partial Derivates

$$A = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

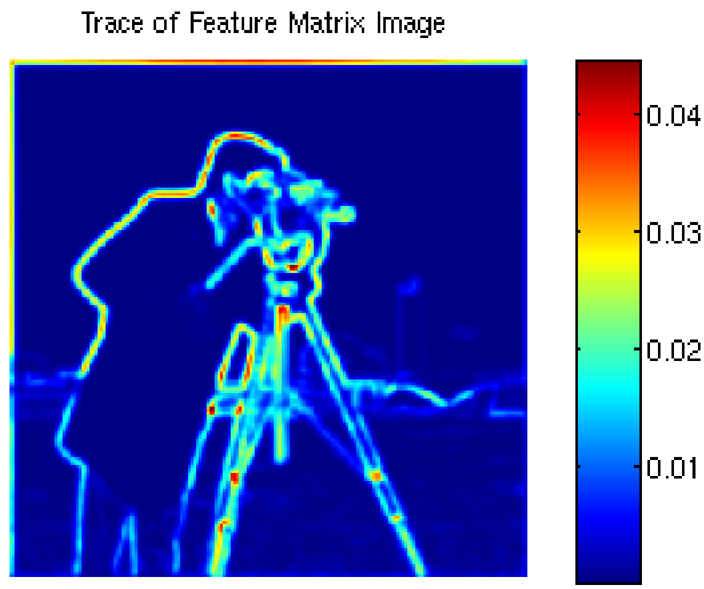
Calculating Feature Strength

We will now attempt to detect significant features in the image utilizing the quantities in the matrix above. We will calculate the determinant and trace of the matrix, and then examine the ratio of these to determine the areas in the image where features are the strongest. The determinant image is shown below.



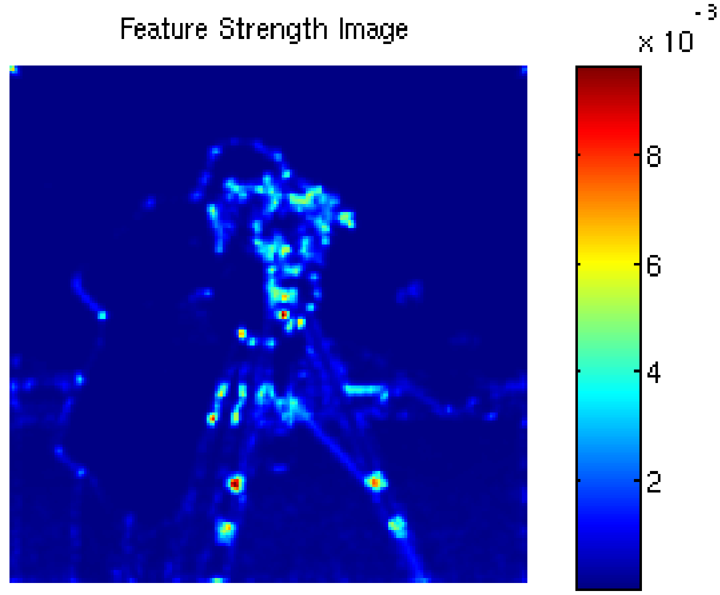
The determinant of our matrix is Ix^2 * Iy^2 - (IxIy)^2, or difference between the product of the squared partial derivatives and the square of the product of the partial derivatives. It therefore makes sense that we will see a strong responce where both partial derivatives are large because we average the partials after squaring in the first term, and square the average of the product of the partial in the second term. This has two effects, it not only highlights where there are large partials, but it also returns significantly larger values where both partials are large. The determinate therefore represents the uncertainty of the localization of our features. We can also explain the determinant as the product of the eigenvales of the feature, which lends intuition as to why we see strong responses for features which are well localized. We therefore see features emerge in the image along edges in both horozontal and vertical directions, and our strongest responses occur at locations where there are edges in both directions (corners). For example, consider the bands on the legs of the camera, which are horozontal stripes of white bounded by the vertical dark edges of the leg. Similarly, consider the point in in the middle of the image, at the top of the central tripod base shaft, where the dark shadow of the camera and the light tripod shaft intersect.

Next we will consider the trace of the image, which is the sum of the squared partial derivatives.



The trace is the sum of the squared partial derivatives of the image, and so gives the strongest responses at edges in the image. This is to be expected, as the trace of our matrix A is in fact equal to the magnitude of the gradient squared. We may also explain the trace of our matrix as the sum of the eigenvalues. This means that the trace will produce larger responces when we have large eigenvalues, which is another explanation for why it detects edges. We see in the trace image the cameraman outlined in a strong silhouette and the legs of the camera outlined as well. We note that the trace does not preserve very many details in the background edges or the interior of the coat. This is because these regions exhibit changes in pixel intensity which are not very notable, and so the partial derivative responses are small.

