CS543 Assignment 2

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Part 1 Fourier-based Alignment:

You will provide the following for each of the six low-resolution and three high-resolution images:

- Final aligned output image
- Displacements for color channels
- Inverse Fourier transform output visualization for both channel alignments without preprocessing
- Inverse Fourier transform output visualization for both channel alignments with any sharpening or filter-based preprocessing you applied to color channels

You will provide the following as further discussion overall:

- Discussion of any preprocessing you used on the color channels to improve alignment and how it changed the outputs
- Measurement of Fourier-based alignment runtime for high-resolution images (you can
 use the python time module again). How does the runtime of the Fourier-based
 alignment compare to the basic and multiscale alignment you used in Assignment 1?

A: Channel Offsets

Replace <C1>, <C2>, <C3> appropriately with B, G, R depending on which you use as the base channel. Provide offsets in the **original image coordinates** (after the image has been divided into three equal parts corresponding to each channel) and be sure to account for any cropping or resizing you performed.

Low-resolution images (using channel as base channel):

Image	<g> (h,w) offset</g>	<r> (h,w) offset</r>
00125v.jpg	(-3, 2)	(-6, 1)
00149v.jpg	(-4, 2)	(-7, 2)
00153v.jpg	(-1, 3)	(-2, 4)
00351v.jpg	(-4, 0)	(-3, 1)
00398v.jpg	(-3, 3)	(-5, 4)
01112v.jpg	(-8, 0)	(-11, 1)

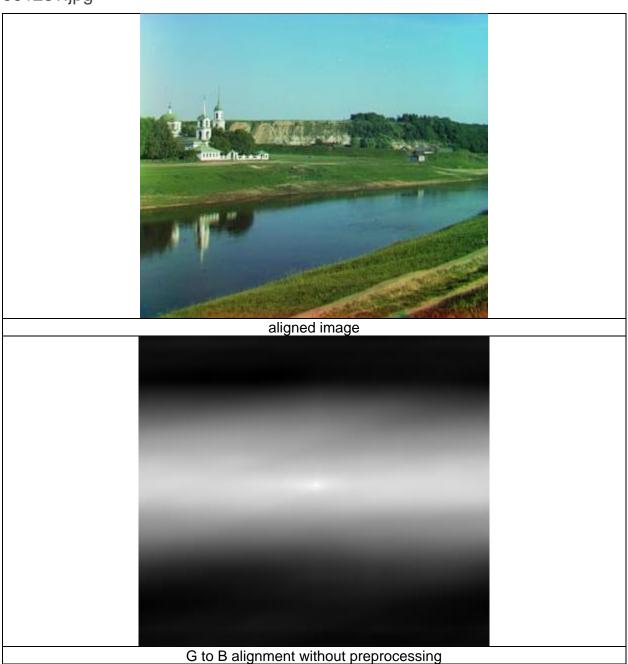
High-resolution images (using channel as base channel):

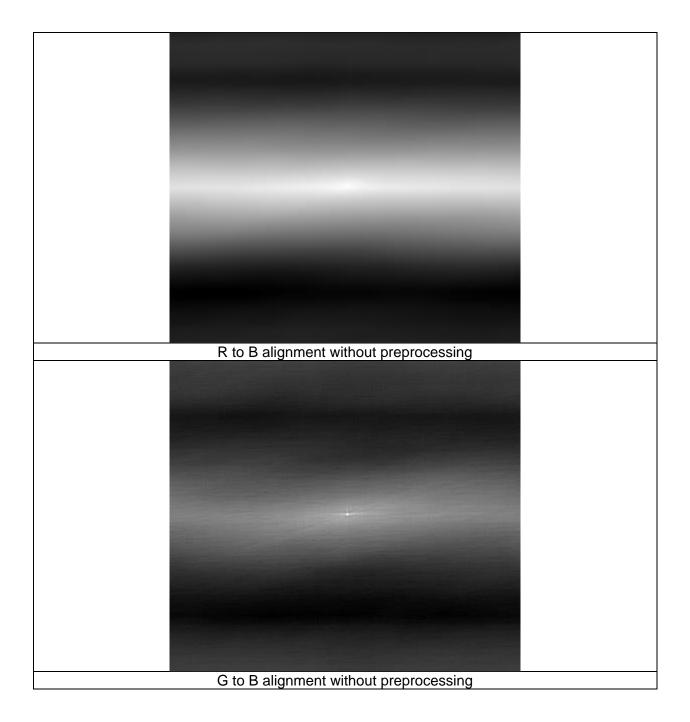
Image	<g> (h,w) offset</g>	<r> (h,w) offset</r>
01047u.tif	(-29, 23)	(-22, 39)
01657u.tif	(5, 23)	(-32, 33)
01861a.tif	(-26, 36)	(-40, 47)

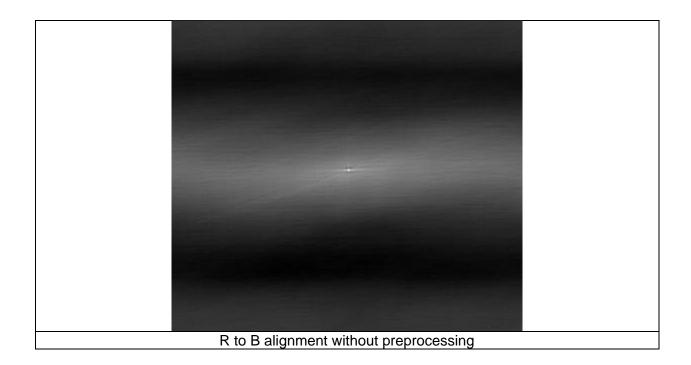
It should be noted that I performed an *arbitrary image cropping* to segment the original images into three distinct channels.

