

1. SIFT Features
  - a. Using CV2's SIFT algorithm to go through grayscale image and compute keypoints
  - b. `sift.detect()` function finds the keypoint in the images. You can pass a mask if you want to search only a part of image. Each keypoint is a special structure which has many attributes like its (x,y) coordinates, size of the meaningful neighbourhood, angle which specifies its orientation, response that specifies strength of keypoints etc.
  - c. [https://opencv-python-tutroals.readthedocs.io/en/latest/py\\_tutorials/py\\_feature2d/py\\_sift\\_intro/py\\_sift\\_intro.html](https://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_feature2d/py_sift_intro/py_sift_intro.html) (Sift explanation)
2. Matching detected keypoints between images
  - a. Tries to find the same keypoint and draw lines to connect them using k-NN or L2 Norm as a metric
3. Compute calibrated coordinates
  - a. Fetching keypoints, making calibrated matrices
4. Least Squares Estimator
  - a. Multiply  $x_1$  and  $x_2$  (grayscale images)
    - i. Each column of  $X_1$  multiplied with  $X_2$ .transpose
  - b. Take the SVD of the above matrices stacked together
  - c. Output is the least squares estimate of the essential matrix
5. RANSAC
  - a. We create a least squares E using 8 sample points from both images
  - b. Using the E, we can use our test indices to find inliers
  - c. Inliers are determined by checking whether their residuals are lower than the specified eps
  - d. We maximize the number of inliers over all iterations (20K default)
6. Plot Epipolar Lines
  - a. Determine fundamental matrix using least squares E and calibration parameters
  - b. Compute epipolar lines using fundamental matrix and uncalibrated points
7. Pose Candidates
  - a. Decompose essential matrix into R and T using SVD
  - b.  $T_1$  and  $T_2$  are given
  - c. For a given estimate of E there are 2 possible solutions, obtained from the SVD
  - d. If determinant of  $R_1$  is negative, bottom of main diagonal in z matrix is determinant of  $U * V$
8. Reconstruct 3D
  - a. For each calibrated point, we triangulate a lambda using the given form

$$\underbrace{(q_i - Rp_i)}_{3 \times 2} \underbrace{\begin{pmatrix} \mu_i \\ \lambda_i \end{pmatrix}}_{2 \times 1} = \underbrace{T}_{3 \times 1}$$

- b. The code filters out all the lambdas which are negative since negative depth isn't possible

- c. We then determine which of the  $R, T$  combinations have the highest added sum of lambdas. The one with the highest sum is the combination that is chosen
- 9. Show reprojections
  - a.  $P_2$  and  $p_1$  projections are
  - b. For image 2:  $K * (\text{inv}(R)P_2 - \text{inv}(R)T)$
  - c. For image 1:  $K * (RP_1 + T)$