Computer Vision Course Assignment

Pedro José Pérez García, 756642
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Contents

Main problem overview

- Take 2 or more pictures of a historical building or monument
- Obtain an additional picture of that place, must date before 1990
- Compute the pose of the camera that took the old photo
  - Position
  - Orientation
- After that, compute the differences in the pictures
  - Many possible approaches

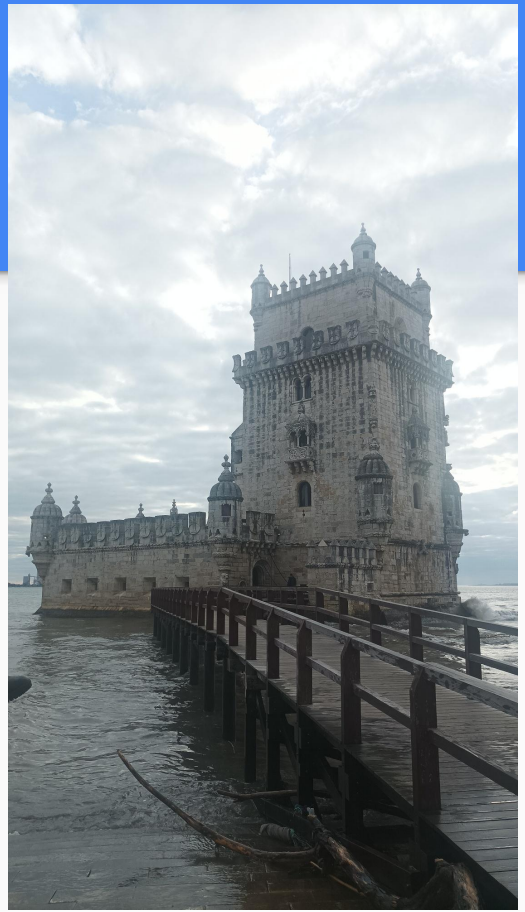
Our chosen old picture

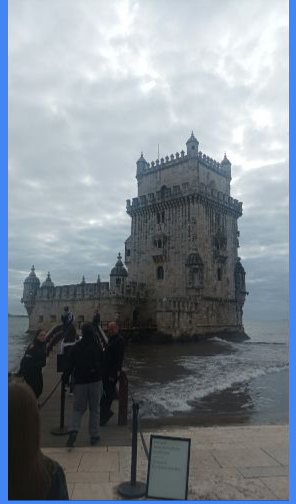
- Torre de Belém, Lisboa
- Taken between 1930 and 1980
- Unknown author

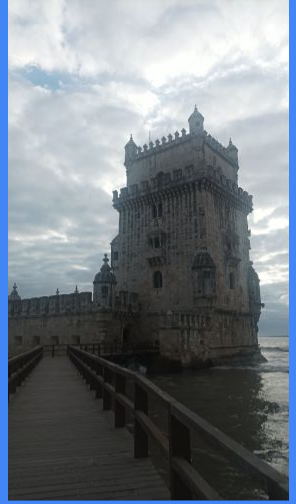
Biblioteca de Arte da Fundação Calouste Gulbenkian

Our pictures

- Torre de Belém, Lisboa
- Taken during my Erasmus stay there
  - Not purposefully taken for Computer Vision
  - Artifacts like lens flare
- Different aspect ratio





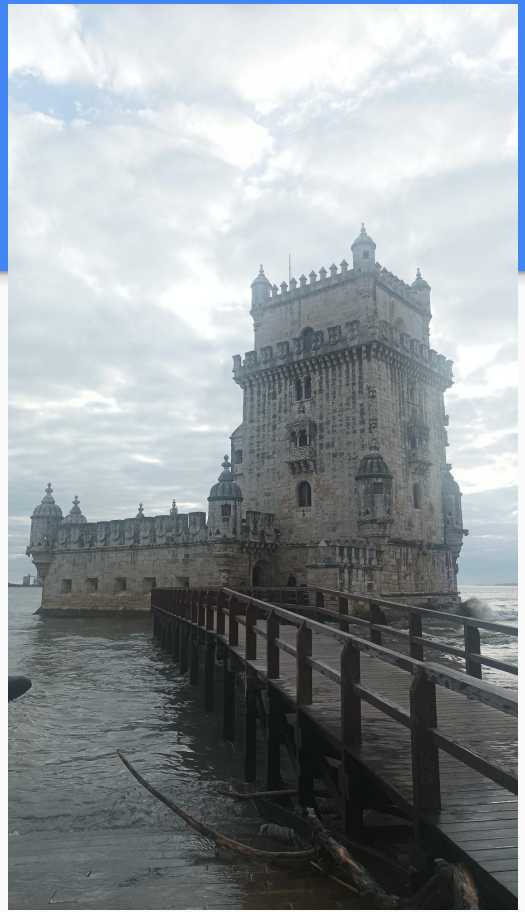







Our pictures

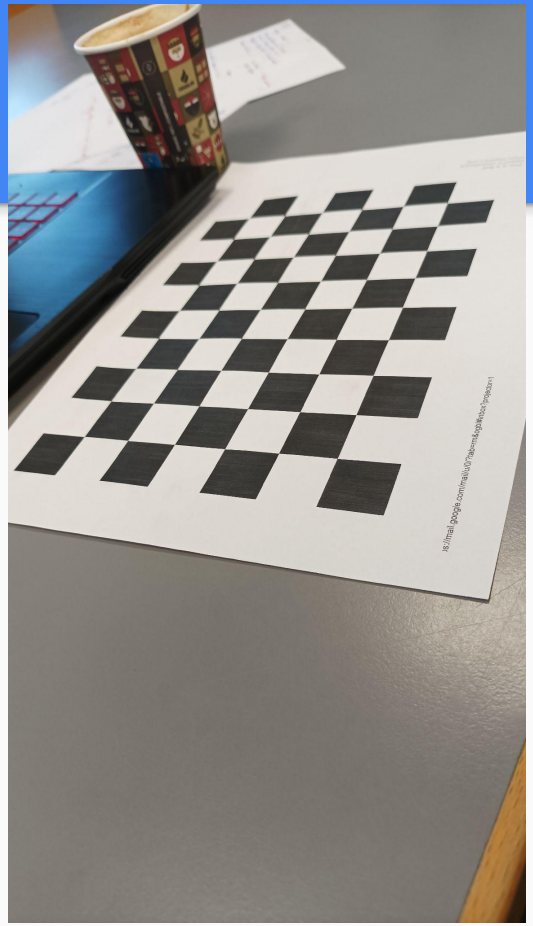
- Torre de Belém, Lisboa
- Taken during my Erasmus stay there
  - Not purposefully taken for Computer Vision
- Different aspect ratio
- 10 different pictures
  - Choose 2?
  - Try them all?



