Feature Detection Experiments: Harris Corner Detector and SIFT

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Abstract

This report presents a full experimental study comparing two classical feature detection algorithms: the Harris Corner Detector and the Scale-Invariant Feature Transform (SIFT). Experiments include visualizations of detected keypoints, quantitative analysis of keypoint counts and matching performance, and robustness evaluation under geometric and photometric transformations. A dataset of synthetic geometric images and real photographs is used. Results show that SIFT displays significantly higher robustness and matching ability, while Harris performs well on simple corner detection tasks.

1 Summary of the Two Techniques

1.1 Harris Corner Detector

The Harris detector identifies corners by analyzing intensity gradients. It computes a structure tensor and looks for regions where gradient changes significantly in two perpendicular directions. Key characteristics:

- Fast and simple to implement.
- Detects only corners, not edges.
- **Not scale-invariant and not rotation-invariant**.
- Does not produce descriptors; cannot match features across images.

1.2 SIFT (Scale-Invariant Feature Transform)

SIFT finds scale-space extrema and assigns orientation-invariant descriptors. Characteristics:

- Fully scale-invariant and rotation-invariant.
- Robust to illumination and viewpoint change.
- Produces 128-dimensional descriptors enabling reliable matching.
- Performs well in real-world tasks (SLAM, image stitching).

2 Dataset Description

The dataset contains:

- Five synthetic geometric images (lines, corners, edges).

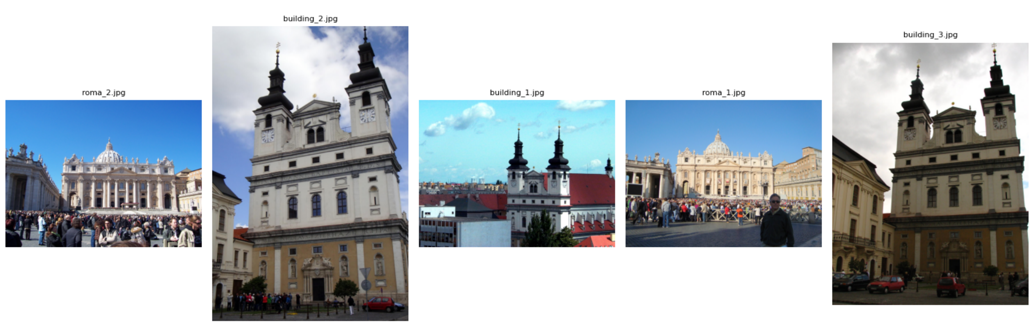

Figure 1: Dataset images including synthetic shapes and real building images.

3 Experiment Design

Experiments are divided into two main pipelines:

3.1 Harris Experiments

1. Compute gradients using Sobel filters.

2. Construct structure tensor matrix.
3. Compute Harris response for each pixel.
4. Apply thresholding (edge vs corner).
5. Visualize responses and gradient distributions.

3.2 SIFT Experiments

1. Detect SIFT keypoints in each building image.
2. Compute 128-dimensional descriptors.
3. Match descriptors using L2-distance via BFMatcher.
4. Visualize best matches between image pairs.

