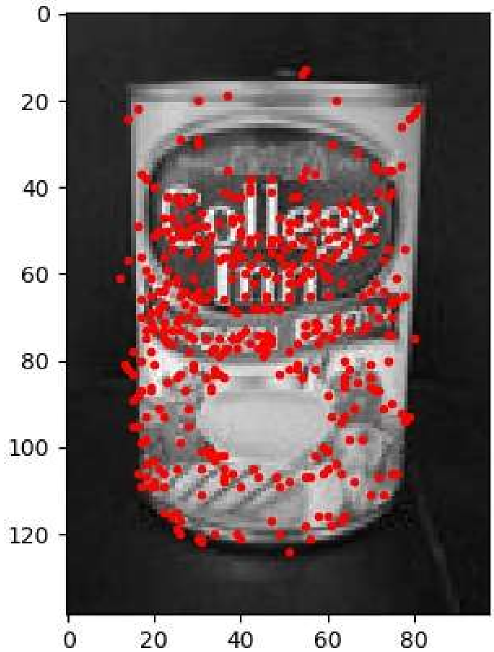
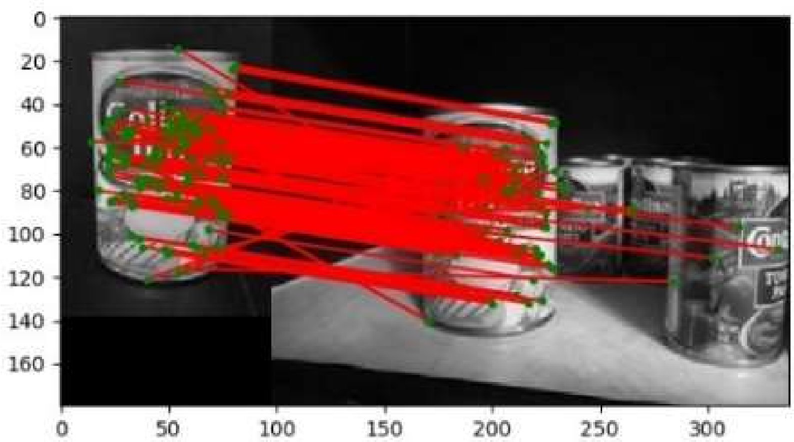
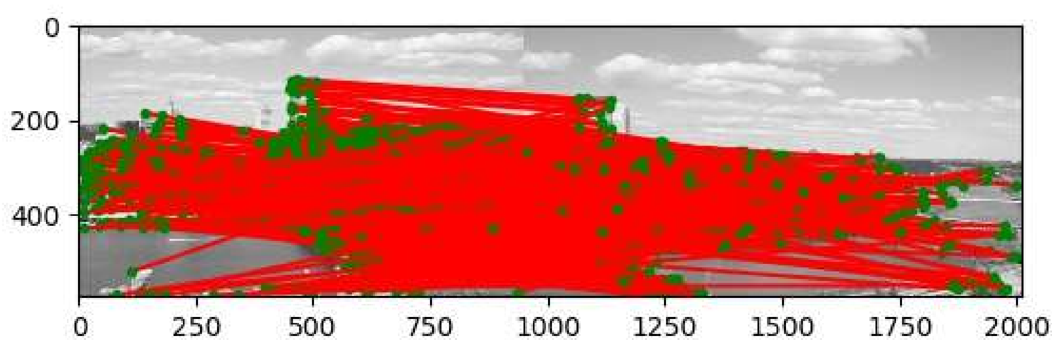
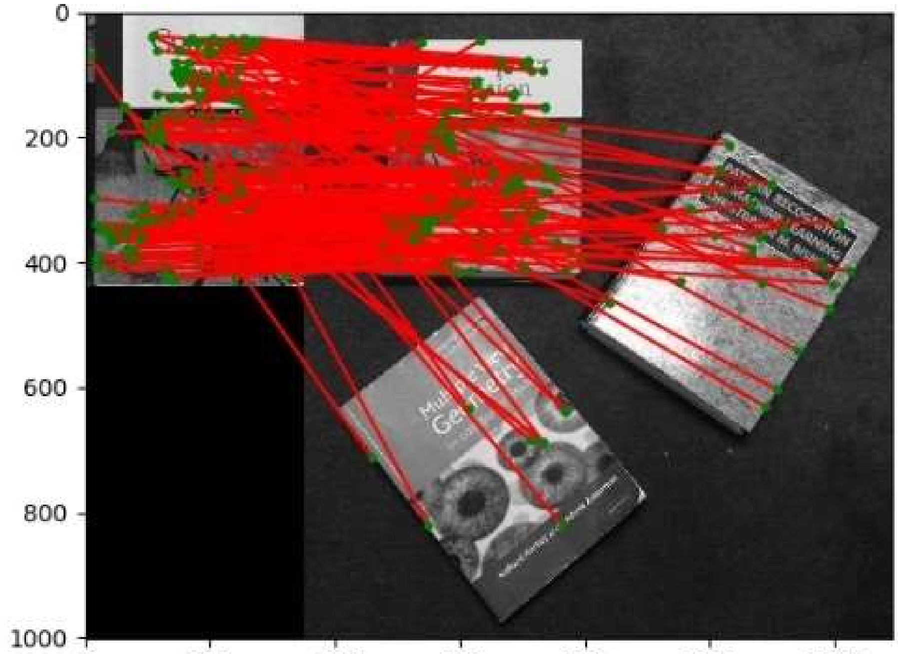
Q1.5 Keypoint Detection Result

