Part 1. Harris Corner Detection

a. Discuss the results of blurred images and detected edge between different kernel sizes of Gaussian filter.

(a) Blurred images: According to the result, images convolved by a 10x10 Gaussian filter are more blurred than images convolved by a 5x5 Gaussian filter. That is because a Gaussian filter with a larger kernel size synthesizes the pixel in the convolved image from a larger area of pixels around the corresponding pixel in the original image. In other words, pixels in a larger kernel-convolved image contain more information of pixels in the original image around it corresponding position.

(b) Detected edge: According to the result, edges detected in an image convolved by a filter of a smaller kernel size are more distinct than those detected in an images convolved by a filter of a larger kernel size. That is because a larger Gaussian filter will not only eliminate more noise in an image but also remove more detail from an image, which makes it more difficult for Sobel operators to detect edges.

b. Difference between 3x3 and 5x5 window sizes of structure tensor.

Two eigenvalues of a structure tensor of generated from a shifting window of size n centered at pixel u are equivalent to amounts of the most significant change and the least significant change of a nxn shifting window centered at pixel u for a constant shifting distance and arbitrary directions.

According to the equation $E(u,v) = \sum_{x,y\in W}[I(x+u,y+v) - I(x,y)]^2$, a shifting window with more pixels in it should have larger E(u, v), that is, a larger shifting window has more change than a smaller shifting window, which is the reason why a 5x5 shifting window resulted in larger smaller eigenvalues than a 3x3 shifting window on the same image.

c. The effect of non-maximal suppression.

Being inputted smaller eigenvalue of an image, non-maximal suppression will:

(1) filter out all pixels with eigenvalue smaller than threshold, then form all remaining pixels into a list L.

(2) in each iteration of while loop, the pixel p with the largest eigenvalue will be extracted and marked as a corner point on the original image, then pixels in L whose distance from p is shorter than minDis will be removed. Not until L is empty will the while loop terminate.

We can tell that there are more corner points detected from the eigenvalues calculated from 5x5 window than 3x3 window, and that is because eigenvalues calculated from 5x5 window are larger and less likely to be filtered out by threshold.

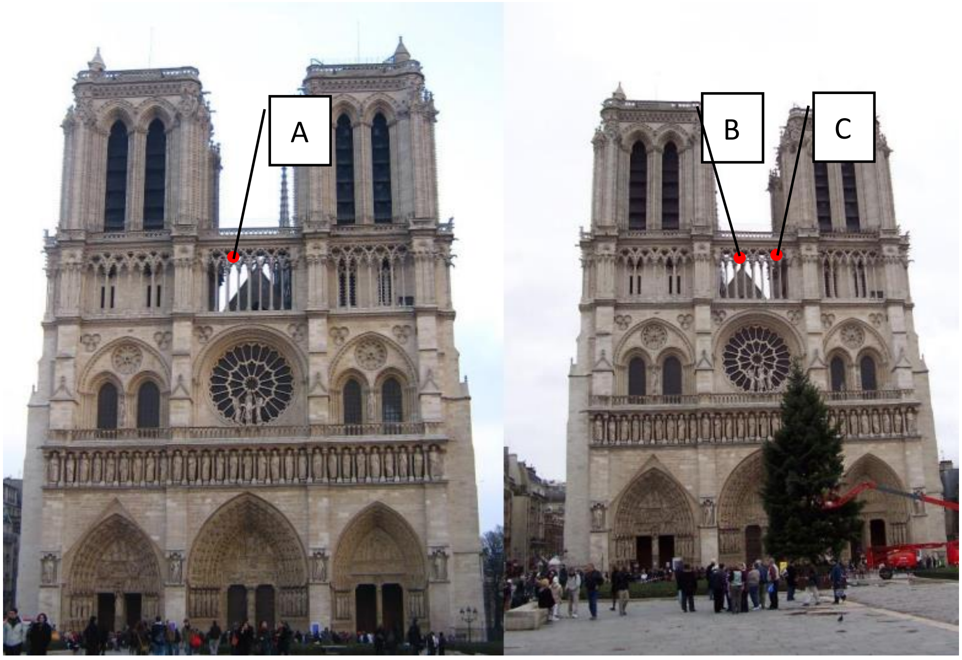
d. Discuss the result from (B). Is Harris detector rotation-invariant or scale-invariant.

According the result from (B), we can tell that Harris detector is rotation-invariant since the corner response R (i.e. eigenvalue) remains the same after an image rotation. However, it is not scale-invariant, since an edge in a larger image may be classified as a corner in a smaller image and some corners in a larger image may be too vague to be detected in a smaller image.