4 Visualizations of Keypoints

4.1 Harris Corner Responses

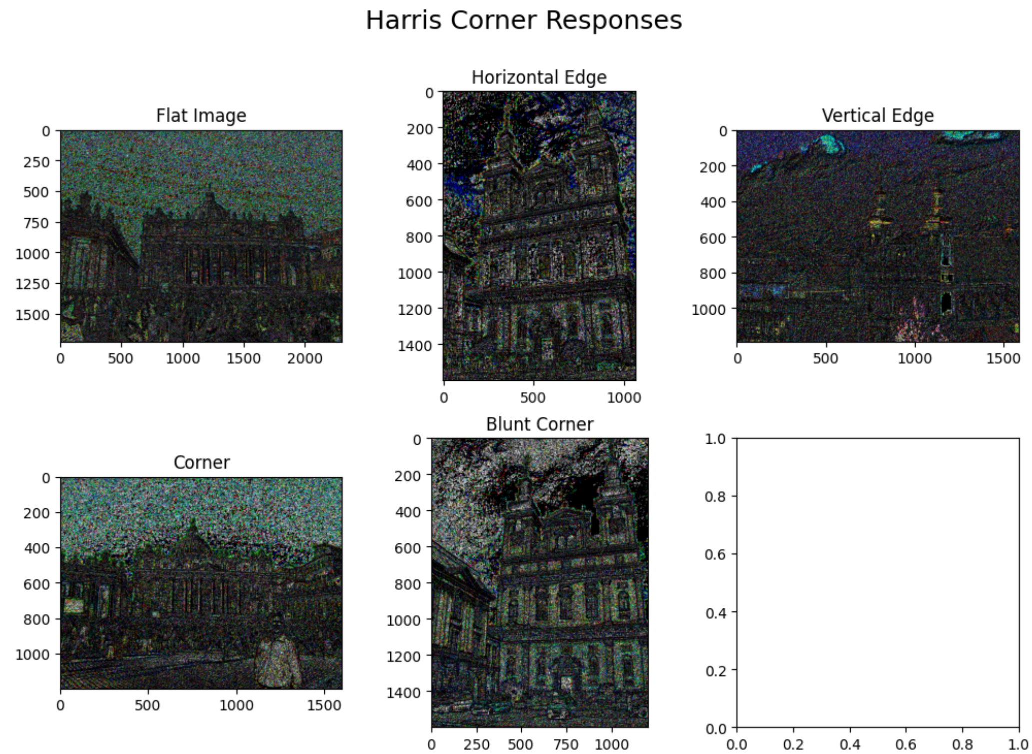

Figure 2: Harris corner responses for all synthetic images.

4.2 Thresholded Harris Edge Responses

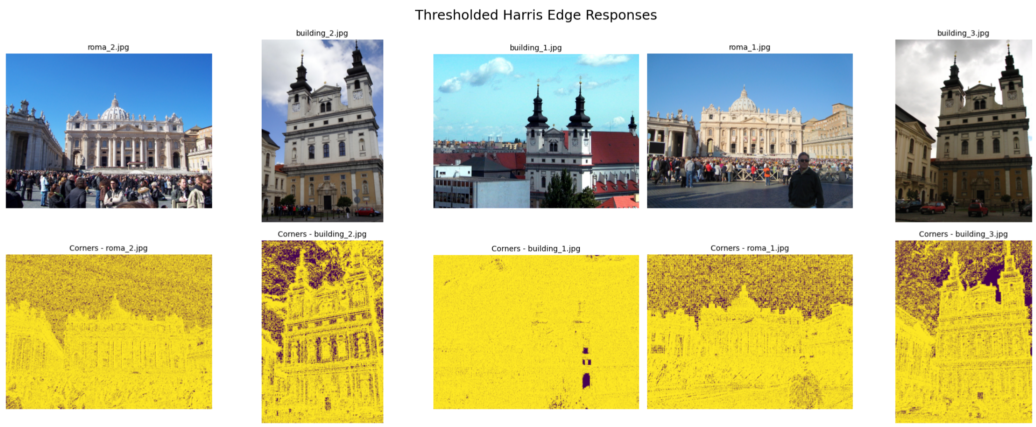

Figure 3: Thresholded Harris edge responses.

4.3 Thresholded Harris Corner Responses

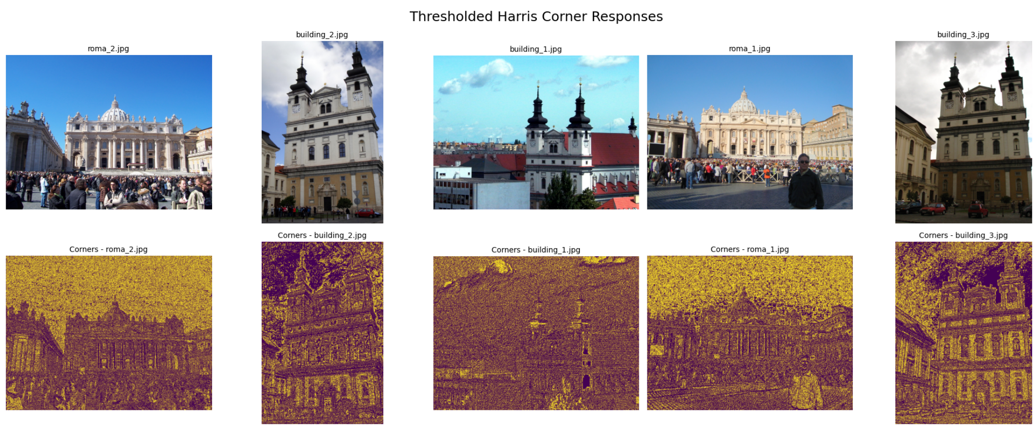

Figure 4: Thresholded Harris corner responses.