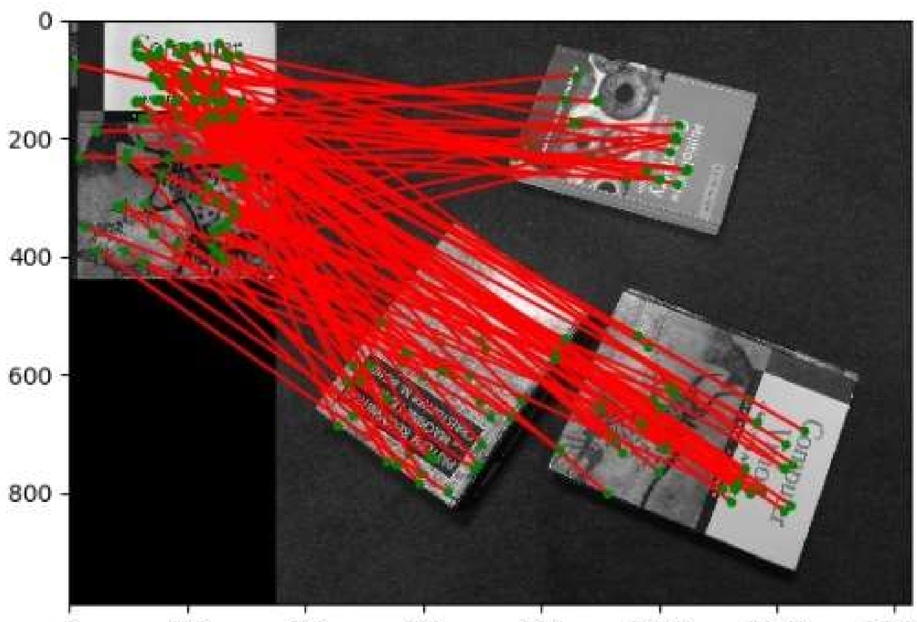


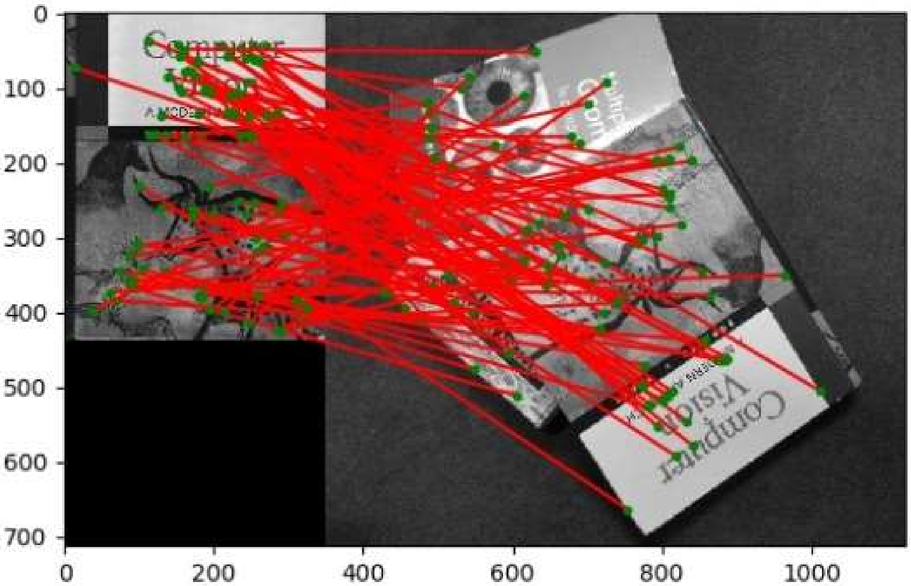
Q2.4

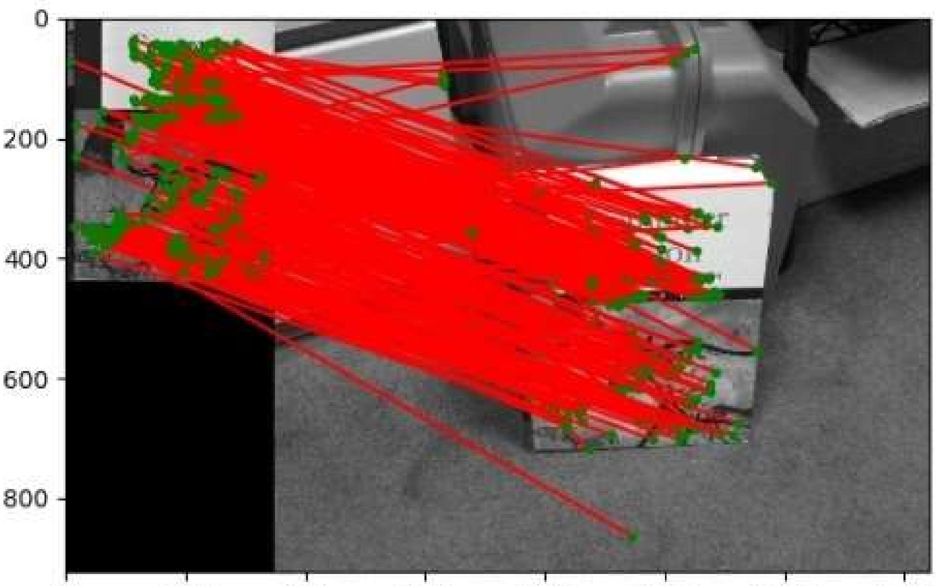

0
20
40
60
80
100
120
140
160
0
50
100
150
200
250
300


0
200
400
0
250
500
750
1000
1250
1500
1750
2000


0
200
400
600
800
1000
0
200
400
600
800
1000
1200

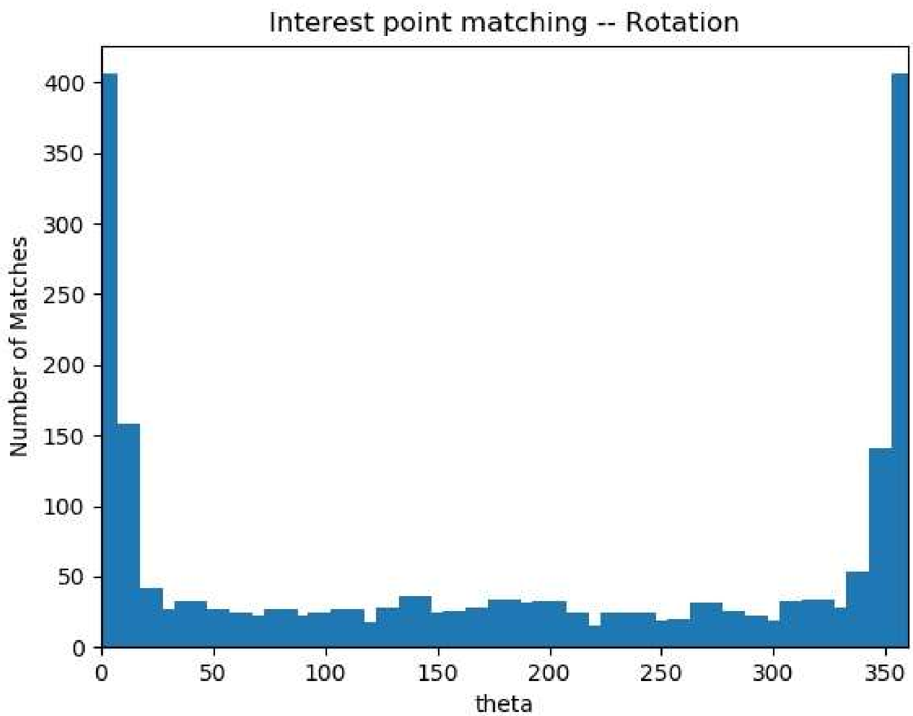

0
200
400
600
800
0
200
400
600
800
1000
1200
1400


0
100
200
300
400
500
600
700
0
200
400
600
800
1000


0
200
400
600
800
0
200
400
600
800
1000
1200
1400

The number of correct matches is great when there is not much rotation of the template. As you can see from the chicken broth example and pf textbook examples. But when the source image has a rotation of the template, the BRIEF descriptor fails because the test patch is not flipping.

Q 2.5



The BRIEF descriptor depends on randomly generated test patches. When the patch is small, or only translation is involved, the BRIEF matches is great. This is because local pixels are highly linearly correlated. This is even true for small scale rotation and affine transform. However, when large rotation or affine warp is involved, we cannot approximate the value of local pixels with high fidelity. So even there exists a perfect match, there is a great chance that the BRIEF descriptor fails to give a match response.

