

29 November 2020
Fundamentals of Computer Vision

Assignment 3 260807622

1. **Homographies and RANSAC** Please see the code as I believe I was able to compute the best fit homography appropriately. However, due to time constraints I the image stitching is not as satisfactory as I would have liked:



Figure 1: Pair of images used for the homography



Figure 2: Image stitching from the homography computed

2. Uncalibrated Stereo

I will show results for two pairs of images. The first pair is below.

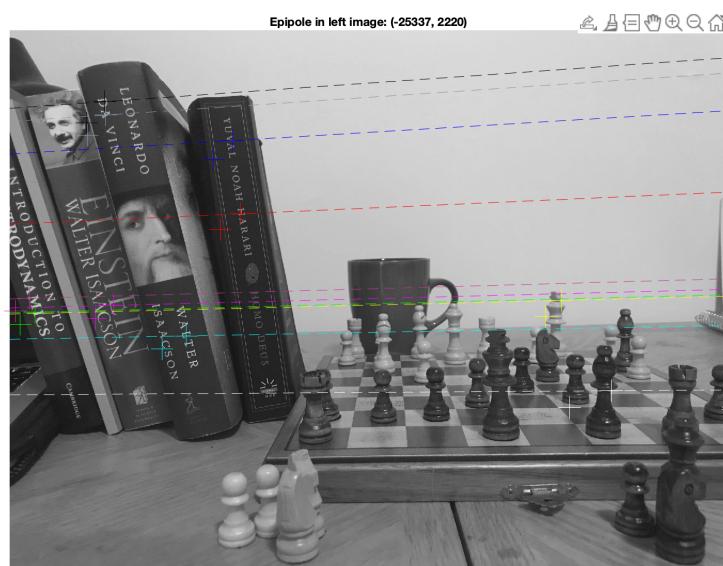


Figure 3: Left image epipolar lines

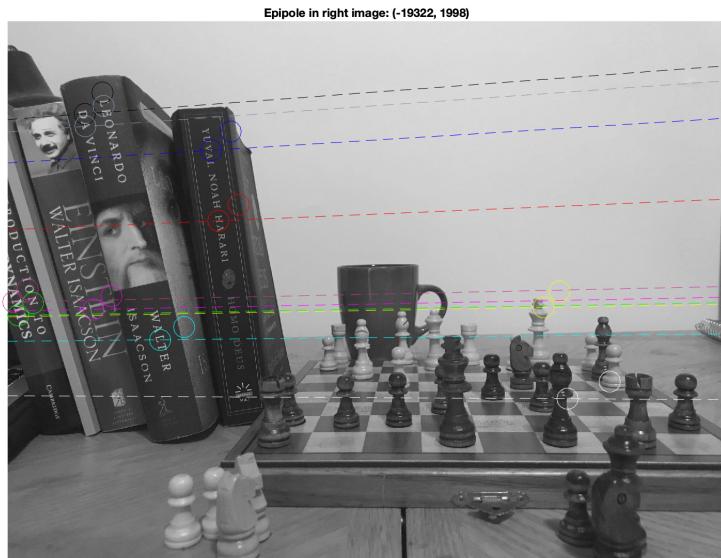


Figure 4: Right image epipolar lines



Figure 5: Rectified stereo images

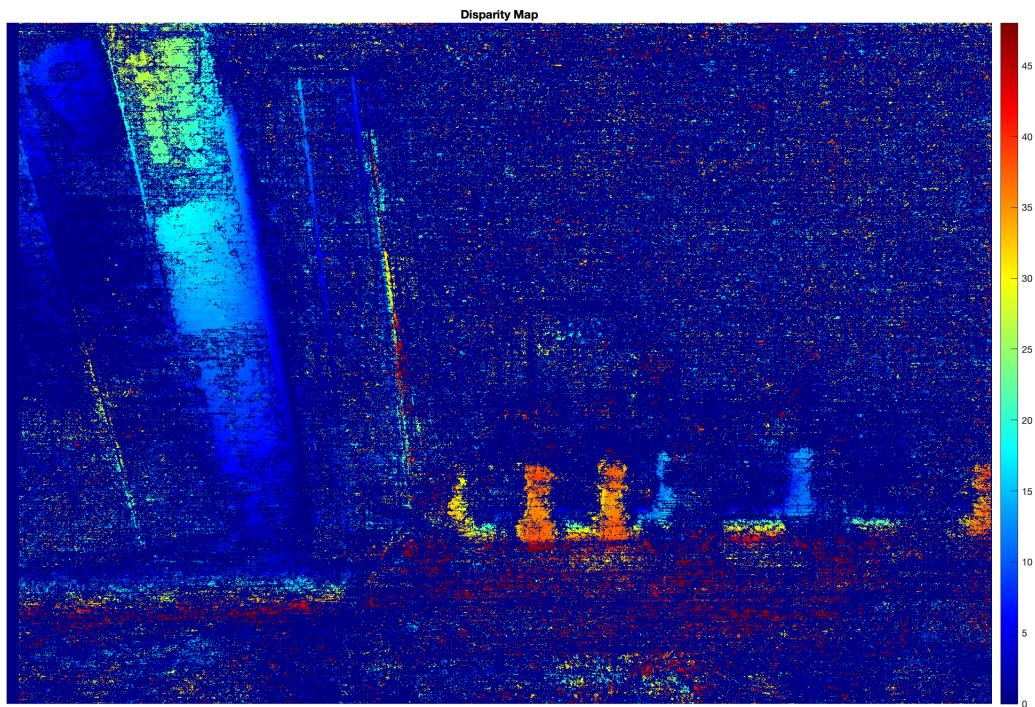


Figure 6: Disparity map of the rectified stereo images

Discussion after first image pair results:

From the results shown below, we see that the epipolar lines and the corresponding matching points found in Figures 1 and 2 mostly come from surface markings in the books displayed on the left of the images. Most runs of the script `homography.m` will show this density of matching points in the surface markings of the books. We hypothesize that the algorithm does not find many SURF features matching points elsewhere because most other objects such as the coffee mug in the back and the table in the front of the image do not have such surface markings. As for the chess board, points in its area are not very locally distinctive and will thus also not provide many matching points. Next we run the code again on a different pair of images, which has more of these surface markings.

Left image; Right Image



Epipole in left image: (55220, -902)

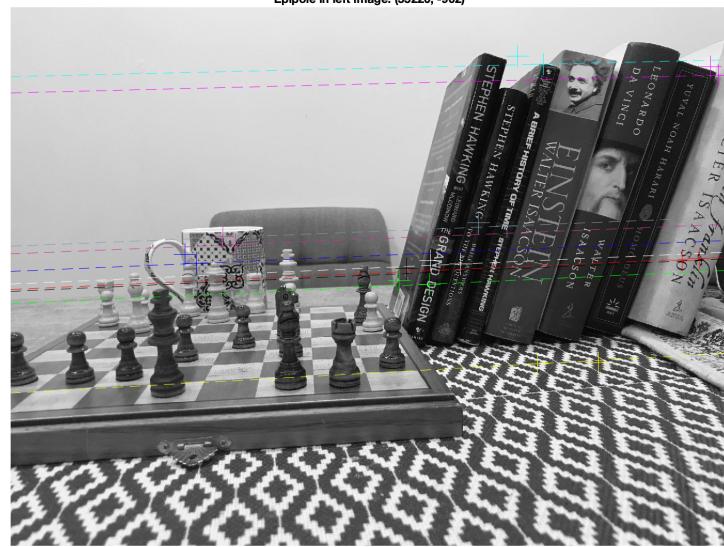


Figure 7: Left image epipolar lines



Figure 8: Right image epipolar lines



Figure 9: Rectified stereo images

Final Discussion:

For the second pair of images we see more evidence that the matching points density follow areas in the image where there are more surface markings (books, coffee mug), with the exception of the mat not providing any matches, as we might have expected false matches due to the repetitive pattern on its surface.

In sum, the algorithm seemed to have worked as the matching points on the corresponding images fall on the correct epipolar line. The fundamental matrix is not exactly correct, as the limited number of matching points in a pair of images puts constraints on its 'precision'. We would thus like dense matching for a better fundamental matrix. For stereo matching however, we need images only to be locally distinctive within each epipolar line, which is still a problem for dense matching.

A more accurate fundamental matrix would in turn lead to a better rectified image, as we can see that in our case, some of the red and cyan images are still clearly distinct in certain areas of the image.

Finally, as for the disparity mappings of the two pairs of images, in Figure 8 (NOTE: Figure 8 is on the next page) we see that the mapping only shows that the books and the coffee mug have the largest responses even though the chess board was the closest object. In Figure 4 however, queen-side knight, bishop and a little bit of the rook, which were the closest objects in the image were correctly identified as such by the disparity mapping. We also note that the table in the foregrounds of both image pairs was not given a high response in the disparity mapping.

The failures of the disparity mapping may be due to failures in the continuity constraint, as matching points tend to lie along lines of constant disparity, or due to failures in the uniqueness constraint, as a point x_l in the left image may have more than one match x_r in the right image.

The uniqueness constraint failure is made evident in the code when we add the parameter ('Unique', true) to the `matchFeatures` function, as this addition results in significantly fewer matching points being found.

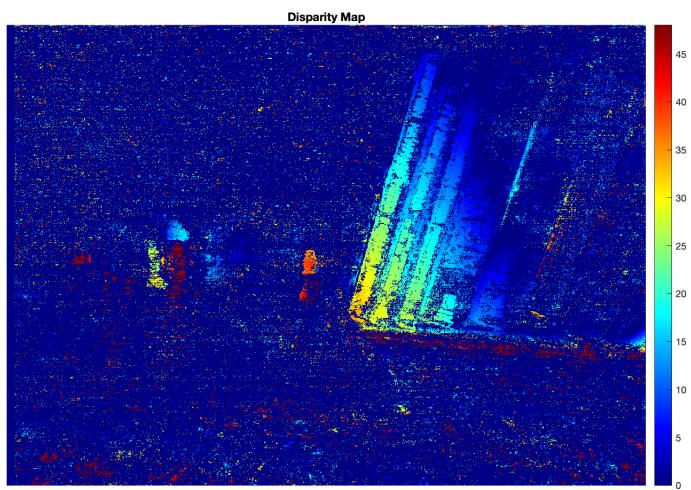


Figure 10: Disparity map of the rectified stereo images