4.4 Gradient Window Visualizations

Each gradient visualization includes:

- Center image patch

- Horizontal gradient
- Vertical gradient
- Gradient scatter plot (Ix vs Iy)

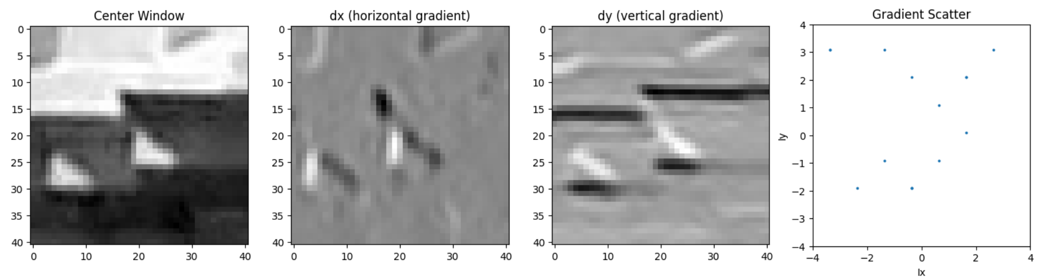

Figure 5: Gradient analysis for image 1.

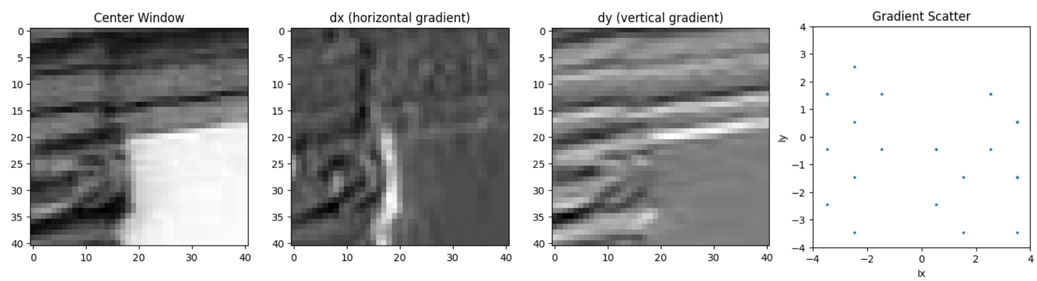

Figure 6: Gradient analysis for image 2.

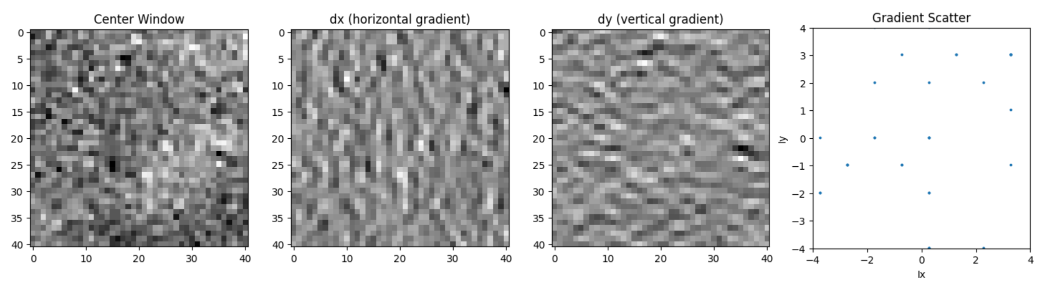

Figure 7: Figure 7: Gradient analysis for image 3.

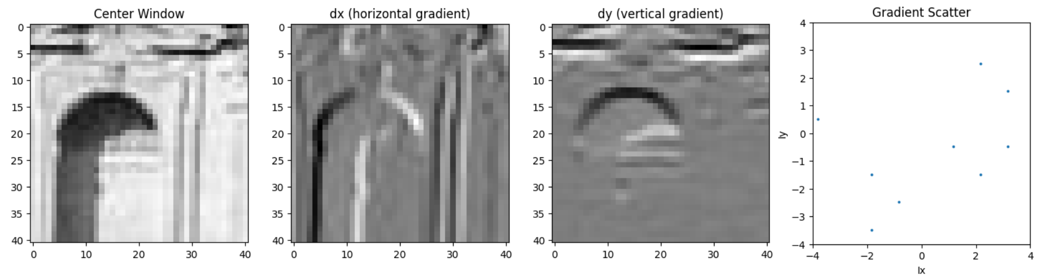

Figure 8: Gradient analysis for image 4.