3. Planar homography theory

(a)

$$\lambda_n \begin{bmatrix} \widetilde{x_n} \\ \widetilde{y_n} \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} \widetilde{u_n} \\ \widetilde{v_n} \\ 1 \end{bmatrix}, for\ n = 1{:}N$$

Form linear system $\boldsymbol{Ah} = 0$, s.t. $\left|\left|\boldsymbol{h}\right|\right|_2^2 = 1.$

$$\begin{bmatrix} 0 & 0 & 0 & -u_1 & -v_1 & -1 & y_1 u_1 & y_1 v_1 & y_1 \\ u_1 & v_1 & 1 & 0 & 0 & 0 & -x_1 u_1 & -x_1 v_1 & -x_1 \\ 0 & 0 & 0 & -u_2 & -v_2 & -1 & y_2 u_2 & y_2 v_2 & y_2 \\ u_2 & v_2 & 1 & 0 & 0 & 0 & -x_2 u_2 & -x_2 v_2 & -x_2 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & -u_N & -v_N & -1 & y_N u_N & y_N v_N & y_N \\ u_N & v_N & 1 & 0 & 0 & 0 & -x_N u_{1N} & -x_N v_{1N} & -x_N \end{bmatrix} \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \\ h_{33} \end{bmatrix} = 0$$

(b)

9 elements

(c)

At least 4 point pairs.

(d)

$$\boldsymbol{h} = \ argmin\left|\left|\boldsymbol{Ah}\right|\right|_2^2, s.t. \left|\left|\boldsymbol{h}\right|\right|_2^2 = 1$$

$\boldsymbol{h} = argmin\frac{\boldsymbol{h^T A^T Ah}}{\boldsymbol{h^T h}}$, take the first derivative and set it to zero. (Lagrange multipliers)

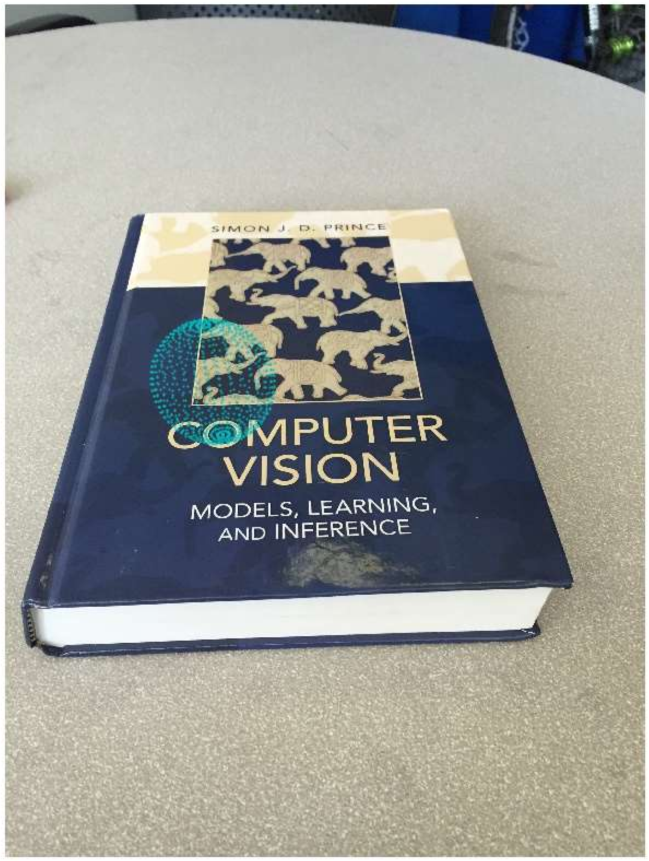
$$\frac{\partial}{\partial h}\left(\boldsymbol{h^T A^T Ah} + \lambda(1 - \boldsymbol{h}^T\boldsymbol{h})\right) = 0$$

$$2\boldsymbol{A^T Ah} - 2\lambda\boldsymbol{h} = 0$$

$error = \boldsymbol{h^T A}^T\boldsymbol{Ah/1} = \boldsymbol{h^T}\lambda\boldsymbol{h},$ the solution must be the eigenvector corresponds to the smallest eigenvalues. This is also equivalent to perform single value decomposition of matrix A. U,S,Vt = SVD(A), where the last column of V is the linear h array. We can even use symmetric transfer error function to improve our homography.

Q6

Q 7


SIMON J. D. PRINCE
COMPUTER
VISION
MODELS, LEARNING,
AND INFERENCE