DIBRIS

DEPARTMENT OF INFORMATICS,
BIOENGINEERING, ROBOTICS AND SYSTEM ENGINEERING

COMPUTER VISION

Third Assignment

Computer Vision Laboratory Report

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Part

1 The 8-Points Algorithm and Normalization

1.1 Introduction

To ensure the correctness of our 8-point algorithm implementation, we first tested it on two benchmark datasets where the point correspondences are known :

- **Rubik** :A 3D object with a standard stereo baseline.
- **Mire** :A calibration pattern with a highly structured grid of points.

For both datasets, we compared the Unnormalized algorithm (using raw pixel coordinates) against the Normalized algorithm (using centered and scaled coordinates). We evaluated the results visually by checking if the estimated epipolar lines pass through the matching points.

1.2 Results and Interpretation

1.2.1 Results on the Rubik Dataset

We first applied the algorithm to the Rubik stereo pair.

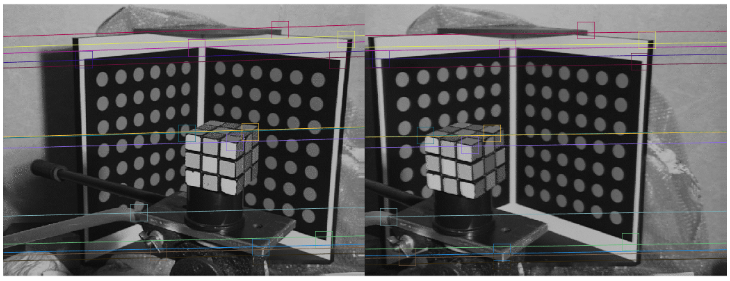

FIGURE 1.1 – Unnormalized estimation on Rubik

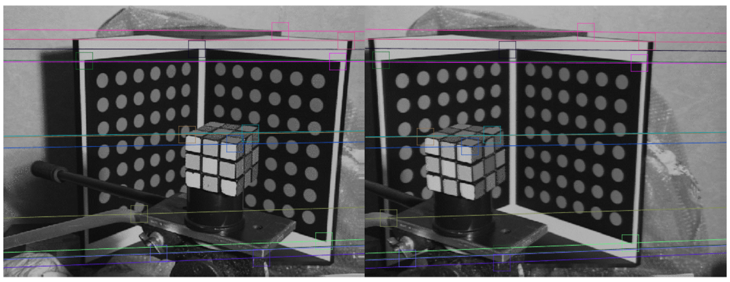

FIGURE 1.2 – Normalized estimation on Rubik

As shown in figure 1.1 (unnormalized), the results are inaccurate. The estimated epipolar lines fail to intersect the corresponding feature points, with significant deviation in the corners of the cube. This error arises because the raw pixel coordinates differ by orders of magnitude from the homogenization constant, leading to an ill-conditioned matrix A. In contrast, figure 1.2 (normalized) demonstrates a correct estimation. By scaling the input data, the numerical instability is resolved, and the epipolar lines align perfectly with the feature points. The error pass from the order of 10^{-1} without normalization to the order of 10^{-3} with the normalization.

1.2.2 Results on the Mire Dataset

Next, we tested the "Mire" dataset. This dataset is interesting because the points are arranged in a strict grid.

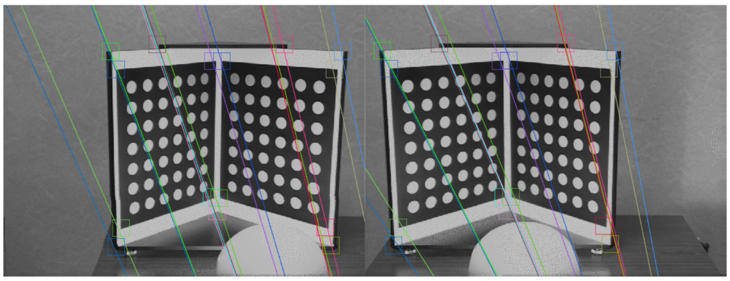

FIGURE 1.3 – Unnormalized estimation on Mire

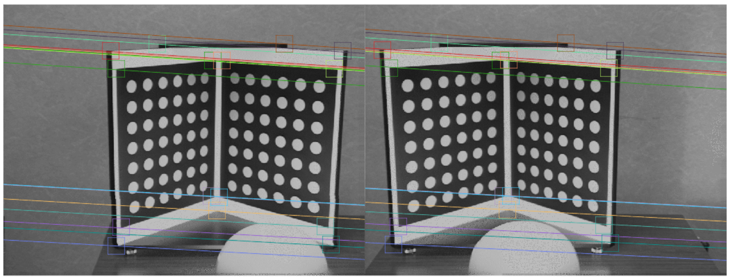

FIGURE 1.4 – Normalized estimation on Mire

The necessity of normalization is most evident here. In Figure 1.3, the algorithm completely fails ; the epipolar lines are nearly vertical and parallel, bearing no relation to the actual camera geometry. However, after applying normalization (Figure 1.4), the estimation recovers the correct geometry, with lines passing precisely through the grid intersections.