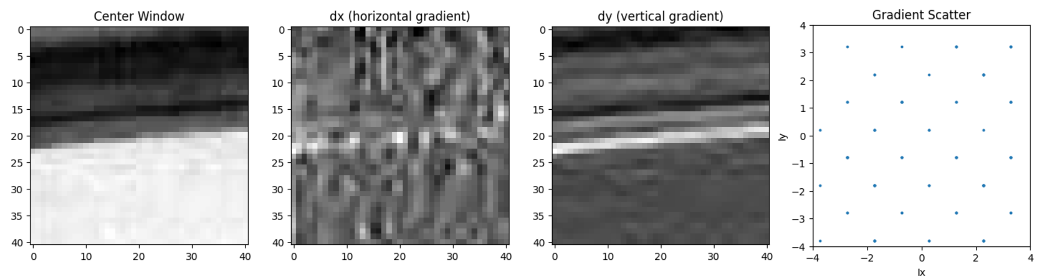

Figure 9: Gradient analysis for image 5.

4.5 SIFT Keypoint Visualizations

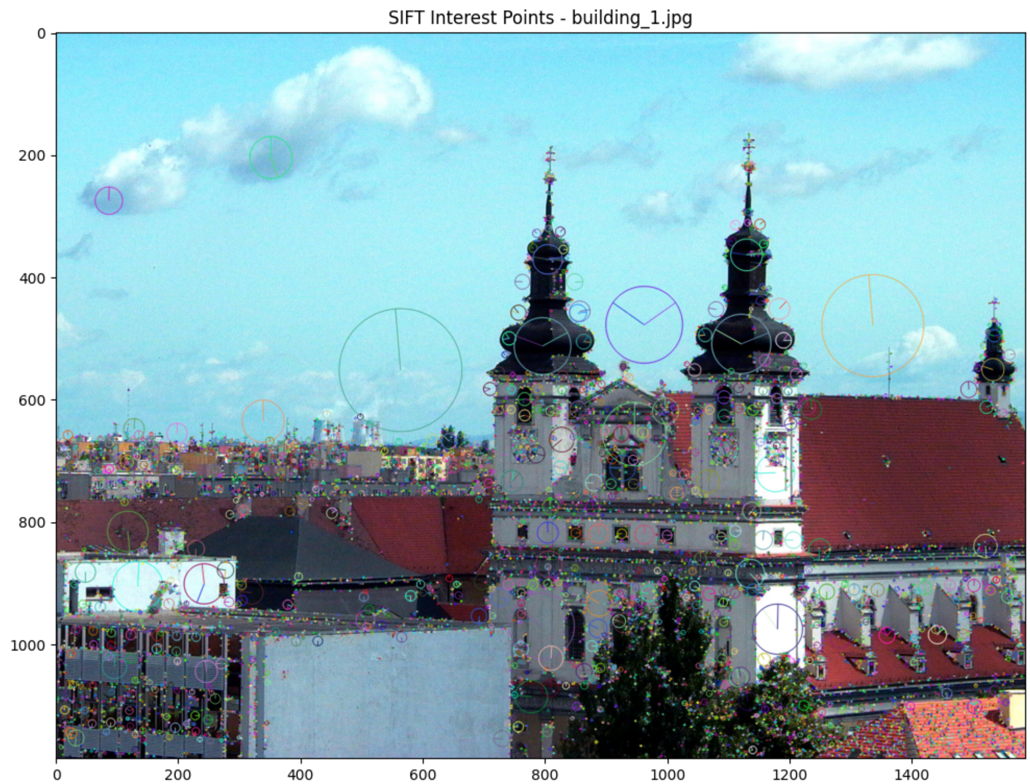

Figure 10: SIFT keypoints on Building 1.