Old camera pose computation

First step: Camera calibration

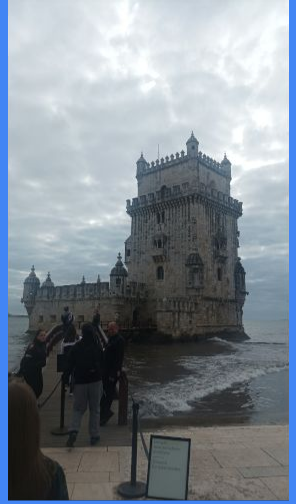
- 8 different pictures, in vertical orientation
- 10x7 checkerboard pattern
- Taken in different orientations
- We follow the example calibration code
  - `cv.findChessboardCorners`
  - `cv.calibrateCamera`
- Store the obtained K_c in text files
  - We also store the radial distortion coefficients

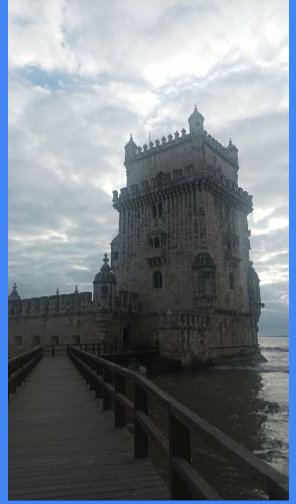


Next step: Keypoint detection and matching

- We have 10 pictures, but we don’t want to choose 2 (yet)
  - Bruteforce them!
- We match every possible pair among our n new pictures
  - Any number (quadratic cost, be careful!)
- The process is controlled by using config files
  - That’s why we save in .txt files after every step
  - We can execute steps independently!
  - Faster debugging of specific steps

```
[stage2]
matches_file_folder =       ../new_pictures
matches_file_name =         matches.txt
new_images_folder =         ../new_pictures
old_images_folder =         ../old_pictures
old_image_name =        torre_de_belem_1930_1980.jpg
matches_output_folder =     ../superglue_output/
```





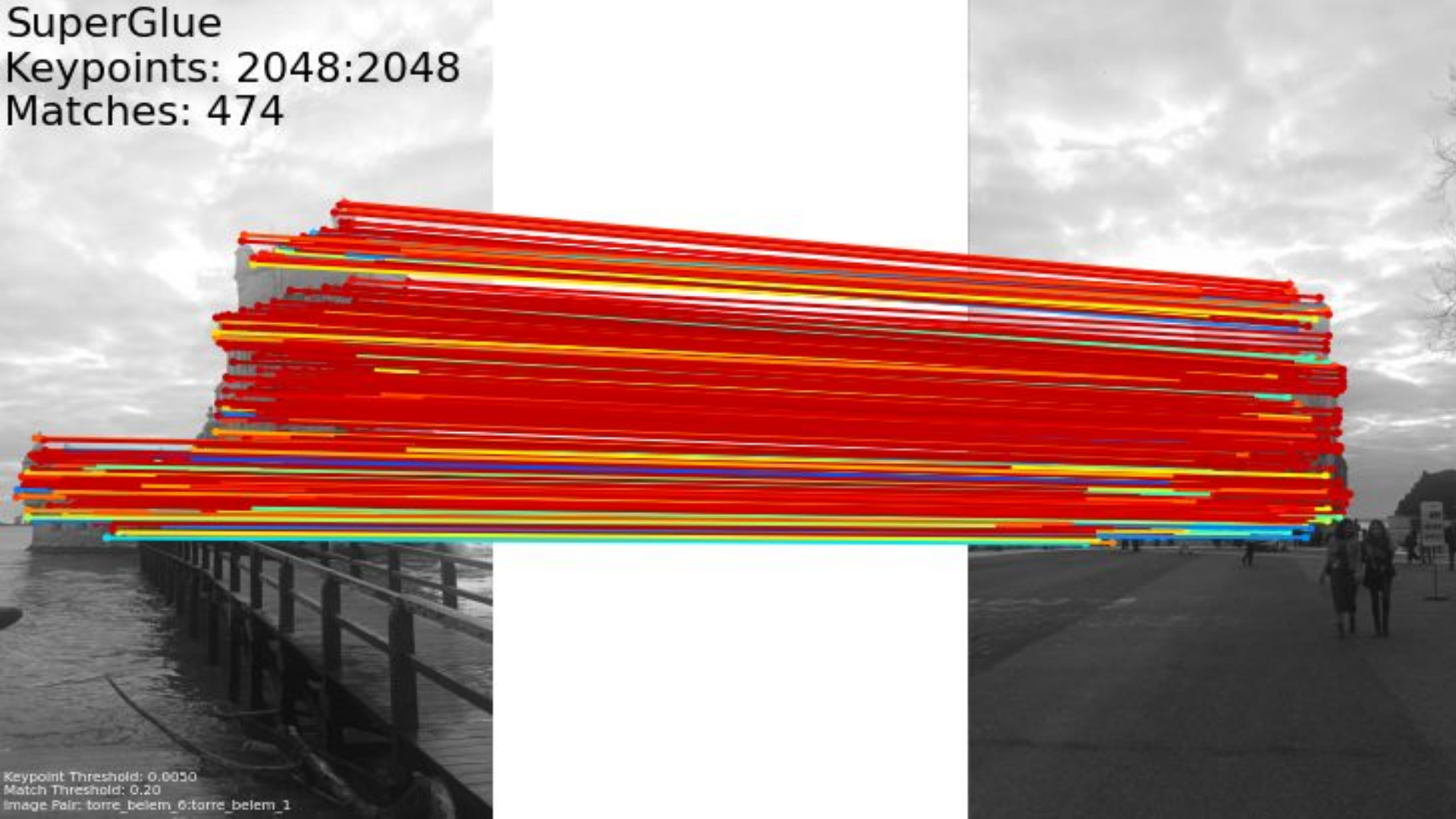





Next step: Keypoint detection and matching

- How do we do it?: SuperGlue
- We also considered LightGlue
  - Newer version, real-time performance
  - We stuck with SuperGlue for familiarity
- `match_pairs.py --superglue outdoor --max_keypoints 2048 --resize -1 -1`