1.3 Conclusion

The experiments on both the Rubik and Mire datasets provide a clear conclusion : coordinate normalization is mandatory. While the unnormalized version produced "okay" but inaccurate results for the Rubik's cube, it completely failed for the Mire dataset. The normalized version, however, produced mathematically perfect results in both cases. Therefore, we will strictly use the normalized 8-point algorithm for the remainder of this report.

Part

2 RANSAC Evaluation

2.1 Introduction

The second part of the laboratory is focused on the implementation of the RANSAC method (RANdom SAmpling Consensus).

To evaluate the effectiveness of the estimator, synthetic noise was introduced by appending 5 pairs of randomly generated coordinates to the valid correspondence set.

2.2 Results and Interpretation

If the 8-point algorithm is used directly, the resulting epipolar lines do not appear parallel, but with the epipole inside the images (figure 2.1). This occurs because the algorithm is highly sensitive to noise and assumes that all point correspondences are perfectly accurate.

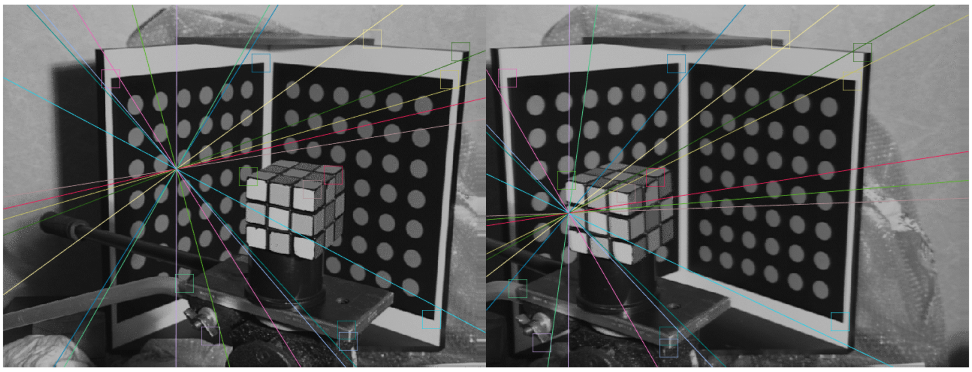

FIGURE 2.1 – 8-points algorithm with noise

RANSAC, on the other hand, is more robust to noise. It tolerates errors in the feature matches and actively attempts to minimize the influence of outliers by repeatedly sampling subsets of points and selecting the model that best fits the majority of inliers.

By setting a threshold of 0.01 and 2000 iterations, the algorithm is able to correctly detect the right epipolar lines as illustrated in figure 2.2.

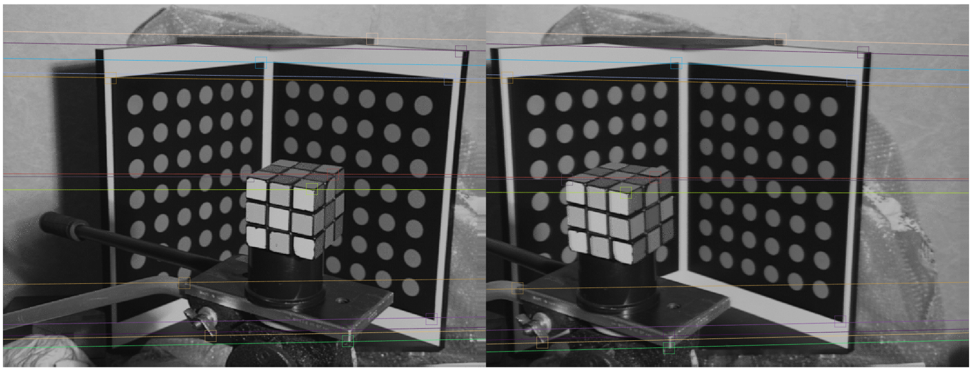

FIGURE 2.2 – RANSAC application

In this case the error of the estimation is in the order of 10^{-3}.

2.3 Conclusion

The comparison between the direct 8-point algorithm and the RANSAC approach demonstrates the necessity of robust statistical methods in computer vision. The introduction of synthetic noise demonstrated the fragility of the linear 8-point algorithm. However, by implementing RANSAC with a threshold of 0.01, the estimator was able to filter the outliers and rely solely on the consistent geometrical constraints of the inliers. The resulting parallel epipolar lines and negligible error (10^{-3}) validate the implementation and underscore RANSAC's ability to recover correct model parameters even in contaminated datasets.