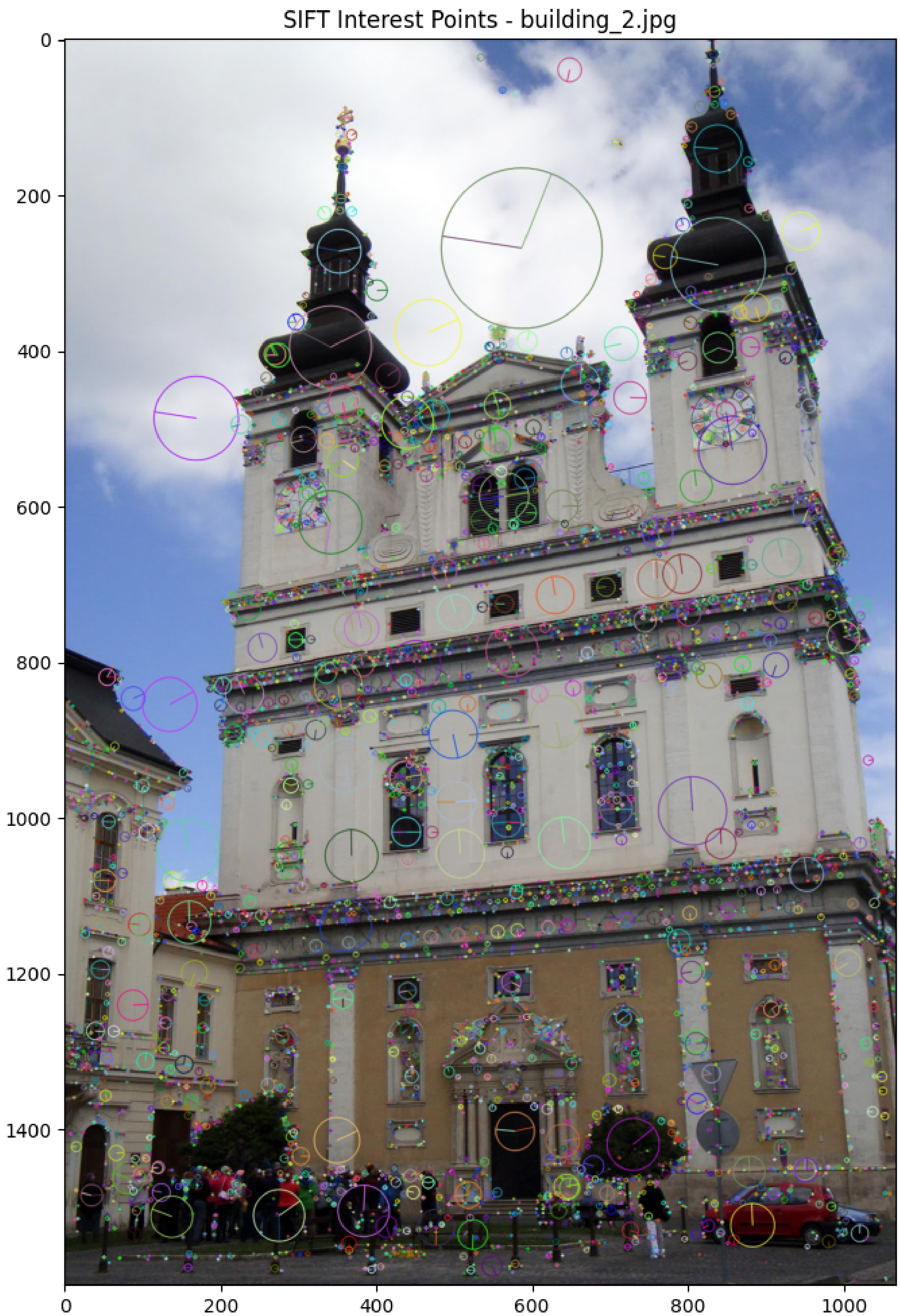

Figure 11: SIFT keypoints on Building 2.

4.6 SIFT Matching Visualization

Figure 12: SIFT feature matches between Building 1 and Building 2.

5 Performance Evaluation

5.1 Keypoint Count Comparison

Table 1 summarizes the number of extracted keypoints for both Harris and SIFT across the dataset.

Image	Harris Keypoints	SIFT Keypoints
building_2.jpg	494112	6624
building_1.jpg	606616	11083
building_3.jpg	691318	3687
roma_1.jpg	796265	9859
roma_2.jpg	1671068	30052