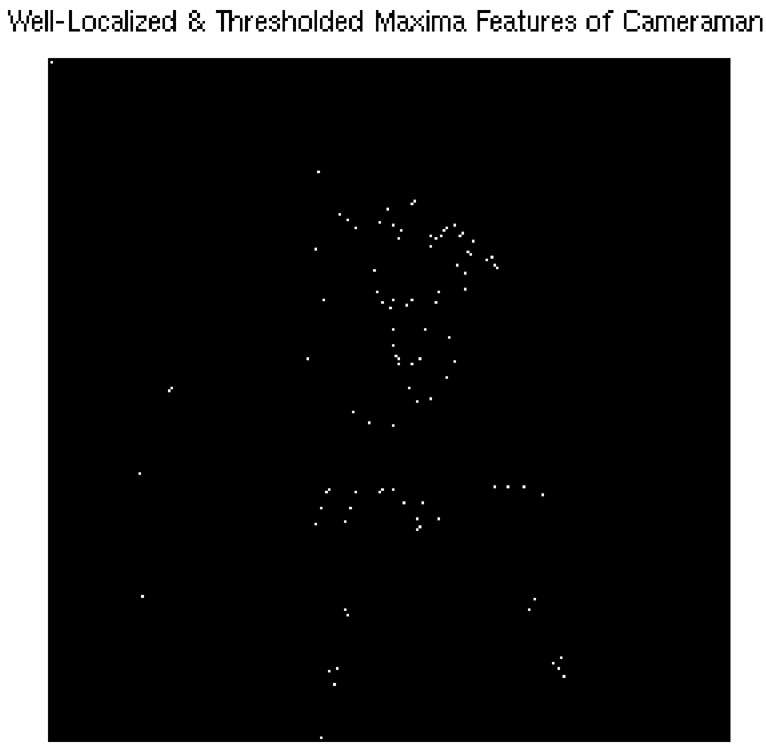
Finally, we consider the ratio of the trace to the determinant.



In the ratio image, we see responses similar to that of the determinate, because this operation also responds to features where both eigenvalues are large. For example, we again see strong responses at the bands on the legs of the camera, and at the top of the central tripod shaft. This makes sense because the ratio of the determinant to the trace is the ratio of the product of the eigenvalues over their sum, which we know maximizes responses where both eigenvalues are large.

Finalizing Feature Detection

Simply considering the ratio of the determinant to the trace gives us an idea where the strong features are in the image, but we need a method to refine the locations of the features we want to consider. Because we wish to mark features which are especially well-localized, we accomplish this by first determining extracting the local maxima in the ratio image. We then apply an appropriately small threshold to the ratio image to eliminate weak responses and create another binary image. Finally, since we want to only consider the features which appear in both of these cases (ie are both local maxima and above the threshold) we may take the product of the two binary images, which returns a matrix containing the locations of features as indicated by nonzero entries.