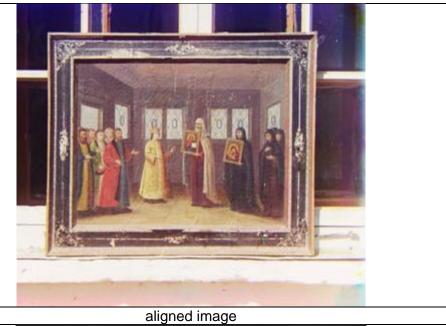
B: Output Visualizations

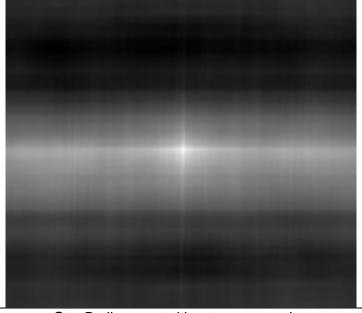
For each image, insert 5 outputs total (aligned image + 4 inverse Fourier transform visualizations) as described above. When you insert these outputs be sure to clearly label the inverse Fourier transform visualizations (e.g. "G to B alignment without preprocessing").



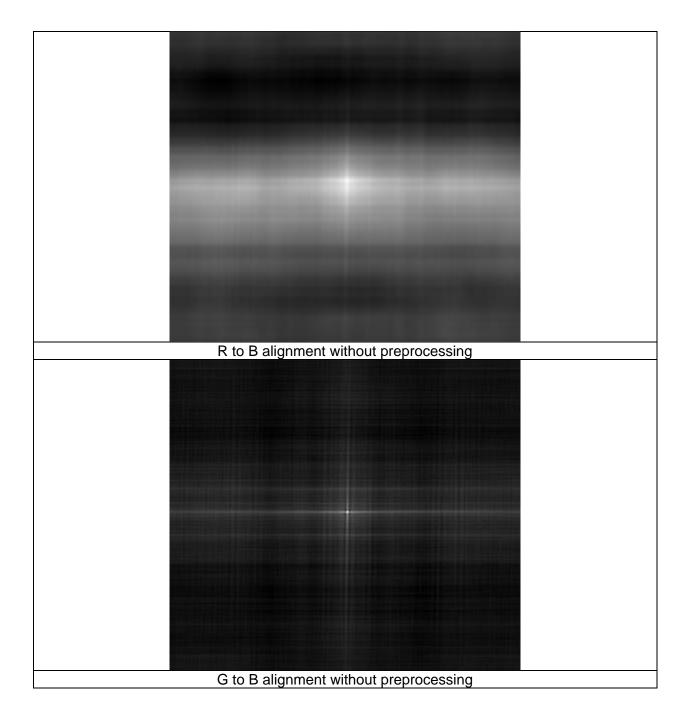