SuperGlue
Keypoints: 2048:1528
Matches: 355
Keypoint Threshold: 0.0050
Match Threshold: 0.20
Image Pair: torre_belem_0:torre_de_belem_1930_1980


SuperGlue
Keypoints: 2048:2048
Matches: 474
Keypoint Threshold: 0.0050
Match Threshold: 0.20
Image Pair: torre_belem_0:torre_belem_1

Third step: Remove Spurious Data

- We want to get the best 2 images from the 10 we have
- We also want to get rid of spurious inliers
- RANSAC (RANdom SAmpling Consensus)
  - For a certain number of iterations:
  - Sample 8 points at random
  - Compute Fundamental matrix F with 8-point algorithm
  - Use F to compute distance to epipolar line (transfer error)
  - For the rest of matches, if distance < threshold, add to possible inliers
  - Get the biggest set of possible inliers as our final inliers

Given a match ***in pixels*** $\{(x_0, y_0, w_0), (x_1, y_1, w_1)\}$, $\boldsymbol{x}_1^T \boldsymbol{F} \boldsymbol{x}_0 = 0$

$$\begin{bmatrix} x_0x_1 & y_0x_1 & w_0x_1 & x_0y_1 & y_0y_1 & w_0y_1 & x_0w_1 & y_0w_1 & w_0w_1 \end{bmatrix} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = 0$$

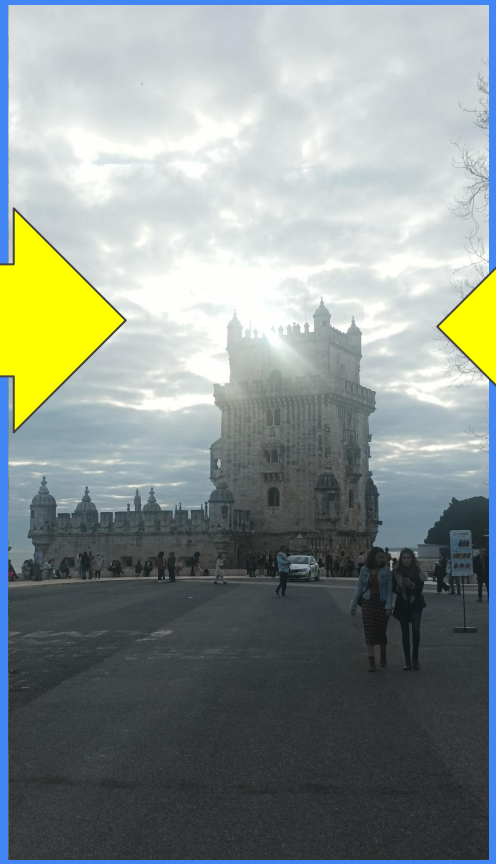
Third step: Remove Spurious Data

- RANSAC gives us the inliers for one image pair **im1-im2**
- We also compute the inliers for **im1-imOLD**
- Get the common inliers:
  - Those that have the “same” points in im1 for their matches
  - Tolerance threshold of 2 pixels, works well with up to 5 pixels
- Search for the best im1-im2-imOLD combination
  - If for any im1-im2, obtained_inliers < current_best inliers, skip the rest of computations

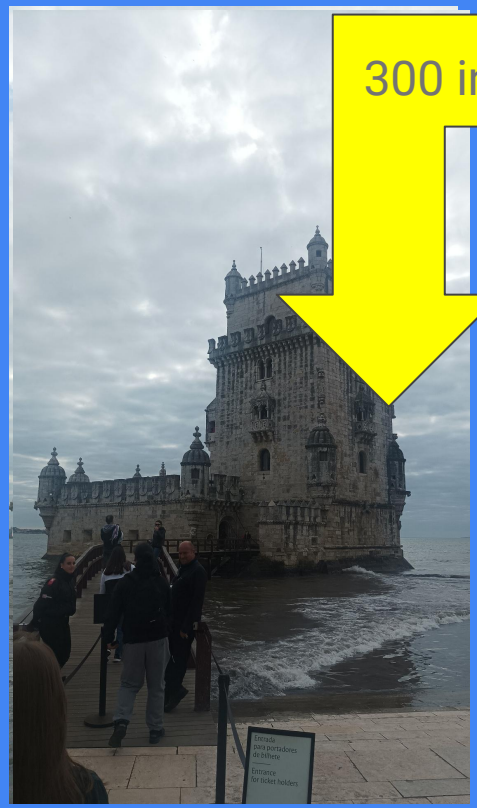
Only 100 in common

400 inliers

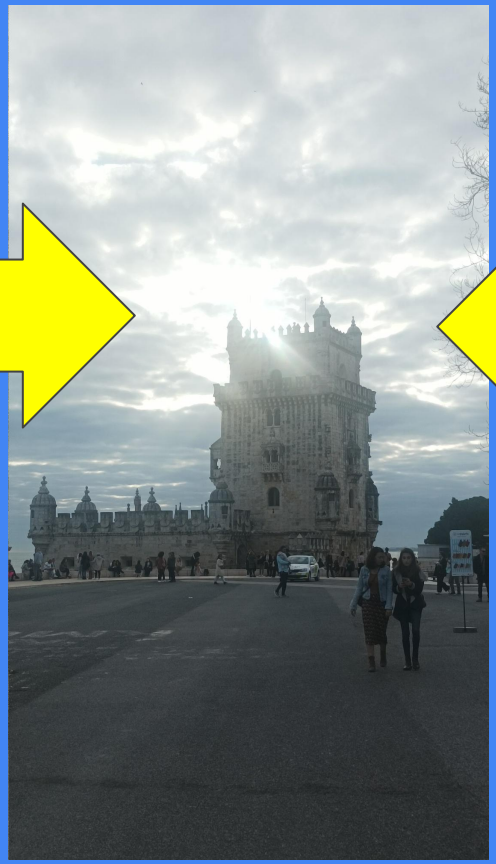
300 inliers



175 in common: best!



