

Lab 4

Triangulation

4.1 Using Ransac

This whole lab is basically concerned with the camera equation

$$\lambda u = PU. \quad (4.1)$$

For the uncalibrated case u , is a 3-vector with the coordinates of a point in the image (and an added 1)

$$u = \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \quad (4.2)$$

and U is a 4-vector containing the coordinates of the corresponding 3D point along with a 1.

A function

```
[Ps, us, U_true] = triangulation_test_case(sigma)
```

is provided for creating a simple test case where you know the correct answer (**U_true**). Gaussian noise of standard deviation **sigma** is added to the image points. Use this example to evaluate the your minimal solver.

Ex 4.1 Make a minimal solver for the triangulation problem, that is, a function

```
U = minimal_triangulation(Ps, us)
```

that takes two camera matrices, **Ps**, and two image points, **us**, and triangulates a 3D point. The image points are a 2×2 array whereas the camera matrices is a cell list with one camera matrix in each cell.

Recall that λ in (4.1) is the *depth*. Points with negative depth would lie behind the camera, so negative depths indicate that something is wrong.

Ex 4.2 Make a function

```
positive = check_depths(Ps, U)
```

that takes N camera matrices, **Ps**, and a 3D point, **U** and checks the depth of **U** in each of the cameras. The output should be a an array of boolean values of length N that indicates which depths were positive. (Matlab will print boolean values as zeros and ones, so don't be confused by this.)

Ex 4.3 Make a function

```
errors = reprojection_errors(Ps, us, U)
```

that takes N camera matrices, \mathbf{Ps} , N image points, \mathbf{us} , and a 3D point, \mathbf{U} and computes a vector with the reprojection errors, that is, the lengths of the reprojection residuals. If a point has negative depth, set the reprojection error to `Inf`.

Ex 4.4 Make a function

```
[U, nbr_inliers] = ransac_triangular(Ps, us, threshold)
```

that implements triangulation using Ransac. Use the number of outliers as loss function. A measurement is deemed as an outlier if the depth is negative or if the reprojection error is larger than `threshold`.

In `sequence.mat` you find a struct array `triangulation_examples` with triangulation examples. Each example has a cell list of camera matrices \mathbf{Ps} and a $2 \times N$ -array \mathbf{us} with image points. It will take some time to triangulate all 32183 examples so start with the first 1000 or so. I used a Ransac threshold of 5 pixels.

Ex 4.5 Make a script `triangulate_sequence` that runs `ransac_triangular` for all (or at least 1000) of the examples from `sequence.mat`. Store all triangulated points with at least two inliers and plot them using `scatter3`. There will always be a few outliers among the estimated 3D points that make it harder to view the plot. You can use the provided `clean_for_plot.m` to clean it up a bit. Like this:

```
Uc = clean_for_plot(Us)
scatter3(Uc(1,:),Uc(2,:),Uc(3,:),'.')
axis equal
```

Can you recognize the building? Save an image for the report.

4.2 Least squares triangulation

Just as in the case of registration, the following pipeline is recommended:

- Use Ransac to obtain a rough estimate of the parameters (U).
- Remove all measurements which are outliers with respect to these parameters.
- Estimate the least squares parameters using the remaining measurements.

Note that in this case a *measurement* is a pair consisting of an image point u_i and a camera matrix P_i . Don't forget that points with negative depths should be outliers.

Ex 4.6 Consider a camera matrix

$$P_i = \begin{pmatrix} \leftarrow & a_i^T & \rightarrow \\ \leftarrow & b_i^T & \rightarrow \\ \leftarrow & c_i^T & \rightarrow \end{pmatrix}, \quad (4.3)$$

a 3D point U and an image point u_i . Write a formula for the reprojection error, $r_i(U)$.

As you can see, the residuals are no longer linear, so computing a least squares solution will be significantly harder than in the previous lab. In fact, we cannot be sure to find the least squares solution. What we can do is to use local optimization to reduce the sum of squared residuals. We start at the solution produced by Ransac and use a few Gauss-Newton iterations.

Ex 4.7 Make a function

```
all_residuals = compute_residuals(Ps, us, U)
```

that takes a cell list with N cameras, a $2 \times N$ array of image points and a 3×1 array U and computes a $2N \times 1$ array with all the reprojection residuals stacked into a single vector/array. This vector is the \bar{r} from the lecture notes.

Ex 4.8 Find formulas for the partial derivatives in the Jacobian of \bar{r} . The Jacobian should be a $2N \times 3$ -matrix. (You don't have to hand in anything.)

Ex 4.9 Make a function `jacobian = compute_jacobian(Ps, U)` that computes the Jacobian given a 3×1 -vector U and a cell array of camera matrices.

Ex 4.10 Use these functions to make a function

```
U = refine_triangulation(Ps, us, Uhat)
```

that uses an approximate 3D point $Uhat$ as a starting point for Gauss-Newton's method. Use five Gauss-Newton iterations. Print the sum of squared residuals after each Gauss-Newton step to verify that it decreases.

Ex 4.11 Try your `refine_triangulation` on the data in `gauss_newton.mat`. First plot the points given in $Uhat$, then refine each point using your function and plot the results using `scatter3`. You should see an improvement. Save a screenshot for the report.

Ex★ 4.12 Compute the camera positions for the data in `gauss_newton.mat` and plot them together with the estimated 3D points. Try to understand why the noise in the estimated points looks as it does.

For the next exercise try the following way to match features,

```
matchFeatures(d1,d2,'Method','Approximate','MaxRatio',0.9,'MatchThreshold',100);
```

The approximate option makes it go significantly faster. A Lowe ratio of 0.9 is very high, but it makes the model more *dense*.

Ex★ 4.13 There are images `duomo.jpg` and `duomo_tilde.jpg` in the lab folder and also a data file `duomo.mat` with two camera matrices. Extract SIFT features from the two images (using `extractSIFT`) and match them using `matchFeatures`. Also store the color of each SIFT point. It doesn't matter from which of the images you select the color information.

Use your triangulation code (don't forget `refine_triangulation`) to triangulate the points and plot them with the right color using `scatter3`. Again, you can use `clean_for_plot.m` to remove outliers among the estimated 3D points. Beware that triangulating all the points will take a little time so work with a subset until you are sure that the code works.

4.3 Essential Matrix

Ex 4.14 Load the data in `P.mat`. There you will find two calibrated camera matrices, $P1$ and $P2$. Make a function

```
E = essentialMatrix(P1,P2);
```

that computes the essential matrix E from $P1$ and $P2$.

Ex★ 4.15 Similar to the reprojection error in the triangulation problem, the essential matrix can also be used for outlier detection using the residual

$$r^2(x, \tilde{x}) = \frac{|\tilde{x}^T E x|^2}{\|SEx\|^2 + \|SE^T \tilde{x}\|^2}, \text{ where } S = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad (4.4)$$

where x and \tilde{x} are the image projections of a 3D point X using some arbitrary camera matrices P and \tilde{P} , respectively. Note that (4.4) does not depend on X . Assuming that you are using a similar threshold for outlier detection, for a set of pixel correspondences, you would get I_1 inliers if you use the residual from the triangulation problem and I_2 inliers if you used the residual from (4.4). Which one is greater, I_1 or I_2 ? Why?

4.4 Report

Submit your code together with images of the reconstructed 3D models. The functions will be tested automatically so make sure they all have the names, inputs and outputs as defined in the lab PM. Write the answer to 4.15 in a separate txt or pdf file.