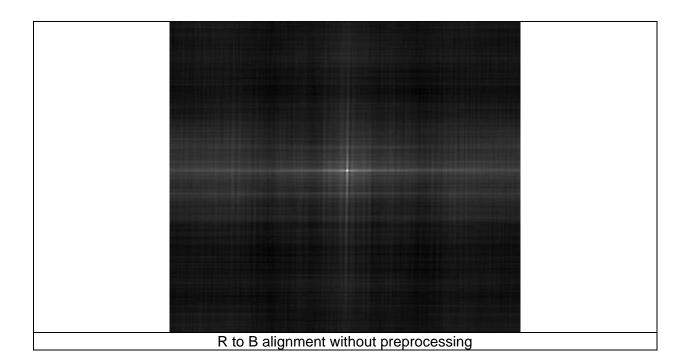


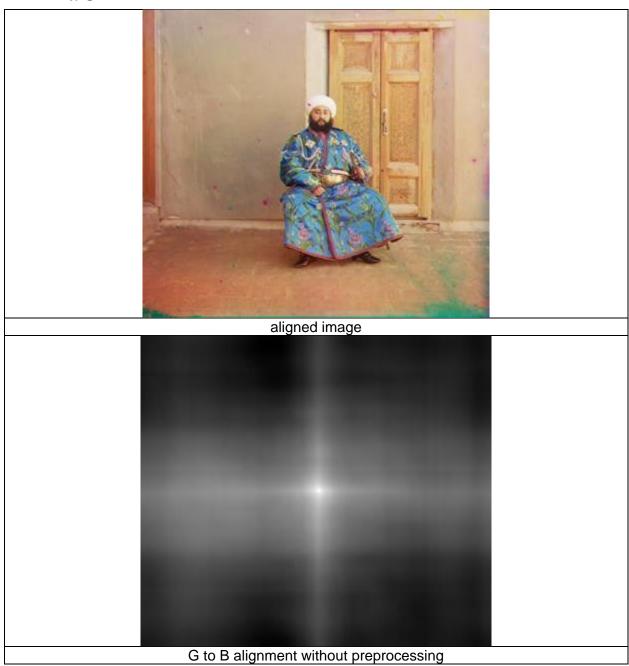


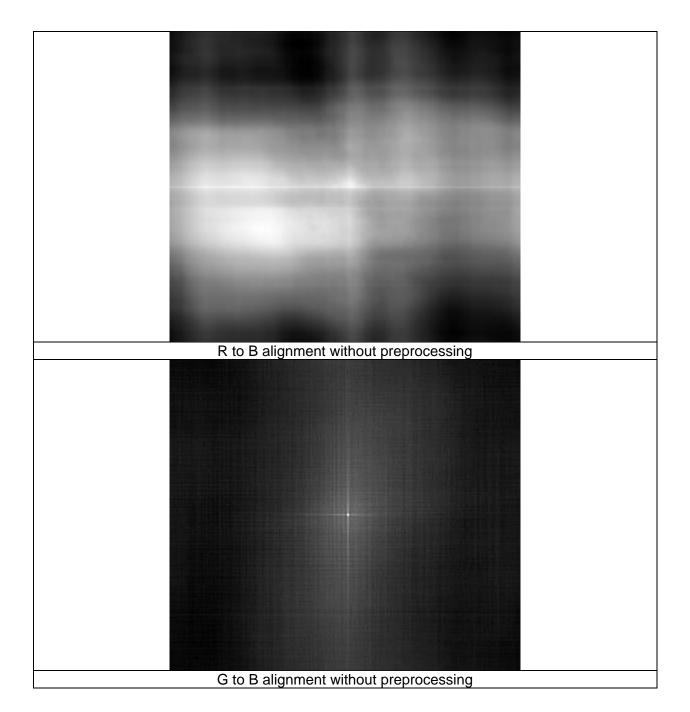


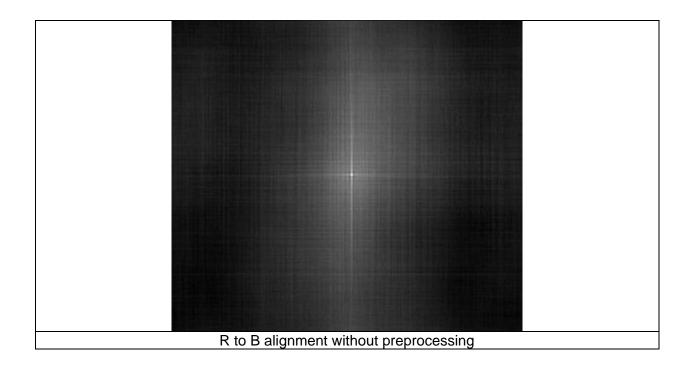
G to B alignment without preprocessing





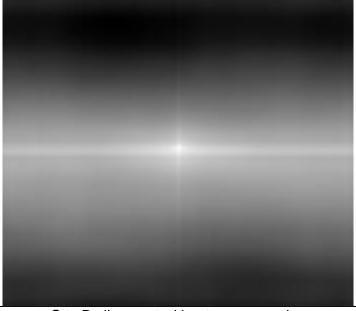




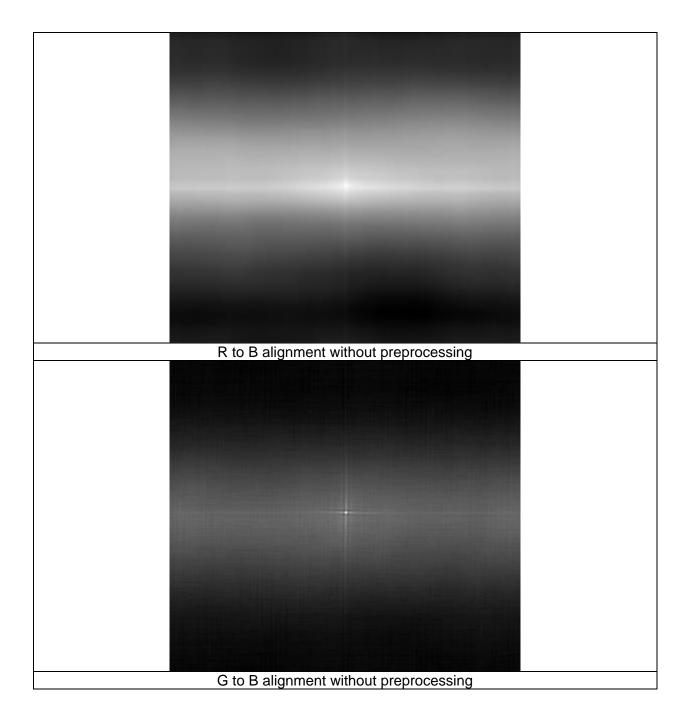


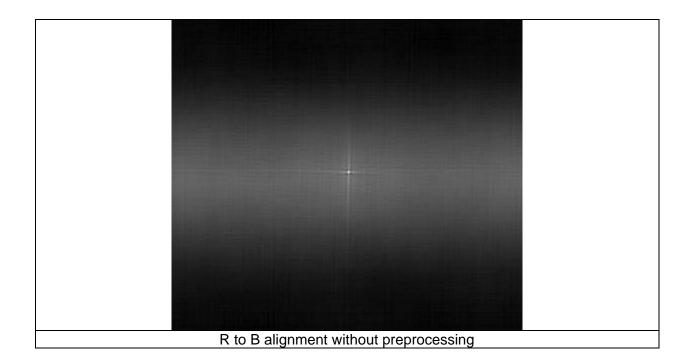


aligned image



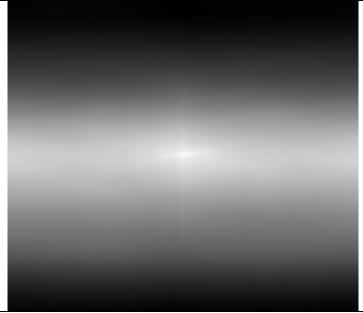