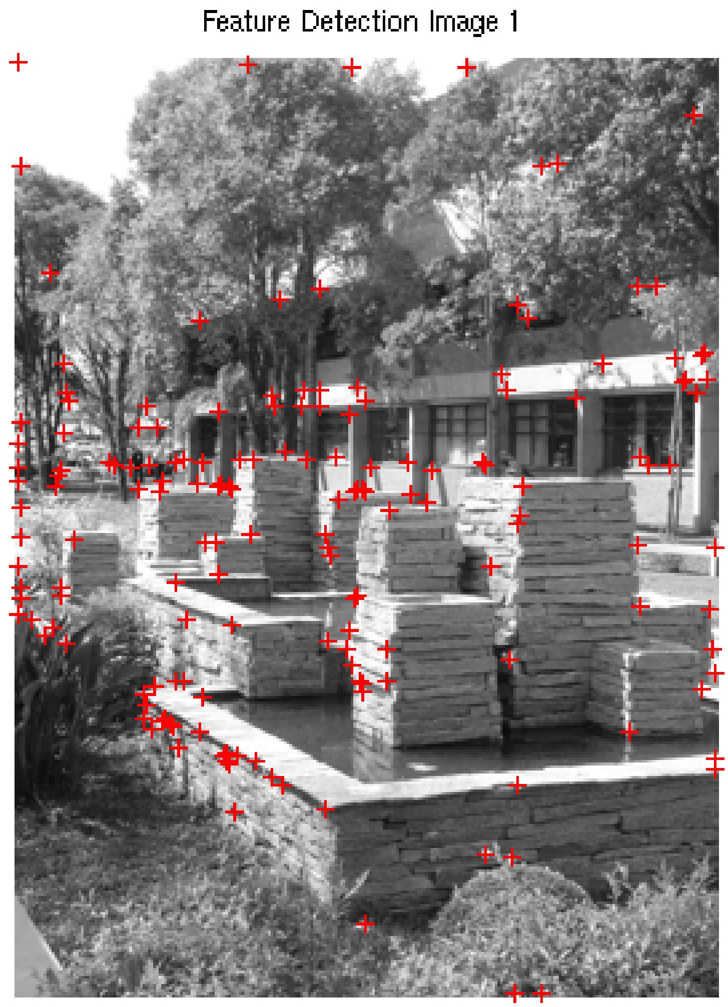


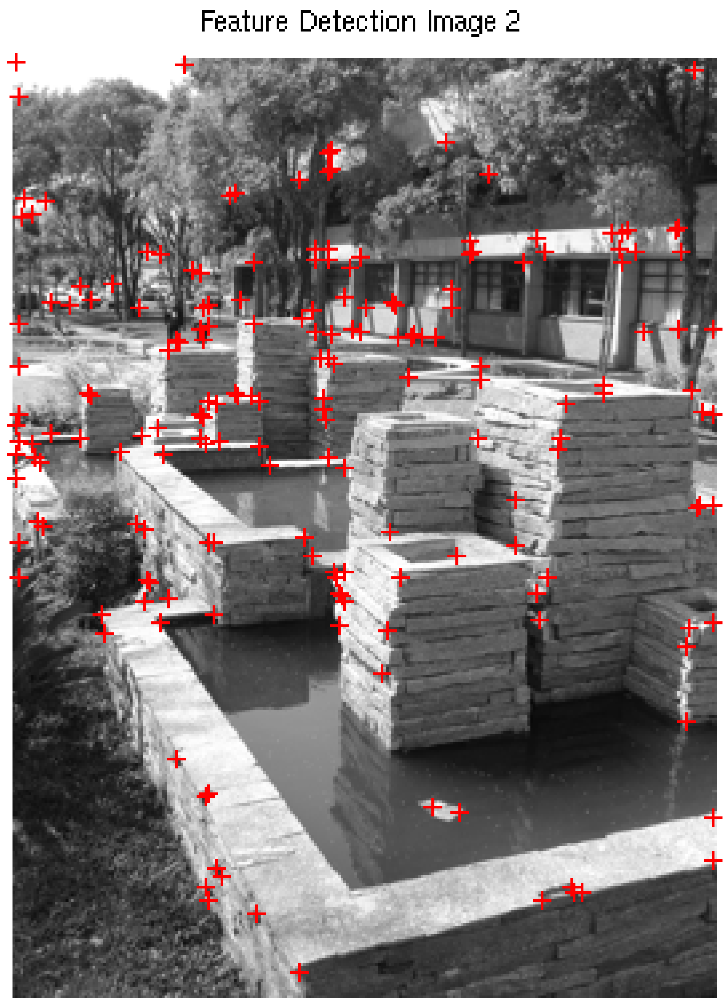
Making a Detection Function

We want to generalize our above approach to apply it to several images, and so we create a function which consolidates all of the above steps.

Estimating repeatability

In an attempt to examine the reliability of our detection function, we will now consider two images of the same scene taken from slightly different points of view and compare the results of our detection between them. The two images and their detected features are shown below.





The features detected are, in general, corners which are well localized. Since the two pictures were taken at different angles, some features may not be correctly located again. In general, the repeatability of the function is fairly good. For instance, the very lower corner of the bottom stone wall is detected in both images, but the foreign floating object is only detected in the second image. This is most likely due to the shallow angle at which the picture was taken. Unfortunately, there are some regions where false positives appear or a high density of responses that do not necessarily correspond to appropriately localized features emerge. If however, we raise our threshold to lower the number of false positives, we lose many of the important responses.

Extra

We can modify our kpdet function so that it returns not only the locations of our detected features, but also the gradient orientations at each of these figures.

Conclusion

In this lab, we developed intuition as to how the eigenvalues associated with a feature can be used to locate key features in an image. We also saw how partial derivaties govern our detection of corners, and developed an algorithm for such feature detection using these principles. Finally, to verify our approach we also consider its repeatability, which is very important for feature matching across images.

Acknowlegements

The cameraman image was loaded from the MATLAB library, and the kpdet images are courtesy of Jerod Wienmann and licensed under a Creative Commons Attribution-Noncommercial-Share Alike 4.0 International License. The image of the matrix A was taken from http://en.wikipedia.org/wiki/Corner_detection and modified by Renn Jervis on 3/3/15. Code snippets taken from Feature Detection lab: http://www.cs.grinnell.edu/~weinman/courses/CSC262/2015S/labs/

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