300 inliers



300 inliers


Image 1, all the inliers with OLD image
0
250
500
750
1000
1250
1500
1750
0
500
1000

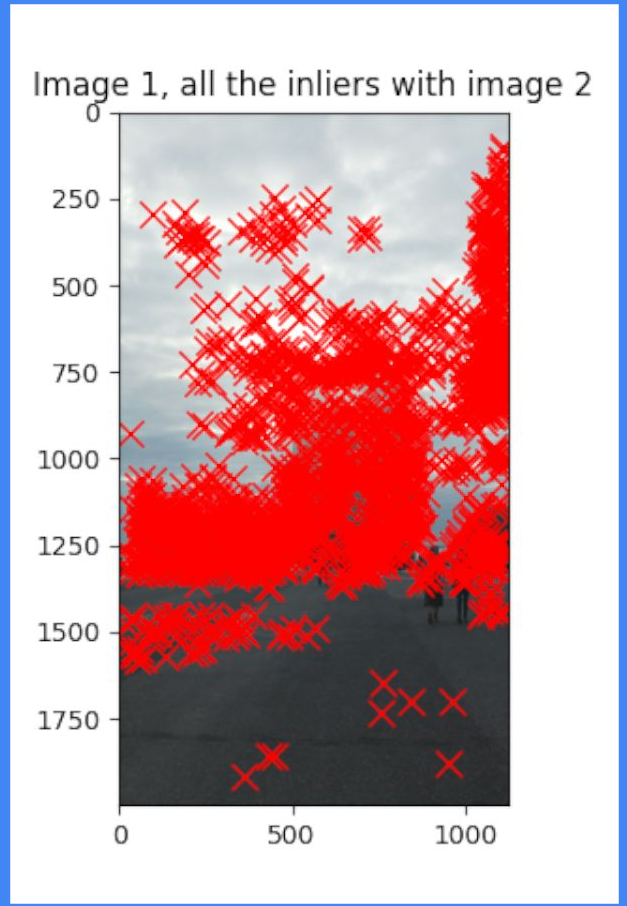


Image 1, all the inliers with image 2
0
250
500
750
1000
1250
1500
1750
0
500
1000

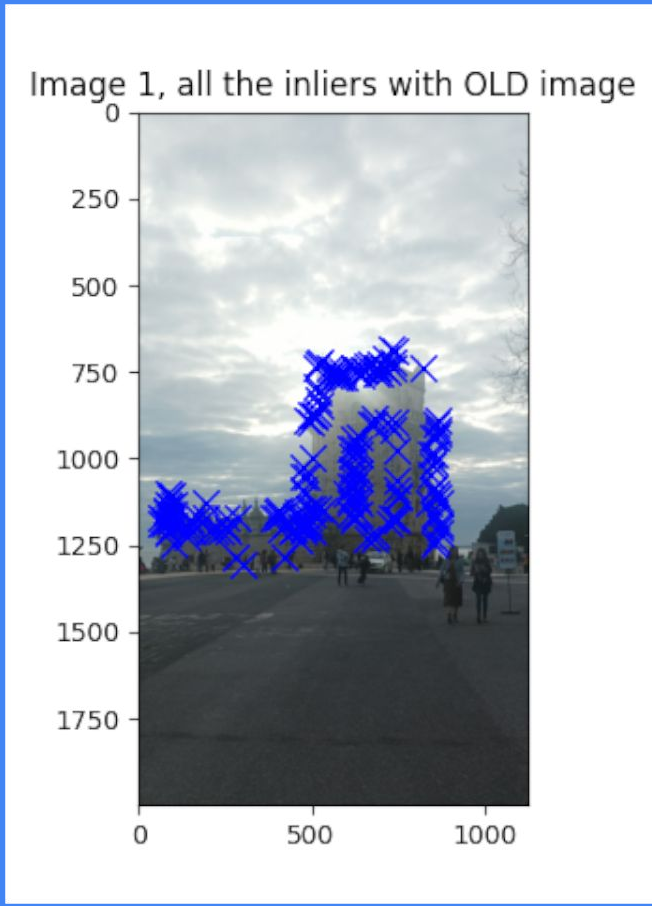
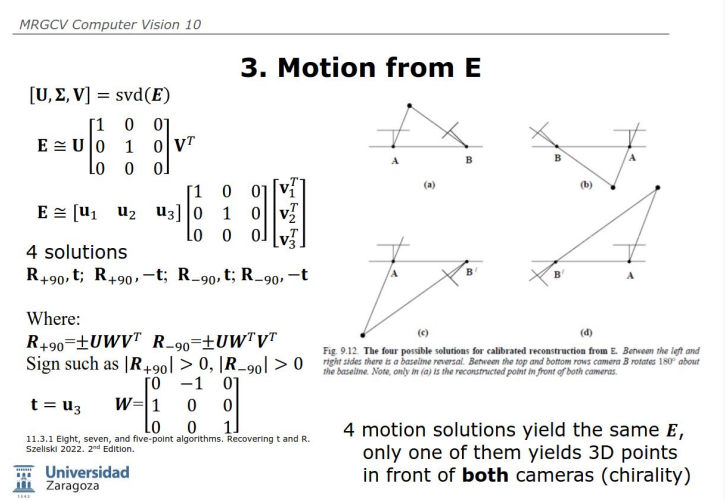


Image 1, all the inliers with OLD image
0
250
500
750
1000
1250
1500
1750
0
500
1000