Part 2. SIFT interest point detection and matching

a. Discuss the cases of mis-matching in the point correspondences

In the beginning, we resorted to 1NN matching method that brutally compares the similarity between every pair of interest points in img1 and img2 and matches every interest point kp_i in img1 with interest point in img2 having the shortest distance from kp_i. Since each interest point in img1 should be matched with an interest point in img2, there might be some pairs or mis-matched points with extremely weak similarity, but we could solve this problem easily by defining a threshold to filter out these poorly related points. However, there were still some min-matching error, e.g., in Pic. 1, although we knew that only point B should be matched with point A, both of point B and point C might be matched with point A because point C might be more similar to point A in a relative small perspective. This kind of error may be resulted from angle of shot or other factors. And, unfortunately, it is difficult to solve this problem with 1NN matching method.

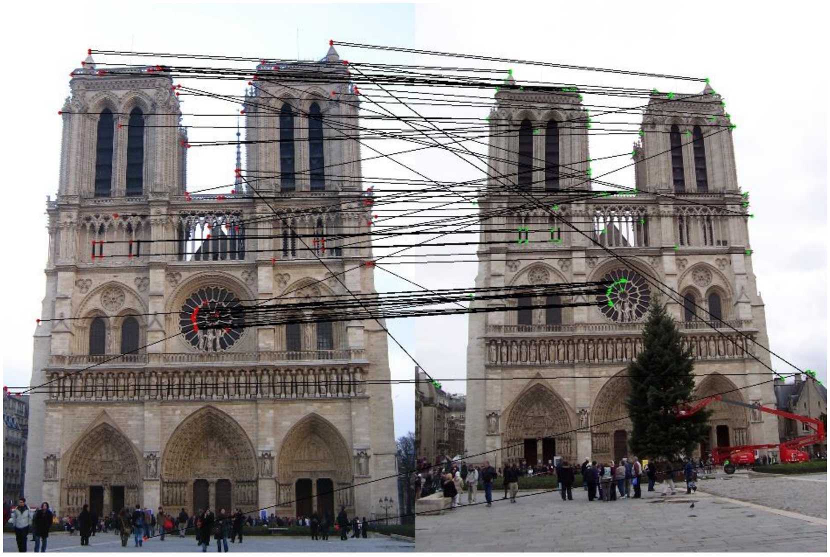


Pic. 1

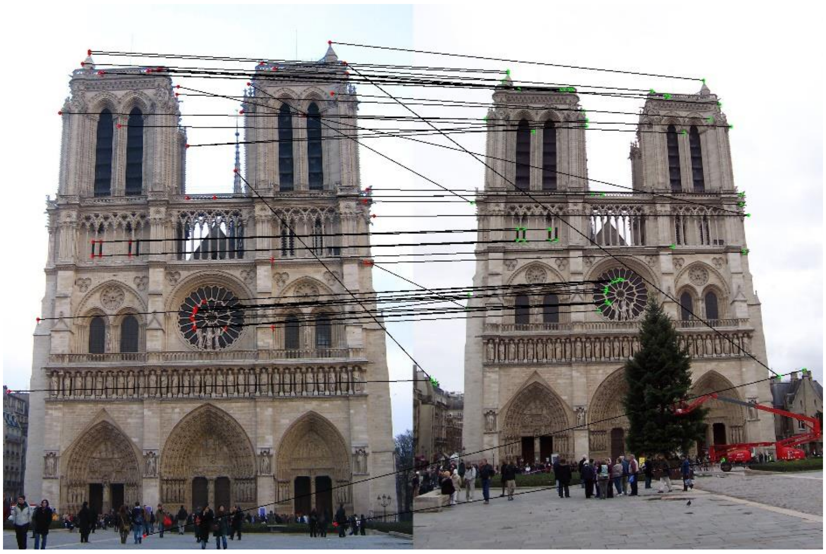
b. Discuss and implement possible solutions to reduce the mis-matches, and show you result.

To solve the mis-matching problem, we can resort to 2NN matching method that selects two interest points $kp_{i,1}$ and $kp_{i,2}$ in img2 having the shortest distance and the second shortest distance from interest point kp_i in img1 and compares the similarity between them. By Predefining a ratio, we can check whether $|kp_i - kp_{i,1}| <$ ratio $\times$ $|kp_i - kp_{i, 2}|$ to perceive the occurrence of mis-matching case. If $|kp_i - kp_{i,2}|$ is smaller than ratio $\times$ $|kp_i - kp_{i, 2}|$, we can tell that $kp_{i,2}$ is unique enough for not causing any min-matching case. Conversely, if $|kp_i - kp_{i,2}|$ is greater than or equal to ratio $\times$ $|kp_i - kp_{i, 2}|$, neither of $kp_{i,1}$ and $kp_{i,2}$ can be matched with kp_i because of the ambiguity of similarity.

Pic.2 and Pic.3 are the results of 1NN matching method and 2NN matching method.



Pic. 2



Pic. 3