I Introduction

In this document we present a visualization of the image pairs used in all the experiments in Section II; discussion about how Lowe’s radius is a good ranking measure when using bidirectional correspondences in Section III; extended results on the Kalman filter estimating the inlier ratio in Section IV; additional results on the convergence analysis of ANSAC in Section V; and extended results on estimating the Homography and Fundamental Matrix in Section VI.

II Image Pairs

In this section we present the image pairs that we used for the experiments presented in Section 3 in the main submission. Figures i and ii show the image pairs used for the Homography estimation experiments. Figures iii and iv show the image pairs used for the Fundamental estimation experiments.

III Ranking Measures

Section 3.1 of the main submission states that the experiments used the Lowe’s radius, i.e.,

\[ r^2 = r_1^2 + r_2^2, \]  

where \( r_1 \) and \( r_2 \) are the Lowe’s ratios (a.k.a. SIFT ratios) for the two different matching orderings in a bidirectional matching context. Recall that the Lowe’s ratio is the ratio between the smallest distance and the second smallest distance between a query and a database descriptors. This section presents visualizations in Fig. v illustrating how the Lowe’s radius is a good metric for bidirectional correspondences. The scatter plots show how correct correspondences (circles) tend to be very close to the origin and wrong correspondences (triangles) are far. Thus, the Lowe’s radius just measures how close the correspondence is to the origin.

In general, thresholding a set of bidirectional correspondences using Lowe’s radius can guarantee a larger inlier ratio in the resultant set than thresholding using either \( r_1 \) or \( r_2 \). This can be confirmed by the data shown in the Table 1. Note that the inlier ratio of the correspondences after thresholding with the Lowe’s radius is at least twice as large as thresholding with \( r_1 \) or \( r_2 \).

IV Kalman Filter for Inlier Ratio Estimation

In this section we present larger images for the experiment results shown in Figure 2 of Section 3.1 in the main submission. Figures vi and vii show the Figures 2 (a) and 2 (b) of the main submission, respectively.
Figure i: Image pairs for homography estimation experiment from the USAC dataset.

Figure ii: Image pairs for homography estimation experiment from the Oxford dataset.

V Convergence Analysis

In this section we present extended results on convergence analysis which were presented in Section 3.2 in the main submission. Figure viii extends the top row shown in Figure 3 of the main submission, which shows convergence results on homography estimation. We can observe that ANSAC overall requires fewer iterations than those of the competing methods when the inlier ratio is larger than 0.5. When the inlier ratio is below 0.5, ANSAC behaves competitively. This is because ANSAC estimates that the risk of producing bad hypotheses using non-minimal samples is high when the inlier ratio is low.

Figure ix presents extended results on the convergence analysis when estimating fundamental matrices. This Figure extends the results presented in the bottom row of Figure 3 in the main submission. We can observe that ANSAC uses more non-minimal samples when the inlier ratio is above 0.5 in this case. When it is below 0.5, ANSAC uses minimal samples to ensure that the risk of producing bad hypotheses is low.

VI Estimation of Homography and Fundamental Matrix

In this section we present extended results on estimating homography and fundamental matrix with ANSAC. Figures x and xi show the results on homography and fundamental matrix estimation experiments, respectively. These Figures extend the results presented in Figure 4 of the main submission.

We can conclude from Figure x that ANSAC converges quickly in time (less than 20 msec). ANSAC takes around the same time as that of USAC to return an estimate. However, ANSAC consistently returns an estimate that is close to the ground truth (as indicated by the success rate bars) and is comparable to that of RANSAC, EVSAC, and PROSAC. On the other hand, note that USAC tends to have a lower success rate, which means that computed estimates with USAC tend to deviate significantly from the ground truth.
This can be attributed to SPRT+LO-RANSAC combination, since SPRT is method with false-negatives, i.e., it skips good hypotheses that its test labels as non-interesting.

We can conclude the same from the fundamental matrix experiment. ANSAC tends to converge comparable or faster than USAC, while it is faster than the other competing methods. The inlier ratio of the estimate models and success rates are comparable to those of RANSAC, PROSAC, and EVSAC. On the other hand, USAC presents a lower success rate than the other methods. This is again attributed to the SPRT module.