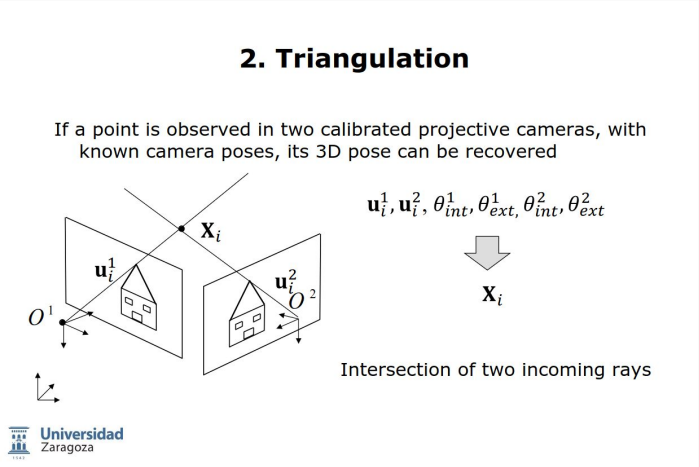
Fourth step: Camera pose computation

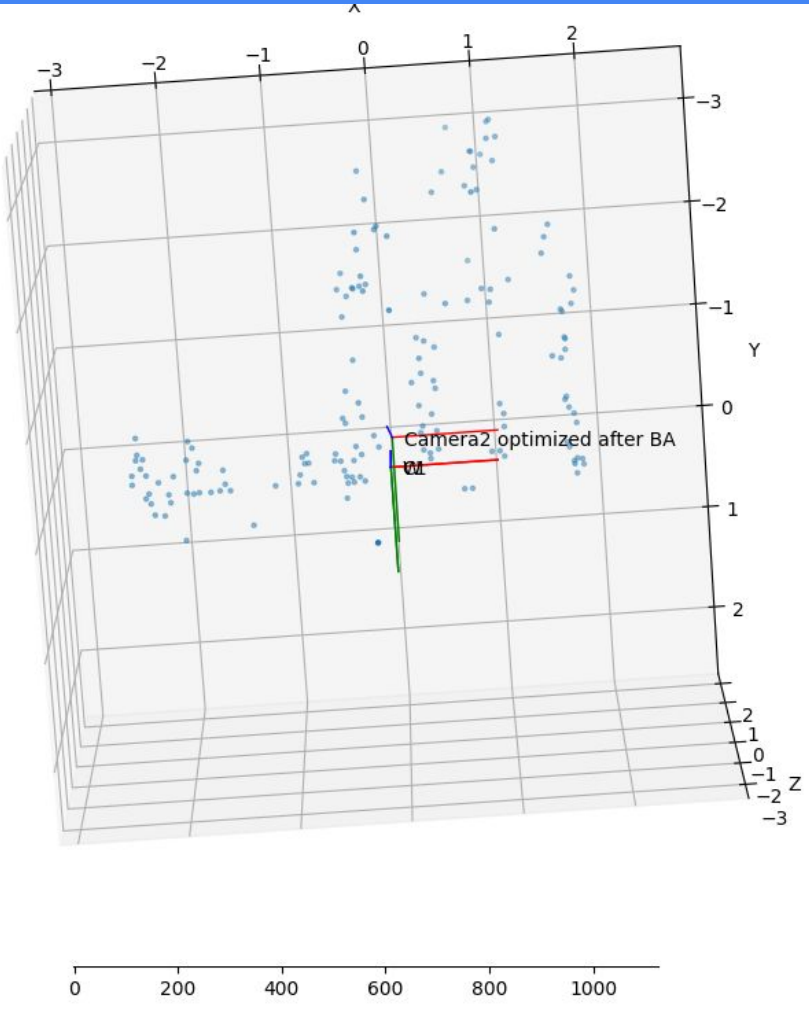
- Load our saved inliers and K_c
- Compute fundamental matrix F from inliers
- Essential matrix $E = K_c^T F K_c$
- With E, perform 3D triangulation
  - Chirality

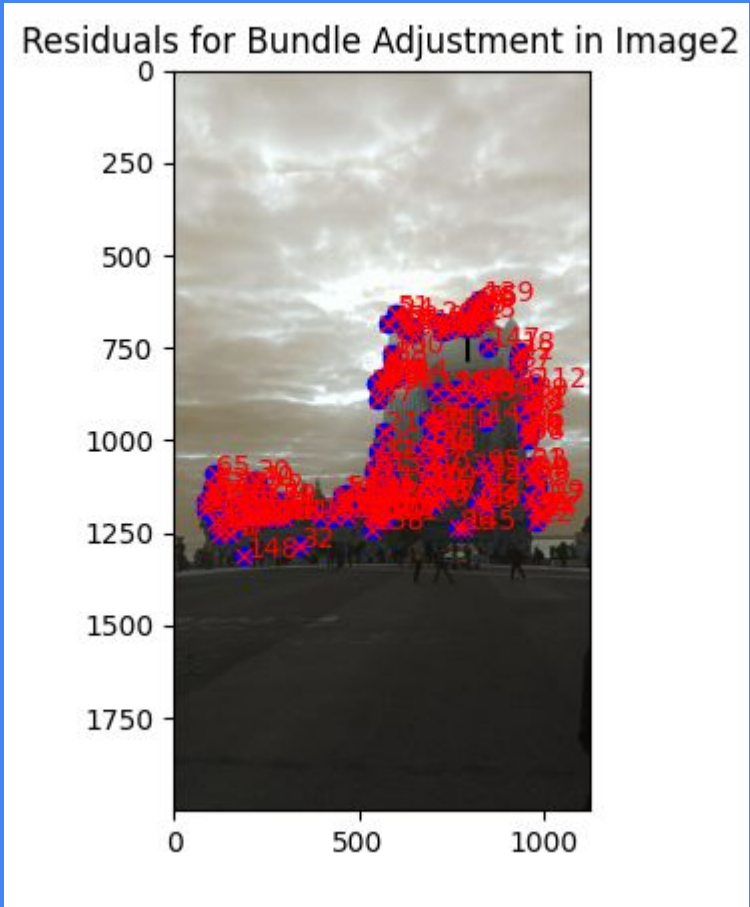


Fourth step: Camera pose computation

- Now we have X_3D
- Also t_c2c1, and R_c2c1 (camera 2 relative to camera 1)
- Bundle Adjustment for 2 views
  - Feed our newly calculated data as initial guess
  - Rotation encoded
  - Translation encoded too, as spherical coords
  - Our residual is the reprojection error

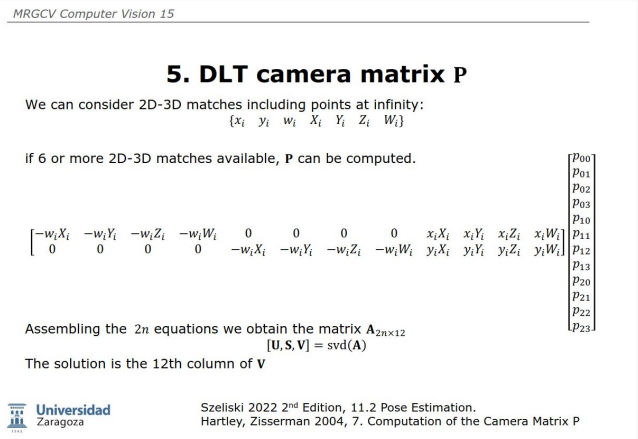



X
Y
Z
Camera2 optimized after BA
0
200
400
600
800
1000


Residuals for Bundle Adjustment in Image2
0
250
500
750
1000
1250
1500
1750
0
500
1000

Fourth step: Camera pose computation

- Why did we use only common inliers among our 3 images?
  - **DLT: Direct Linear Transformation**
  - With >= 6 2D-3D matches, we can compute P, projection matrix
  - If our 2D matches are common we can use the triangulated 3D points X_3D!