G to B alignment without preprocessing



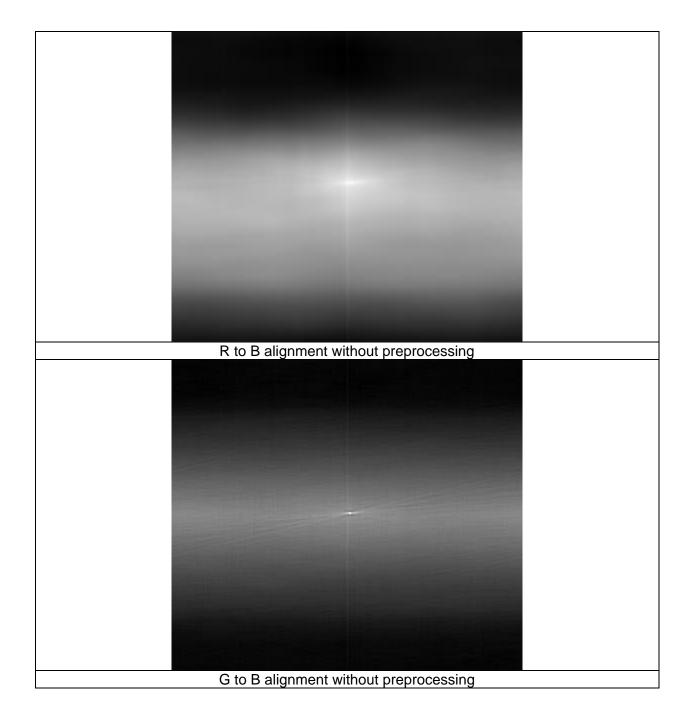


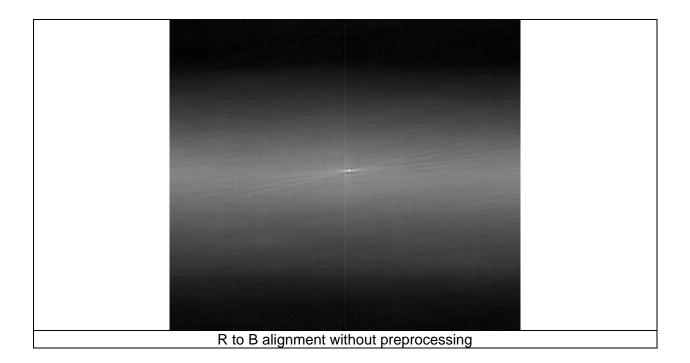


aligned image



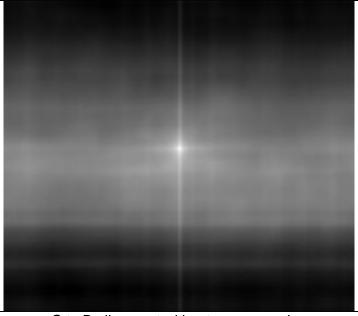
G to B alignment without preprocessing



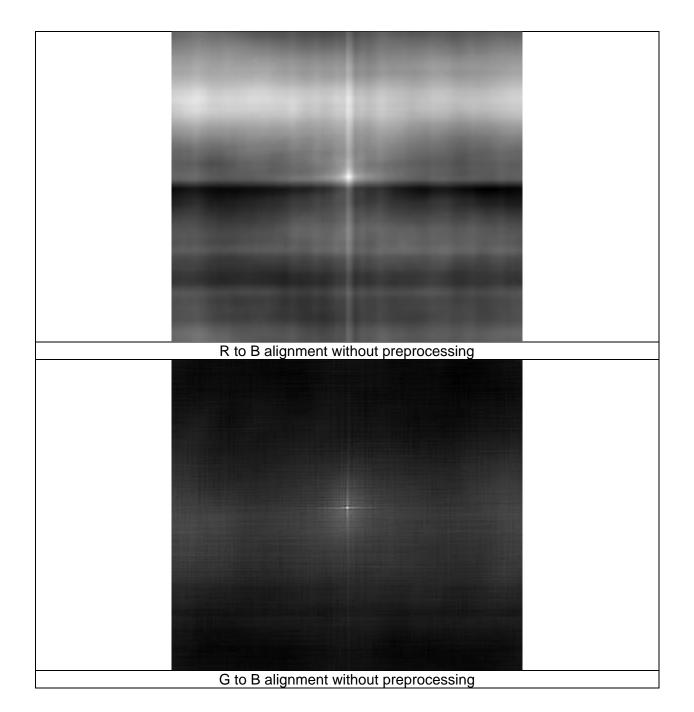


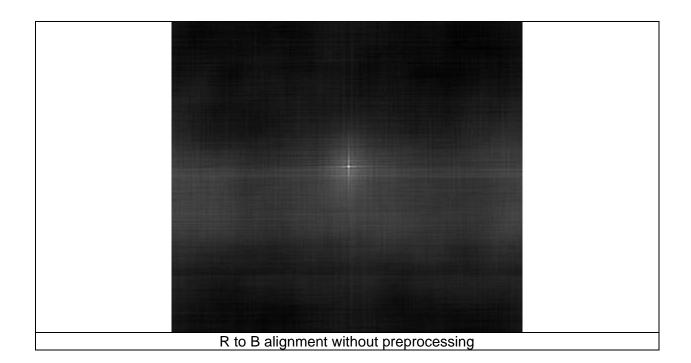


aligned image



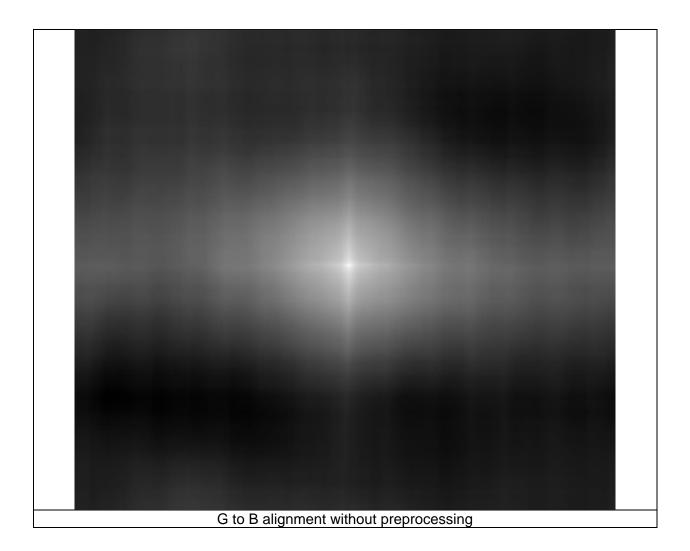