Part
3

Estimation on Real Image Pairs

3.1 Introduction

In this chapter, we apply the method to a real-world stereo pair of one of the laboratory equipment. We generate feature matches automatically using Positions and Normalized Cross-Correlation (POSNCC) with SDV. In particular, with $\sigma = 100$ and a threshold of 0.8. Since this process introduces outliers, we employ the RANSAC algorithm to filter out incorrect matches and robustly estimate the Fundamental Matrix.

3.2 Results and Interpretation

3.2.1 Feature Matching

We first applied the POSNCC algorithm to find correspondences between the two views of the image. Figure 3.1 shows the detected matches.

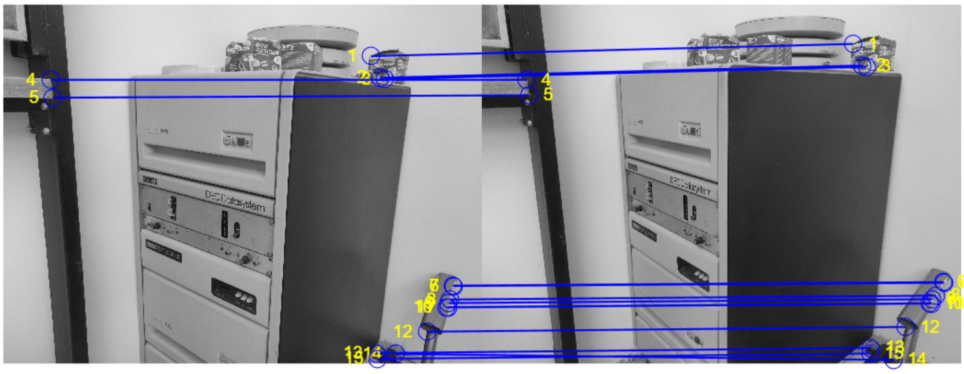

FIGURE 3.1 – Matches detected by the POSNCC algorithm

* **Interpretation :**

The blue lines connect the features found in the left image to their counterparts in the right image. We can see that the algorithm successfully locked onto high-contrast areas, such as the corners of the blackboard (top-left) and the text on the boxes. However, because this process is automatic, we assume that not every single match is perfect. Some lines might connect unrelated points, which is why we cannot trust the raw data blindly.

3.2.2 Epipolar Geometry

We then computed the Fundamental Matrix using the 8-point algorithm within a RANSAC loop to reject outliers. This method filters out the "bad" matches and keeps only the consistent ones. Figure 3.2 shows the final validation.

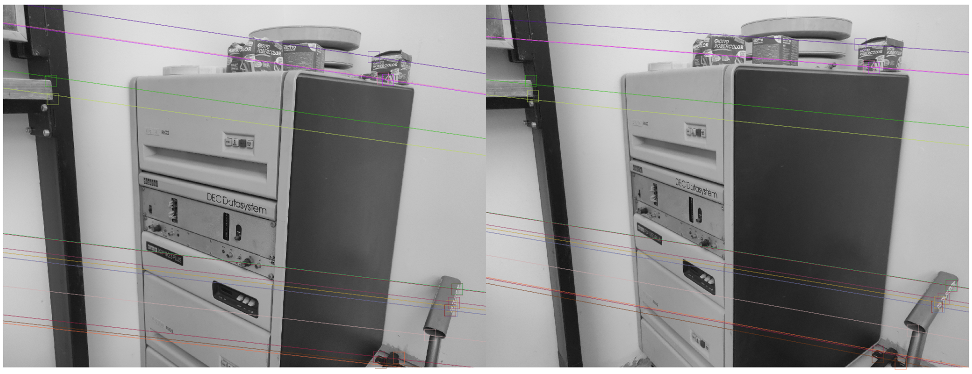

FIGURE 3.2 – Estimation results using RANSAC

∗ **Interpretation :**

The results here are much cleaner. The small colored squares highlight the "inliers" ,the points that RANSAC accepted as valid. Most importantly, the colored epipolar lines pass exactly through the center of these squares and every line pass through the same points in the two images. This confirms that the estimated matrix F is correct The error is

$$e = (0.0002, 0.0009, -0.0010)$$

It's noticeable also that the lines on the front of the machine tend to converge towards the right side of the image ; this indicates the location of the epipole and tells us how the camera moved relative to the scene.

3.3 Conclusion

This chapter demonstrated that our approach works effectively on real-world images, not just on perfect datasets. By combining automatic matching (POSNCC) with RANSAC, we were able to handle the noise and incorrect matches that naturally occur in real scenes. The final result confirms that the pipeline is robust and capable of estimating the correct geometry without needing manual intervention.