Robotic Vision Final project: Visual localization

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1 Camera calibration

Task 1.1

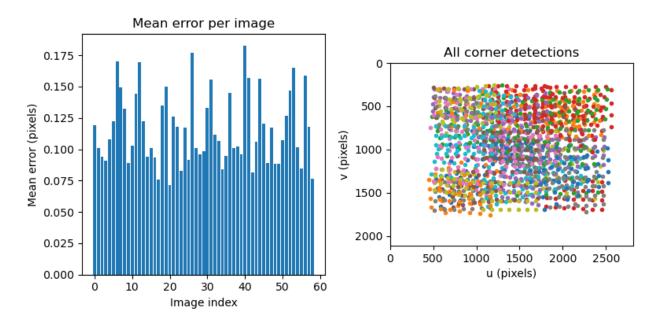
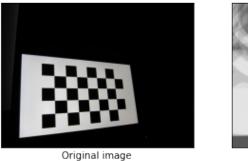
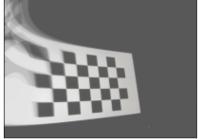


Figure 1: Results of the camera calibration

- a) There are several potential reasons that would result in significantly higher errors. This could be due to a strong tilt that often times also comes with changes of illumination. The visual tilting effect can also occur if the checkerboard is at the edge of the camera frame even though it is parallel to the image plane. To test this one could take a subset of pictures with a high visual tilting and calculate the error. If it applies there should be a significant difference to the error of the whole set.
- b) In general the accuracy looks quite alright. Whereas you can notice that it gets worse the closer you get to a corner. There you can still observe some distortion. So if you were to extend the calibration picture database, it should be with pictures close to the image frame and especially the corners.

Task 1.2





Undistortion uncertainty

For the code see 'task_handinds.ipynb'.

a) When the purpose is to build intuition for the uncertainty in distortion parameters, using the calibration images is not necessary. After all, performing undistort() with 'incorrect' coefficients is equivical to performing distortion - the variant strength of which represents the uncertainty.

- b) It as our opinion that the settings that keeps cropping and scaling to a minimum, and keeps invalid pixels, are preferable. This is because the variations in black borders makes changes in the image easier to identify
- c) The effects of undistortion is hardly noticeable. Amplifying the standard deviation by a factor of 100 confirms that there is indeed some effects, and that the majority of this is near the corners of the image. This is intuitive, as its further from the 'center' of radial distortion, and the conclusion from 1.1b.

2 Model creation

Task 2.1

Implemented in 'example_match_features.py'.

a)

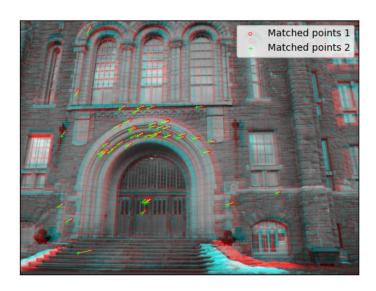


Figure 2: Best 50 correspondences by descriptor distance.

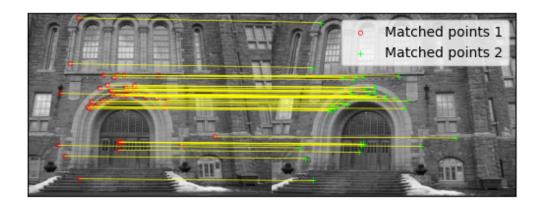


Figure 3: 50 matches side by side.

b)

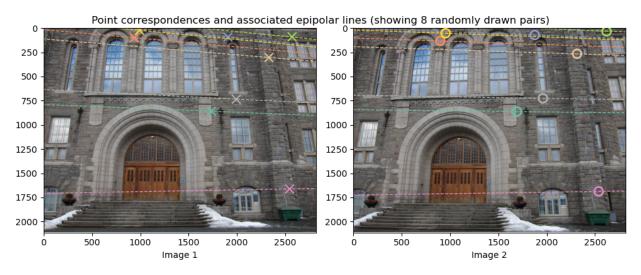


Figure 4: 8 inlier correspondences with their epipolar lines.

- c) In the included figures we used a maximum ratio og 0.9 and set the uniqueness parameter to true. By playing around with these parameters we found that decreasing the max ratio results in way fewer matches, it also minimizes wrong matches. Beside of the already pre-implemented knn distance metric we also tried out an ORB detector using the Hamming distance (commented out).
- d) For estimating the relative pose and the 3D point coordinates we simply reused the RANSAC approach from HW5. This gave us a total of 10966 inliers out of 12191 matches. In the following figure you can see the point-cloud of the best solution.

[Click, hold and drag with the mouse to rotate the view]

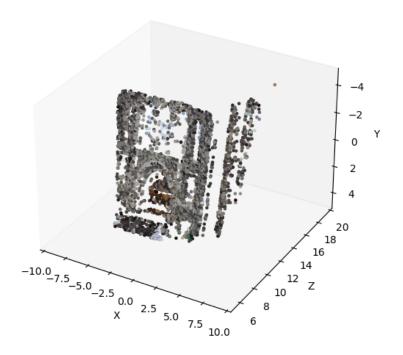


Figure 5: Reconstructed 3D point cloud.

e) The above point cloud consists of 10964 visible of 10966 total inlieres what is the pest found solution. These reconstructions have been saved for later usage together with their correspondent feature descriptors.