G to B alignment without preprocessing

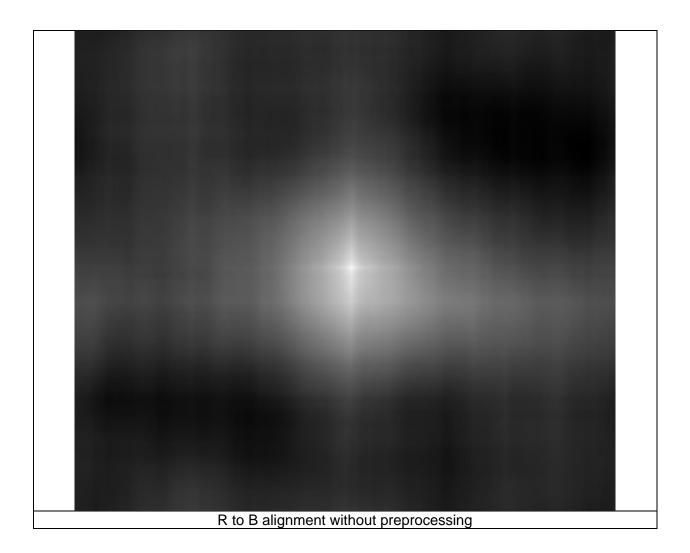


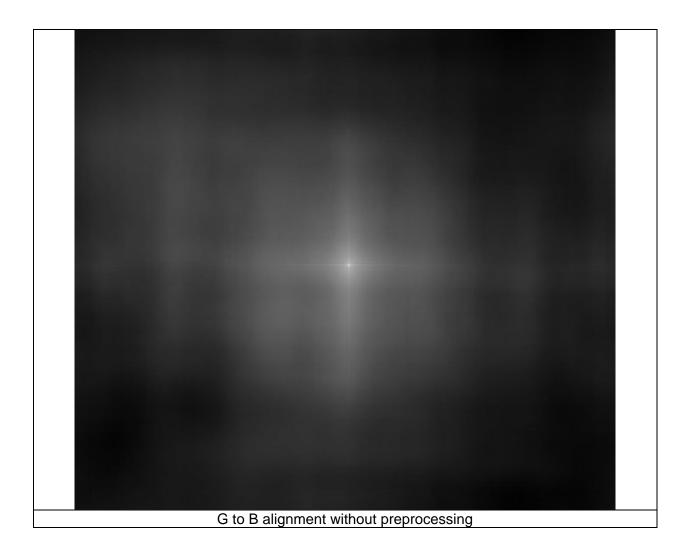


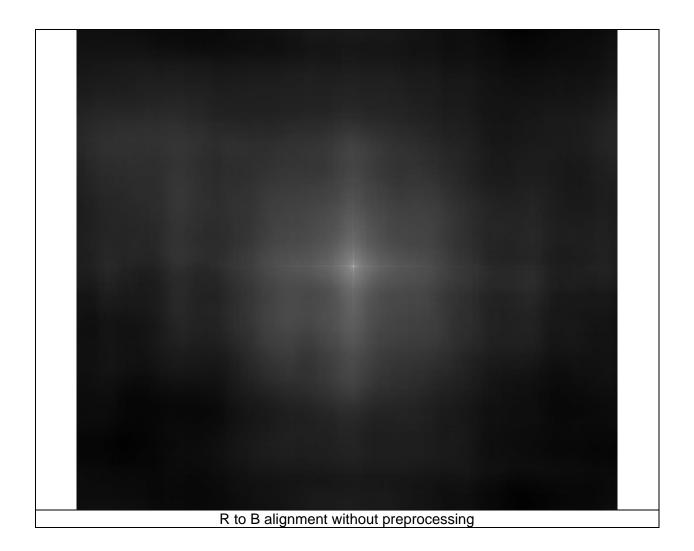
01047u.tif





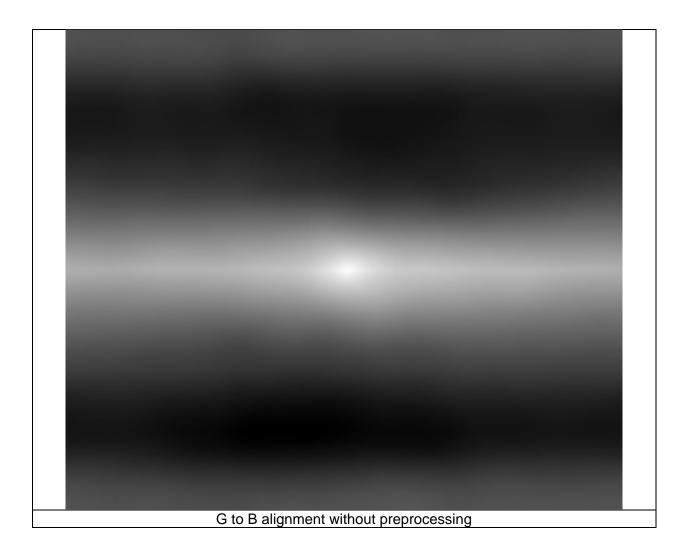


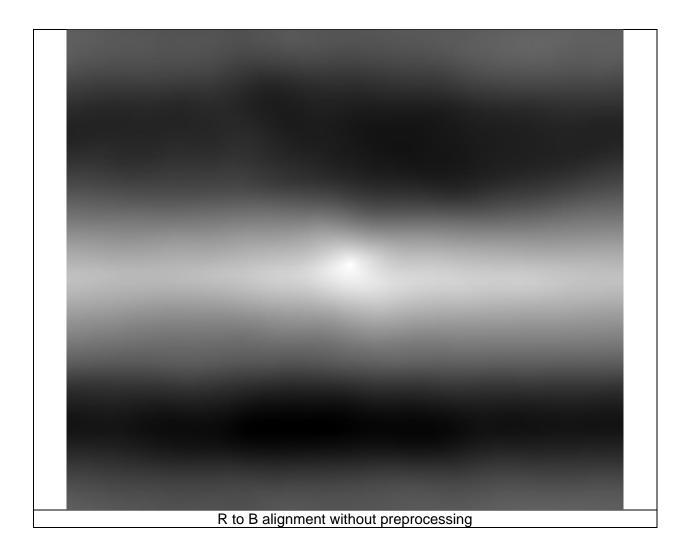


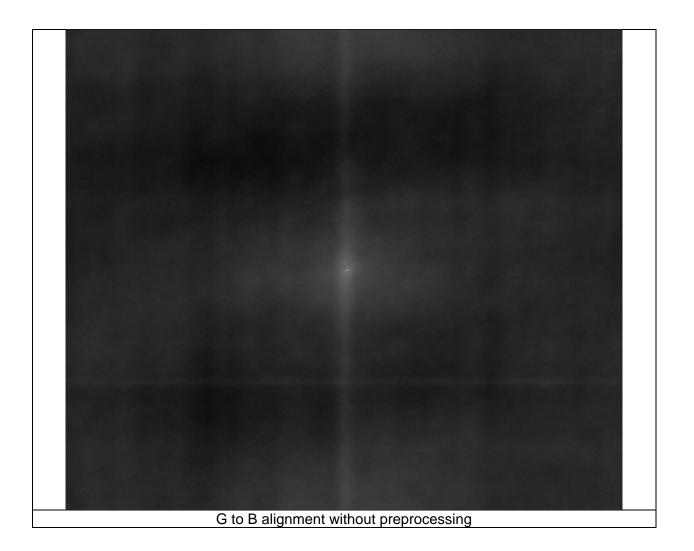


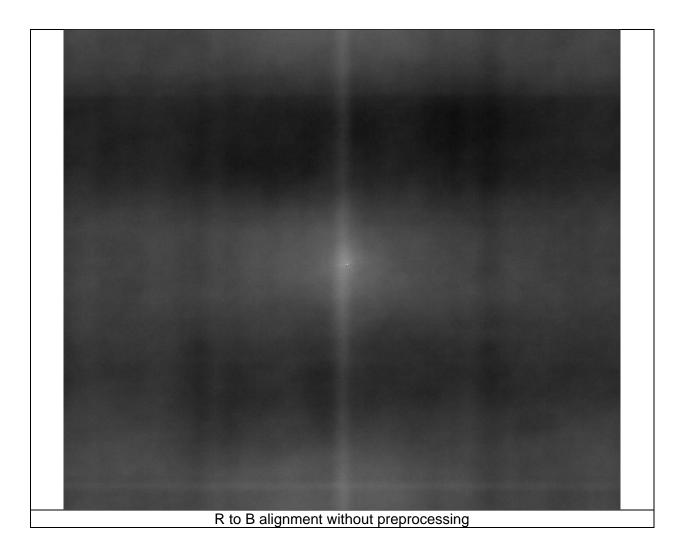
01657u.tif





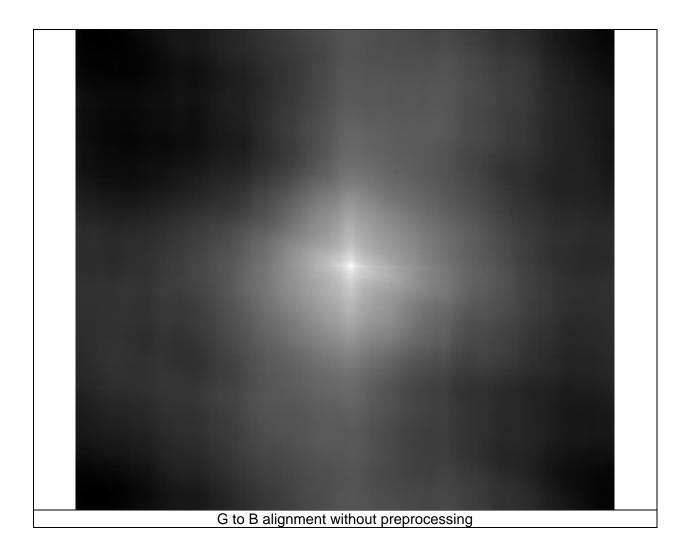