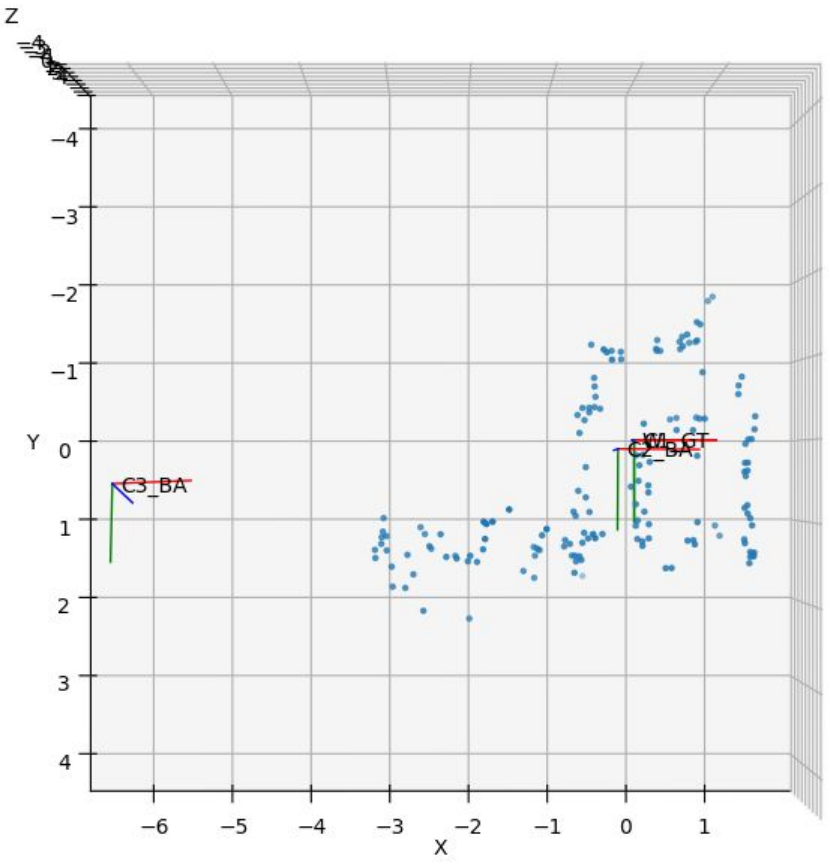


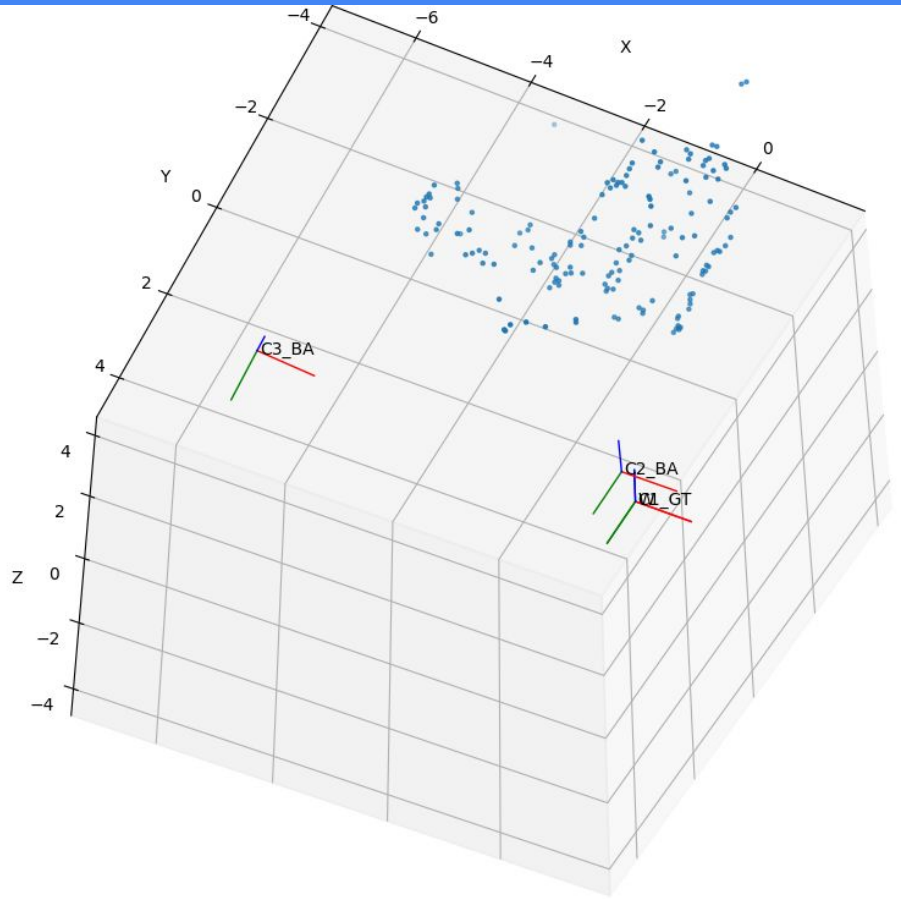
Fourth step: Camera pose computation

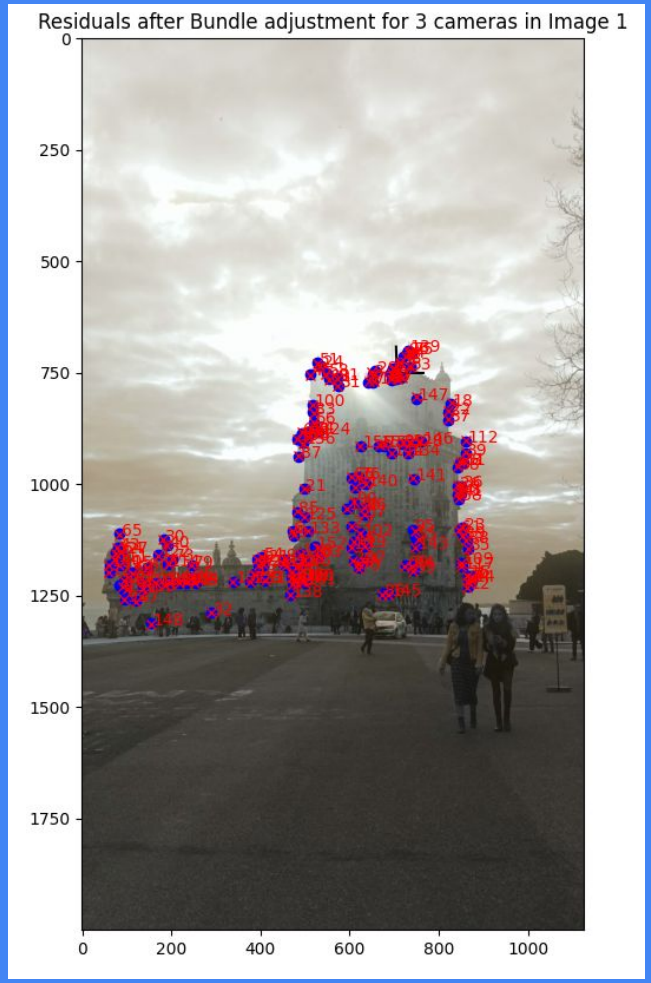
- We get a first estimation for P_3, projection matrix for camera 3
  - Decompose it
  - cv.decomposeProjectionMatrix didn't work for us
  - https://stackoverflow.com/questions/55814640/decomposeprojectionmatrix-gives-unexpected-result fixed the issue
  - We obtain a K_c3 matrix and ignore R_c3c1, t_c3c1

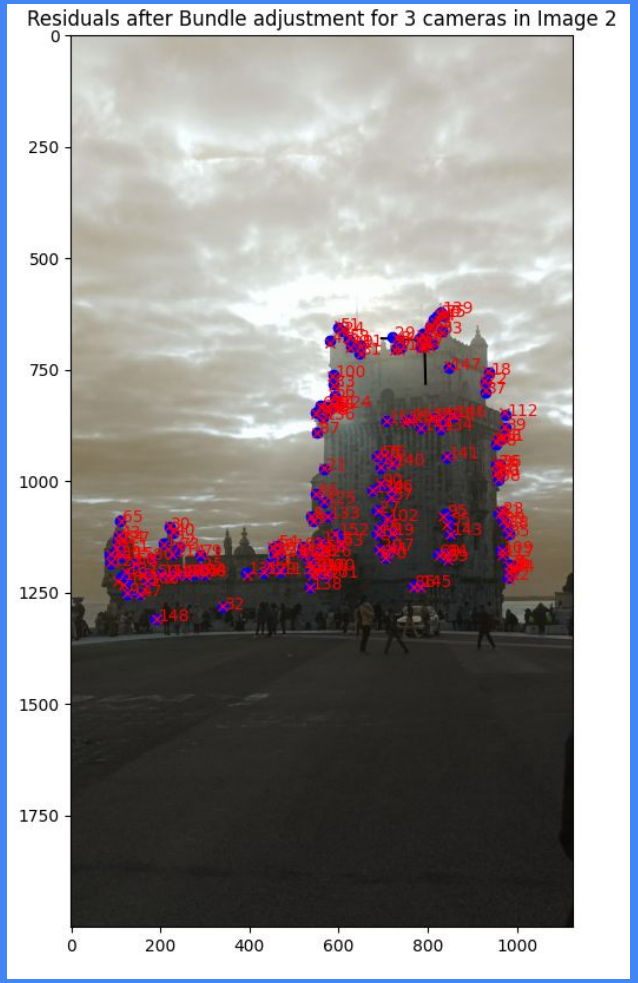
Fourth step: Camera pose computation

- Feed K_c3 into a PnP algorithm to refine our rotation and translation
  - This rotation and translation will be our initial guess for the final optimization
- 3 view Bundle Adjustment
  - Same as before, but optimize one more camera
  - Updated residual function to support N cameras
  - Final result!


Z
Y
X
C3_BA


X
Y
Z
C3_BA
C2_BA


Residuals after Bundle adjustment for 3 cameras in Image 1
0
250
500
750
1000
1250
1500
1750
0
200
400
600
800
1000


Residuals after Bundle adjustment for 3 cameras in Image 2
0
250
500
750
1000
1250
1500
1750
0
200
400
600
800
1000