Task 2.2

Bundle adjusment refers to a general method of reconstruction problems, and can in this context be used to refine an existing, suboptimal estimation of camera motion and 3D structure. It works by solving a minimization problem with the square reprojection error. The parameters are the 3D coordinates for the j...; points and the camera parameters (rotation, translation and intrinsics). The objective function is

$$E = \sum_{i=1}^{m} ||P_i \widetilde{\underline{\mathbf{x}}} - \widetilde{\underline{\mathbf{x}}}'||$$

If using the "Sparse BA" formulation, minimizing with Levenberg-Marquardt, one can leverage the sparsity of the Jacobian to increase computational efficiency. The Jacobian contains an substructure relating to each camera angle (motion) and each measurement point (3D coordinate). If there are for instance 3 cameras and 4 points, the Jacobian's structure would be as such:

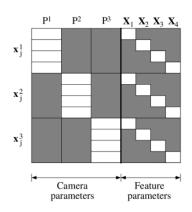


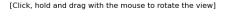
Figure 6: Sparse bundle adjustment matrix structure.

Task 2.3

To scale the 3D coordinate system to a meters, we need to figure out the scaling factor. This can be obtained by knowing the real distance between 2 points (in meters) and dividing that by the measured distance on the current 3D representation. Applying this scaling factor to all the points in the system will result in the axis being in meters.

3 Localization and uncertainty analysis

Task 3.2



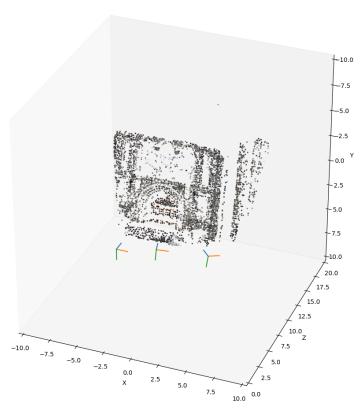
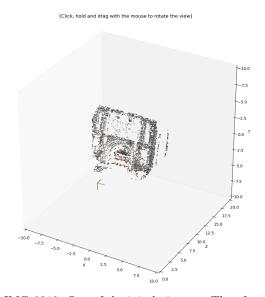


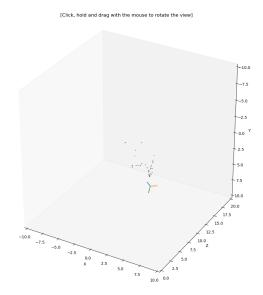
Figure 7: The figure shows the generated point point cloud and three located camera poses of: IMG_8207 , IMG_8215 , IMG_8228 .

As can be seen in the above figure, our localization works. If you look at the pictures you can verify that the estimated poses and locations fit. In general one can say the further a picture is taken from the initial ones, the less matching points are found and the reprojection error increases. On the other hand this means that if

you try to localize one of the initial images, you find loads of matches and the error is very low. The figures below you can see one inlier point cloud of an initial image and one where the camera is far away.



(a) IMG_8210: One of the inital pictures. Therefor a lot of inliers are found.



(b) IMG_8216: Picture is made far from the side. Only 35 inliers are found.

Task 3.3

The amount of inliers matches and the reprojection error already give a first estimate how good the localization is. Another property that can be used for further validation are the color values. Whereas for this it might be necessary to perform histogram equalization before using the images.

Task 3.4

Pose parameter std. deviations:

image	IMG_8207	IMG_8215	IMG_8228
Rotations:	[9.6468e-4 6.3234e-4 3.7941e-4]	[2.2752e-3 1.4374e-3 1.0056e-3]	[5.5933e-4 4.5021e-4 3.0571e-4]
Translations:	[0.1107 0.1508 0.0472]	$[0.1210 \ 0.2374 \ 0.1809]$	$[0.0607 \ 0.0677 \ 0.0308]$

Task 3.5

Pose parameter std. deviations with weighting:

image	IMG_8207	IMG_8215	IMG_8228	
Rotations:	[7.2157e-7 3.0878e-7 2.7816e-7]	[5.5433e-6 1.9041e-6 2.4646e-6]	[6.0389e-7 2.7063e-7 2.9049e-7]	
Translations:	$[8.2479e-4\ 0.2137\ 1.3348e-3]$	$[0.0118 \ 0.1006 \ 0.0125]$	$[5.4322e-3 \ 0.0696 \ 2.0152e-3]$	
Even though the standard deviations are improving with weighting, you can not really spot a difference in				
the figures.				

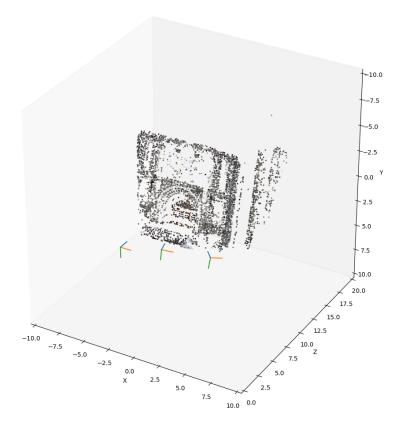


Figure 9: Localized images IMG_8207, IMG_8215, IMG_8228 with weighting.