Thus, from these experiments we can conclude that ANSAC provides a faster or comparable convergence than that of USAC, while providing a comparable quality of estimates in terms of inlier ratio and success rate.
Figure v: Scatter plots of Lowe’s ratios from symmetric correspondences. The correct correspondences (blue circles) tend to be very close to the origin and wrong correspondences (red triangles) are far.

Table 1: Inlier ratio comparison after thresholding correspondences using Lowe’s radius, and Lowe’s ratios for bidirectional correspondences. Lowe’s radius thresholding achieves a higher inlier ratio since it removed several incorrect correspondences. On the other hand, using regular Lowe’s ratio yields a lower inlier ratio for bidirectional correspondences.

<table>
<thead>
<tr>
<th>Image Pair</th>
<th>( \varepsilon_{\text{sym}} )</th>
<th>( \varepsilon_1 )</th>
<th>( \varepsilon_2 )</th>
<th>( \varepsilon_{\text{sym}} / \max(\varepsilon_1, \varepsilon_2) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>H-USAC 1</td>
<td>0.48</td>
<td>0.17</td>
<td>0.17</td>
<td>2.82</td>
</tr>
<tr>
<td>H-USAC 2</td>
<td>0.21</td>
<td>0.06</td>
<td>0.07</td>
<td>3.00</td>
</tr>
<tr>
<td>H-USAC 3</td>
<td>0.28</td>
<td>0.10</td>
<td>0.09</td>
<td>2.80</td>
</tr>
<tr>
<td>H-USAC 4</td>
<td>0.28</td>
<td>0.10</td>
<td>0.09</td>
<td>2.80</td>
</tr>
<tr>
<td>FM-USAC 2</td>
<td>0.19</td>
<td>0.07</td>
<td>0.07</td>
<td>2.71</td>
</tr>
<tr>
<td>FM-USAC 3</td>
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<td>0.06</td>
<td>0.06</td>
<td>3.33</td>
</tr>
<tr>
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<td>0.11</td>
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<tr>
<td>FM-USAC 5</td>
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<td>0.20</td>
<td>0.20</td>
<td>2.40</td>
</tr>
</tbody>
</table>
Figure vi: Kalman filter estimating the inlier ratio of the ranked subsets for homography estimation. This figure shows the results presented in Figure 2 (a) in the main submission, enlarged for better visualization.
Figure vii: Kalman filter estimating the inlier ratio of the ranked subsets for fundamental matrix estimation. This figure shows the results presented in Figure 2 (b) in the main submission, enlarged for better visualization.
Figure viii: Convergence analysis for ANSAC when estimating homography on Oxford and USAC image pairs. This Figure extends the results presented as the top row in Figure 3 of the main submission. We can observe that ANSAC requires fewer iterations than the competing methods, especially when the inlier ratio is above 0.5. ANSAC on the other hand behaves competitively when the inlier ratio is below 0.5. This is because ANSAC uses more non-minimal samples when it estimates that the risk of generating good hypotheses is low, and uses minimal samples otherwise.
Figure ix: Convergence analysis for ANSAC when estimating fundamental matrices on Strecha and USAC image pairs. This Figure extends the results presented as the bottom row in Figure 3 of the main submission. We can observe that ANSAC requires fewer iterations than the competing methods, especially when the inlier ratio is above 0.5. ANSAC on the other hand behaves competitively when the inlier ratio is below 0.5. This is because ANSAC uses more non-minimal samples when it estimates that the risk of generating good hypotheses is low, and uses minimal samples otherwise.
Figure x: Homography estimation experiment considering RANSAC, EVSAC, PROSAC, USAC, and ANSAC using image pairs from Oxford and USAC datasets. We can observe that ANSAC returns an estimate in the same time or faster than that of USAC. However, ANSAC returns estimates with a comparable quality as that of RANSAC, EVSAC, and PROSAC according to the inlier ratio and the success rate.
Figure xi: Fundamental matrix estimation experiment considering RANSAC, EVSAC, PROSAC, USAC, and ANSAC using image pairs from Strecha and USAC datasets. We can observe that ANSAC returns an estimate in the same time or faster than that of USAC. However, ANSAC returns estimates with a comparable quality as that of RANSAC, EVSAC, and PROSAC according to the inlier ratio and the success rate.