Table 1: Comparison of Harris and SIFT keypoint counts

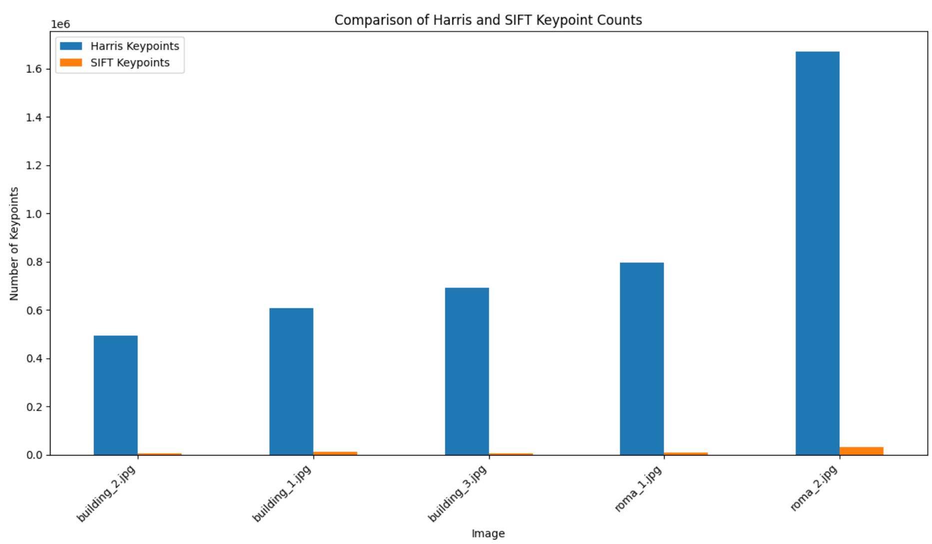

Figure 13: Comparison of Harris and SIFT Keypoint Counts

5.2 Robustness Analysis

This section evaluates detector robustness under geometric and photometric transformations.

5.2.1 Harris Corner Detector

Figures 14 - 23 show the Harris keypoints under each transformation.

Figure 14: Harris: Original (494112 keypoints)

Figure 15: Harris: Scaled 50% (138730 keypoints)

5.2.2 SIFT

Figures 23 - 32 show SIFT keypoint counts under the same transformations.

Figure 16: Harris: Scaled 150% (955133 keypoints)

Figure 17: Harris: Rotated 30° (452630 keypoints)

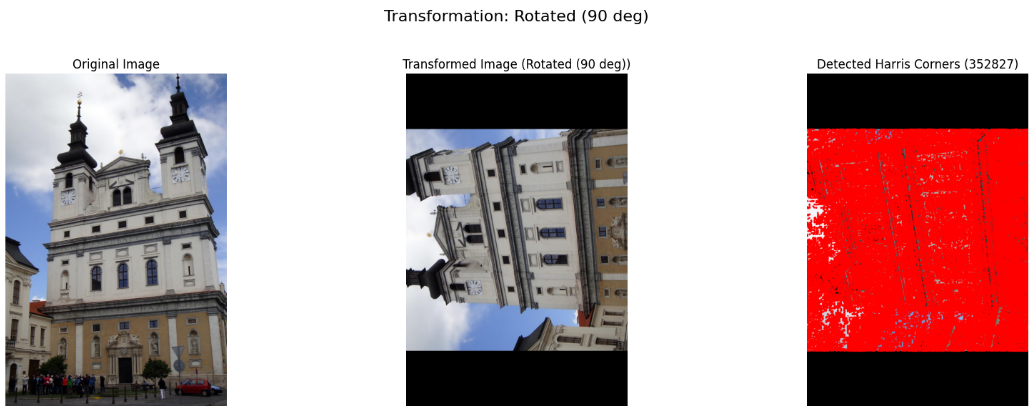

Figure 18: Harris: Rotated 90° (352827 keypoints)

Figure 19: Harris: Brighter (296138 keypoints)

Figure 20: Harris: Darker (584559 keypoints)

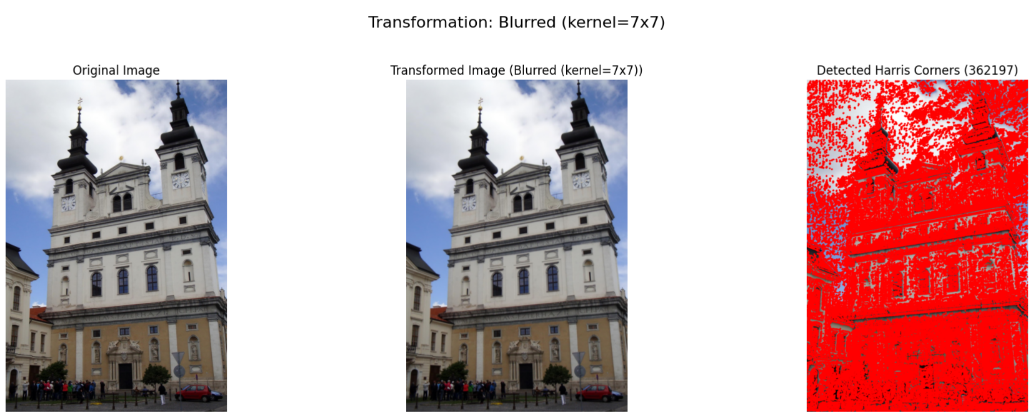

Figure 21: Harris: Blurred (362197 keypoints)