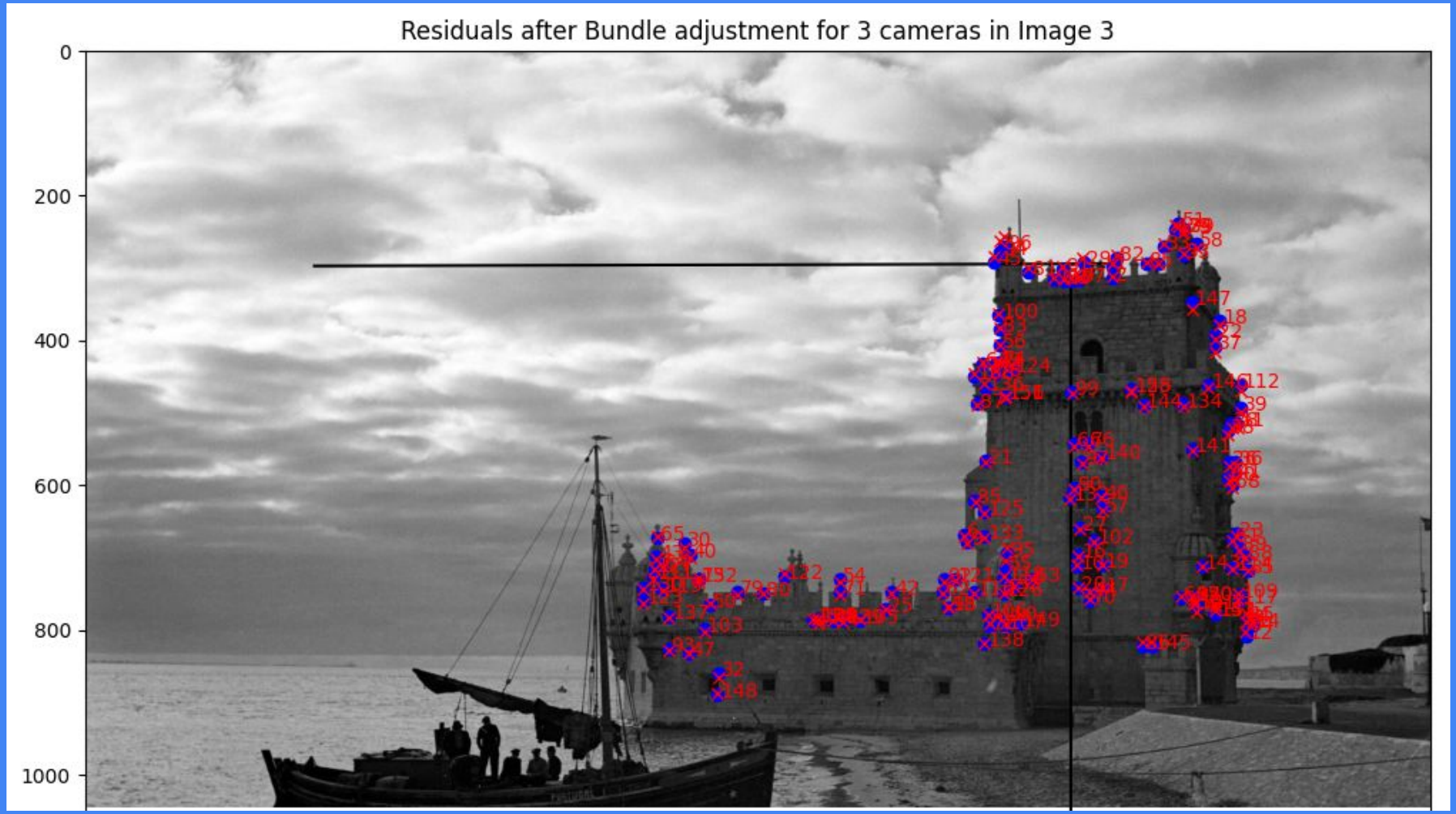

Residuals after Bundle adjustment for 3 cameras in Image 3
0
200
400
600
800
1000

Image differences

Image differences: our approach

- Compute homography
  - OpenCV's method instead of ours
  - We wanted to go for accuracy
- Warp the new image into old

Image differences: our approach

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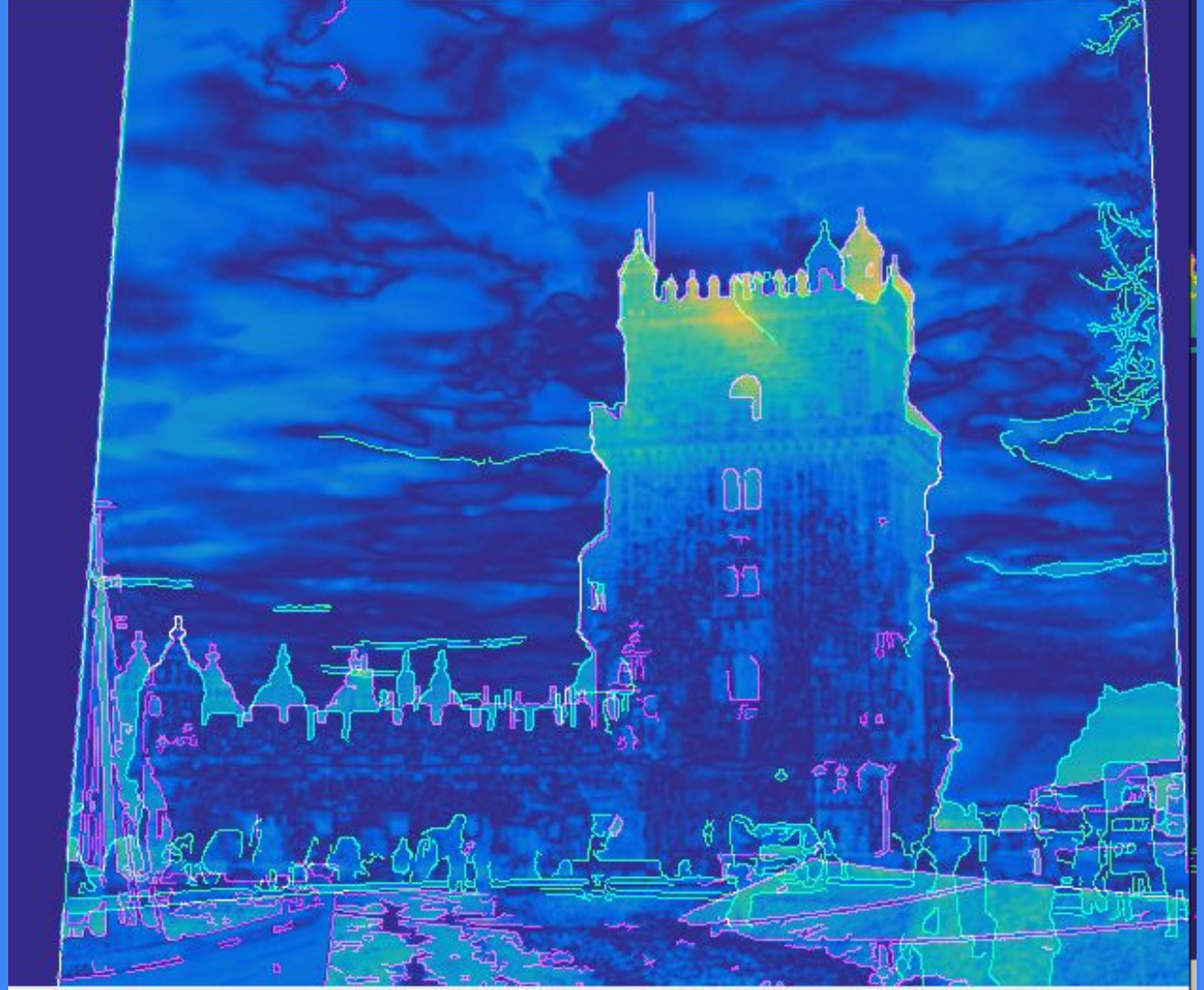
- Crop non-overlapping area
- Apply grayscale
- Equalize histograms

Image differences: our approach

- Compute homography
  - OpenCV's method instead of ours
  - We wanted to go for accuracy
- Warp the new image into old
- Crop non-overlapping area
- Apply grayscale
- Equalize histograms
- Apply small Gaussian blur
- Apply absdiff

Image differences: our approach

- Apply a colour gradient
- Overlay Canny edges
  - 1 colour for each image
- We experimented with thresholding, with and without Otsu
  - Bit operations like and, xor, etc..
  - Did work sometimes but only for specific images
  - Too ad-hoc to be considered a solution



Thank you for your attention

Any questions?