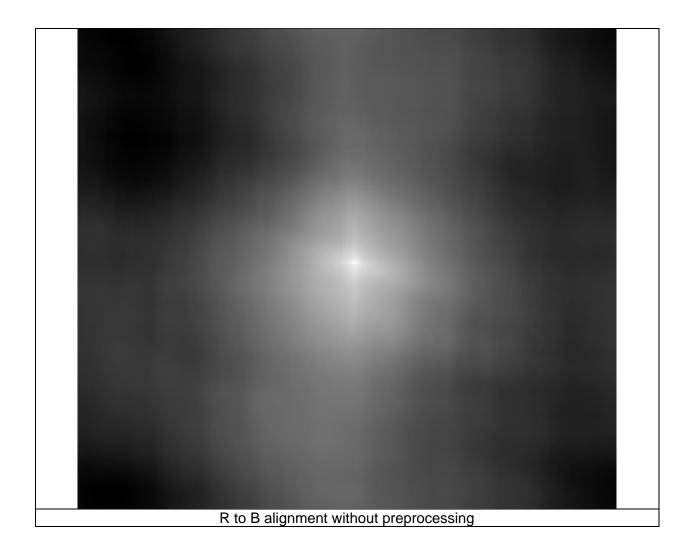


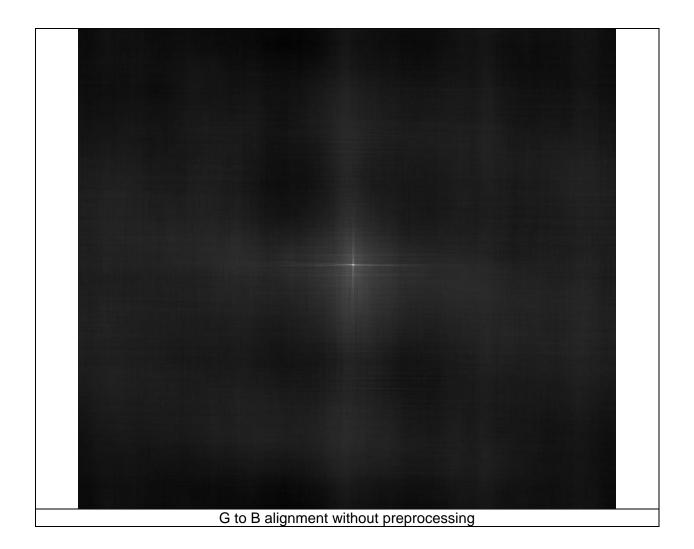


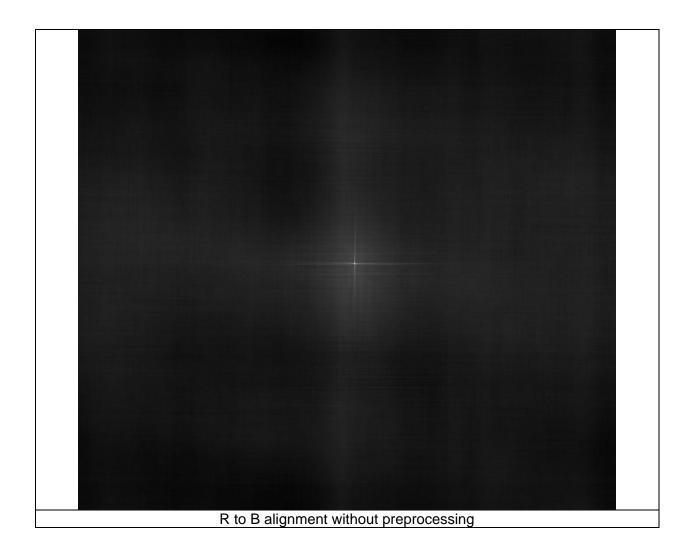
01861a.tif











C: Discussion and Runtime Comparison

The peak of the Inverse Fourier transform output becomes significantly more pronounced following preprocessing steps such as sharpening. Consequently, the alignment results improve noticeably when preprocessing is applied.