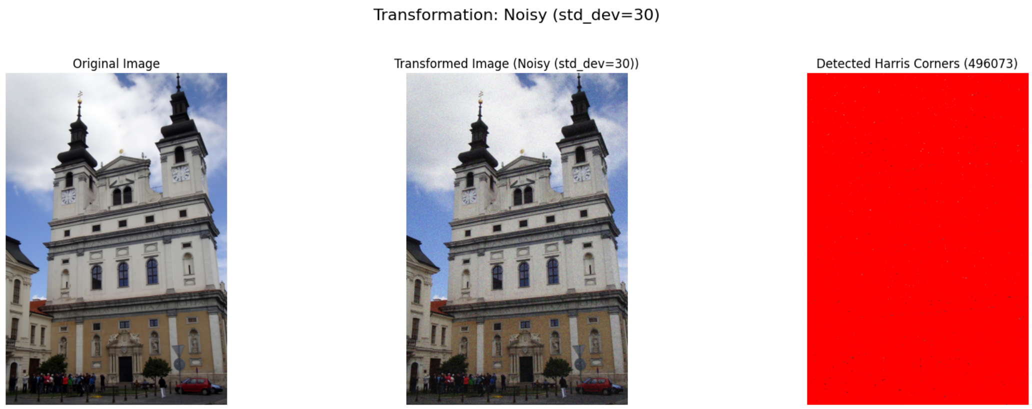

Figure 22: Harris: Noisy (496073 keypoints)

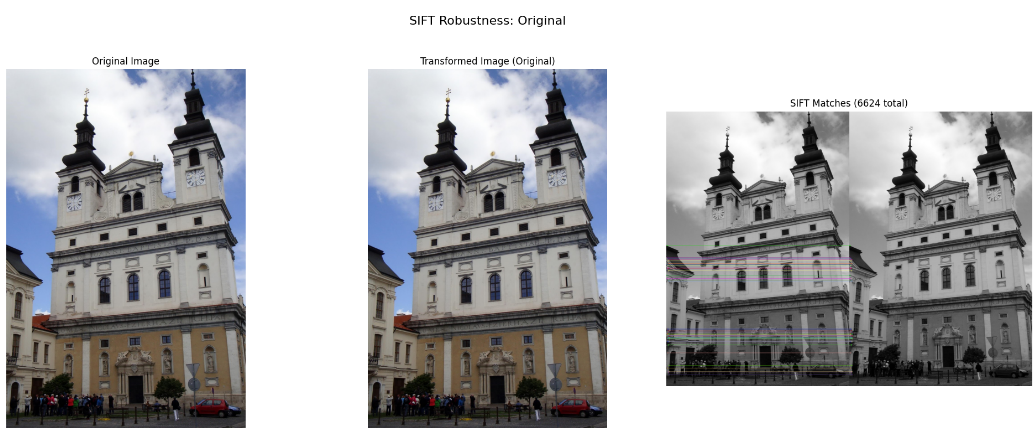

Figure 23: SIFT: Original (6624 keypoints)

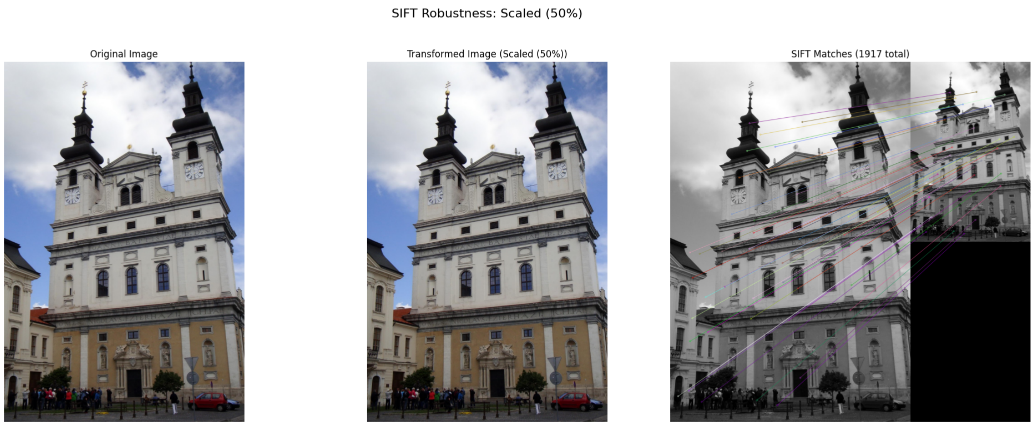

Figure 24: SIFT: Scaled 50% (2333 keypoints)