An example of failure

In certain instances, the maximum value acquired without preprocessing can be misleading, as illustrated in the above figure. Preprocessing, on the other hand, has the capability to effectively rectify this issue.

Runtime comparison:

File name	Run time without preprocessing	Run time with preprocessing
merged_00125v.jpg	0.02905	0.03305
merged_00149v.jpg	0.02861	0.04118
merged_00153v.jpg	0.02902	0.04140
merged_00351v.jpg	0.03562	0.03133
merged_00398v.jpg	0.03355	0.04133
merged_01112v.jpg	0.03129	0.04005
merged_01047u.tif	6.551	5.639
merged_01657u.tif	8.104	5.720
merged_01861a.tif	8.365	5.579

When contrasting these findings with those obtained in Assignment One, it is evident that the computational time has been notably diminished by approximately 50%. This observation underscores the superior efficiency of the Fast Fourier Transform (FFT) method over the Normalized Cross-Correlation (NCC) technique in the context of image alignment.

Part 2 Scale-Space Blob Detection:

You will provide the results for 4 different examples chosen by your own:

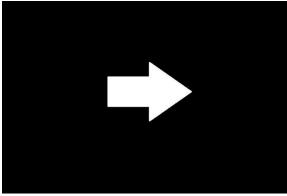
- Original image
- Each of the five modified images (shift, rotate, scale)

You will provide the following as further discussion overall:

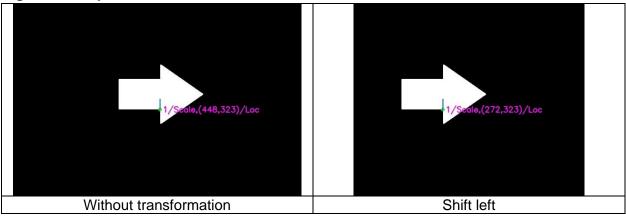
• Explanation of any "interesting" implementation choices that you made.

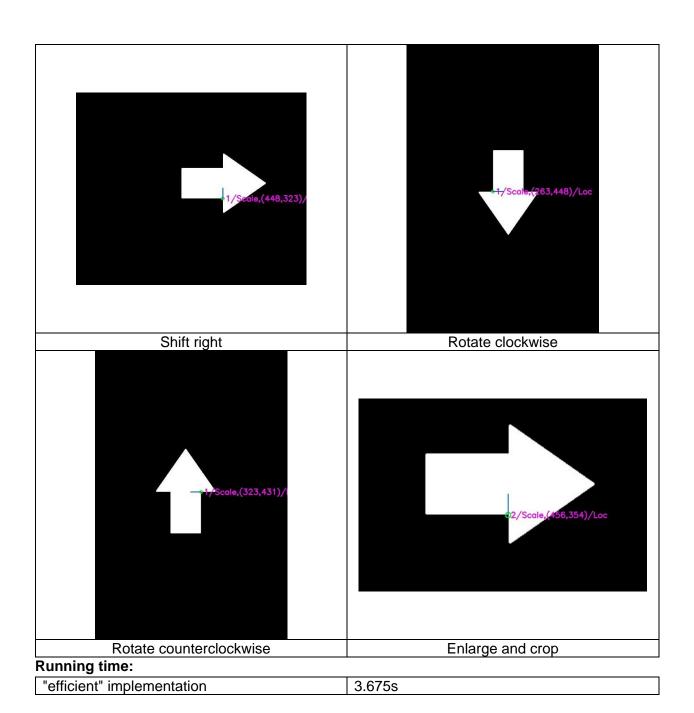
Example 1:

Original image:



Source: https://www.meccanismocomplesso.org/en/opencv-python-harris-corner-detection-a-method-to-detect-corners-in-an-image/, adapted by author for CV assignment, fall 2023





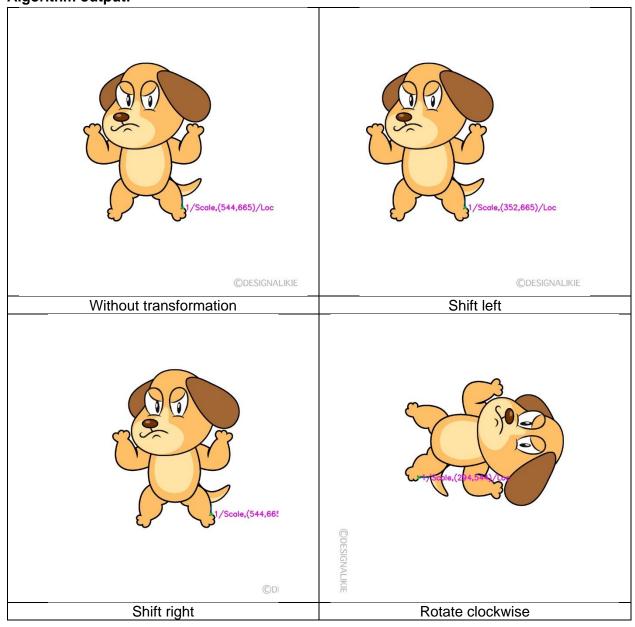
Example 2:

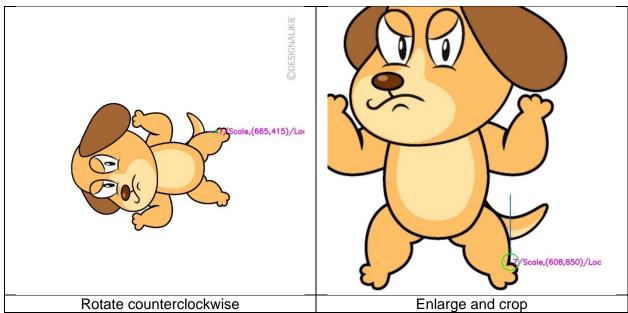
Original image:



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Source: https://charatoon.com/?id=396, adapted by author for CV assignment, fall 2023





Running time:

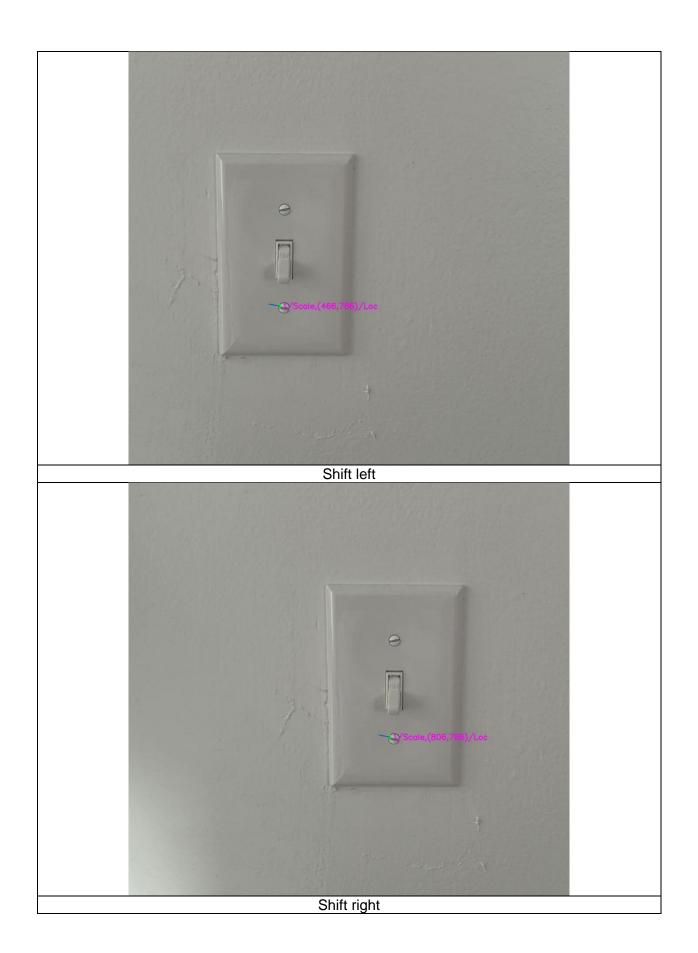
"efficient" implementation	6.609s
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Example 3:

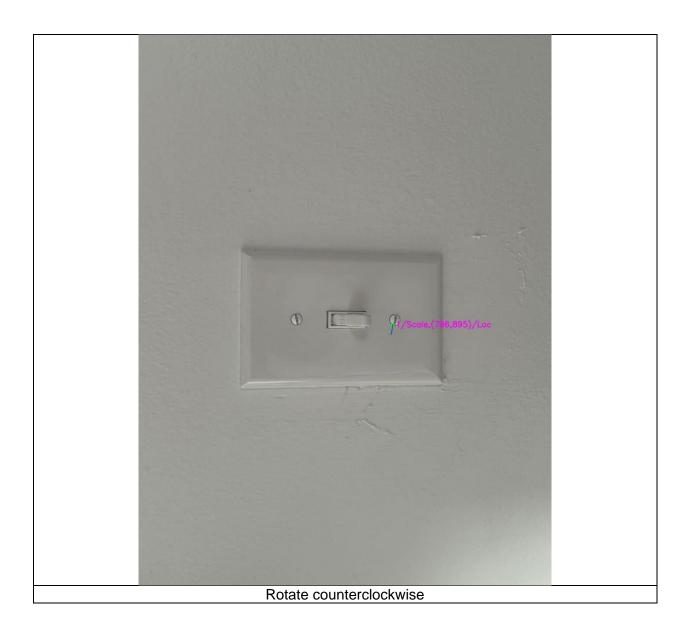
Original image:

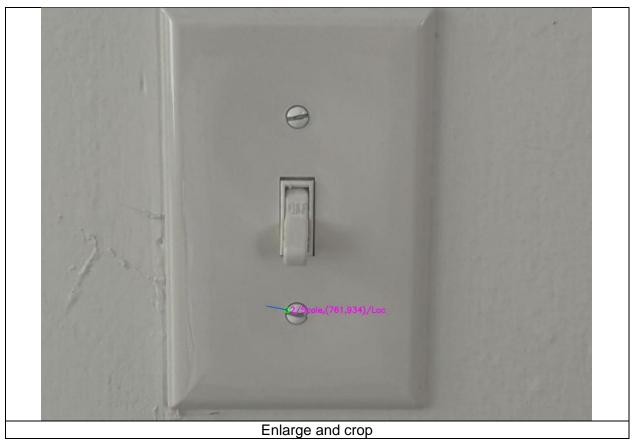












Running time:

"efficient" implementation	15.572s
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Example 4:

Original image:







Shift left



Shift right







Running time:

"efficient" implementation	15.321s
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Discussion:

To enhance visualization, I adjust the corner detection threshold in the Harris detector to a value of one. This setting ensures that only the corner with the highest corner value undergoes further processing for blob detection. As a result, the output typically displays only a few corners, often just one.

The Harris detector, a function provided by the OpenCV library, is employed to identify corners within the image. For each corner detected, I determine the optimal scale value by evaluating log responses across a range from 1 to 7. It's important to note that I scale the log response by the square of the scale as normalization. The window size for blob detection is subsequently set to six times the best scale value. After applying an arctangent function, each pixel within the window represents an orientation value. To identify the most prevalent orientation, I utilize a histogram function.

An issue arises regarding the orientation value's output range, which is $(-\pi, \pi]$, while the input range expected by the histogram function should ideally be $[-\pi, \pi)$. To address this, I resolved the issue by mapping output values equal to π to negative π .