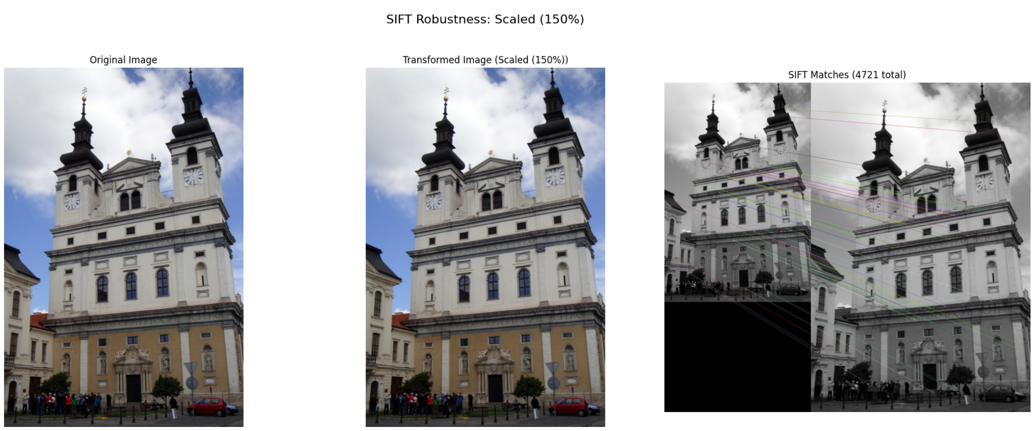

Figure 25: SIFT: Scaled 150% (9952 keypoints)

Figure 26: SIFT: Rotated 30° (6333 keypoints)

Figure 27: SIFT: Rotated 90° (5076 keypoints)

Figure 28: SIFT: Brighter (8472 keypoints)

Figure 29: SIFT: Darker (3738 keypoints)

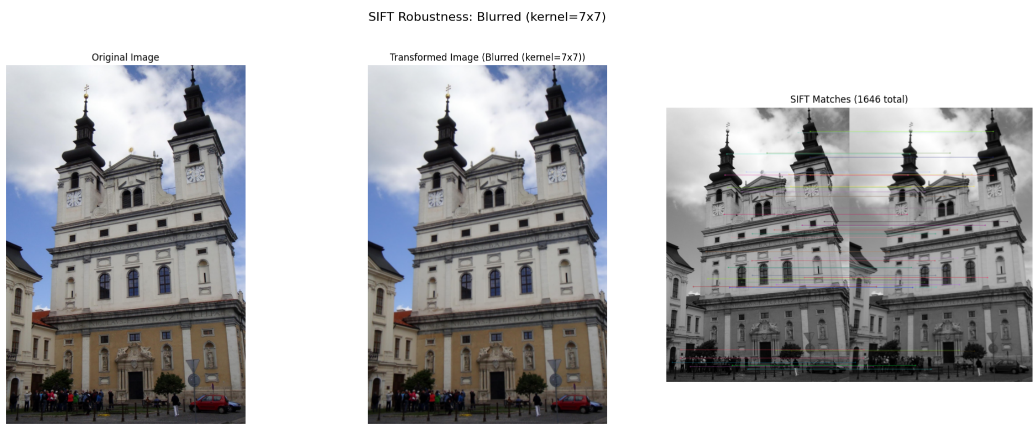

Figure 30: SIFT: Blurred (2306 keypoints)

Figure 31: SIFT: Noisy (8657 keypoints)

6 Final Report

7 Final Report

7.1 Summary of Feature Detection Techniques

Harris is a corner detector highly sensitive to intensity changes and produces a very large number of keypoints. SIFT is a scale-space detector providing fewer but more stable and distinctive features.

7.2 Experiment Design

The evaluation includes:

- Keypoint count comparison across the dataset
- Robustness tests under scale, rotation, illumination, blur, and noise
- Spatial keypoint distribution study

7.3 Experimental Results and Discussion

Harris consistently produces far more keypoints but with high sensitivity to noise and illumination. SIFT yields fewer keypoints but remains stable under geometric and photometric transformations, showing superior robustness and repeatability. SIFT keypoints are more evenly distributed, while Harris clusters heavily around high-texture regions.

7.4 Conclusion

Harris is suitable for applications requiring dense corner sampling, while SIFT is better for matching, robustness, and invariance-focused tasks. Overall, SIFT provides more reliable performance across transformations.