Object Detection Report

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1. Introduction

This report details the development and evaluation of an object detection program using C++ and OpenCV. The project aimed to accurately detect a specific object within a scene using feature detection, descriptor matching, homography computation, and bounding box visualization. The focus was on detection accuracy over real-time performance, with multiple methods tested and prioritized based on accuracy, even at the cost of longer execution times.

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2. Implementation of Object Detection

This section outlines the implementation of object detection based on the assignment parameters, referred to as the 'Standard Test.' It provides an overview of the variables and methods used, with testing results included later to justify design choices.

2.1 Feature Detection & Descriptor Extraction

Method Implemented:

- After running speed tests and analysing feature matching and inlier counts, SIFT was chosen for its superior accuracy despite the longer execution times.

2.2 Descriptor Matching

Method Implemented:

- Testing different matching methods with the SIFT detector showed similar feature matching results. However, due to SIFT producing many float-type descriptors, FLANN was selected based on test performance.

2.3 Homography Computation

Method Implemented:

- RANSAC was applied with cv::findHomography() to compute a robust homography matrix. This step was crucial in filtering outlier matches and ensuring that the detected object's boundary box is properly localized in the scene.

2.4 Bounding Box Visualization

- **Technique:**
  - The object's corners in the scene were defined by the detector and matcher, and cv::perspectiveTransform() was used to project these points into the scene.
  - The projected points were then connected using cv::line() to draw a bounding box around the detected object in scene.
  - This gave a visual representation of the object detection in the scene, though did not give value representations of the accuracy, this was addressed in later testing. Due to the method of

accuracy detection I used, the provided sample could not be used due to a lack of all visible corners, while these could be approximated, I thought it to be more suitable to test with similar objects in environments with more visible corners.

2.5 Testing Results and Choice Justification

Detector

Approach:

- Both SIFT and ORB detect KeyPoints and compute descriptors using OpenCV's detectAndCompute(). The detector will be selected based on the number of inliers it produces from the KeyPoint matches it finds in both images, since this is a static program rather than a real time application accuracy is the determinant.

Test Results:

I started with a feature cap of 5000 for both detectors, which they each reached—making it a suitable benchmark for comparing accuracy. To ensure consistency, both used FLANN for feature matching, with LSH indexing for ORB. I varied Lowe's ratio between 0.6 and 0.8 for comparison, logging the results in Figure 1.

Parameters	Inliers	Good Matches	Ratio
SIFT Lowe @ 0.6	256	402	0.64
SIFT Lowe @ 0.7	293	499	0.59
SIFT Lowe @ 0.8	385	646	0.60
ORB Lowe @ 0.6	36	50	0.72
ORB Lowe @ 0.7	88	144	0.61
ORB Lowe @ 0.8	190	400	0.48

Figure 1. Test Results

While ORB achieved a better inlier-to-match ratio on average, SIFT produced a significantly higher number of inliers overall.

Visual inspection of feature matches revealed further insights: although both detectors generated reasonably accurate bounding boxes, ORB often matched non-ideal keypoints within the scene—leading to background interference. In contrast, SIFT consistently matched keypoints between the object and scene with greater precision and minimal noise;

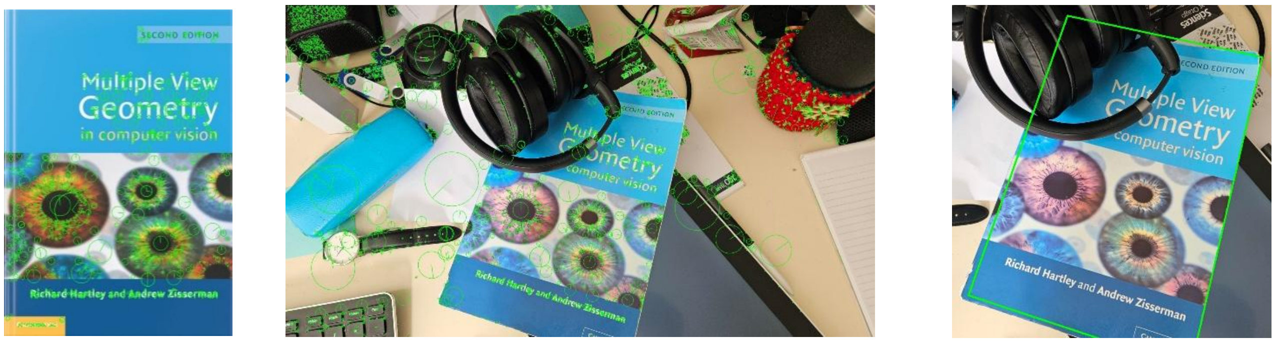


Figure 2 Object and Scene KeyPoints with Boundary Box drawn using the SIFT detector and FLANN matcher

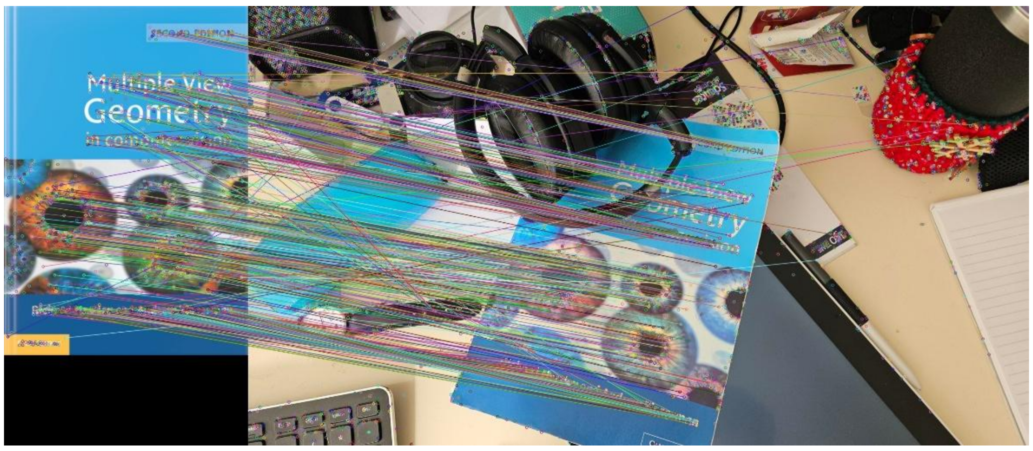


Figure 3 Feature Matching using OpenCV and SIFT KeyPoints

In contrast, ORB's key points focused heavily on gradient and colour differences, often detecting corners across the background. As a result, its feature matching tended to prioritize background elements over the object itself.

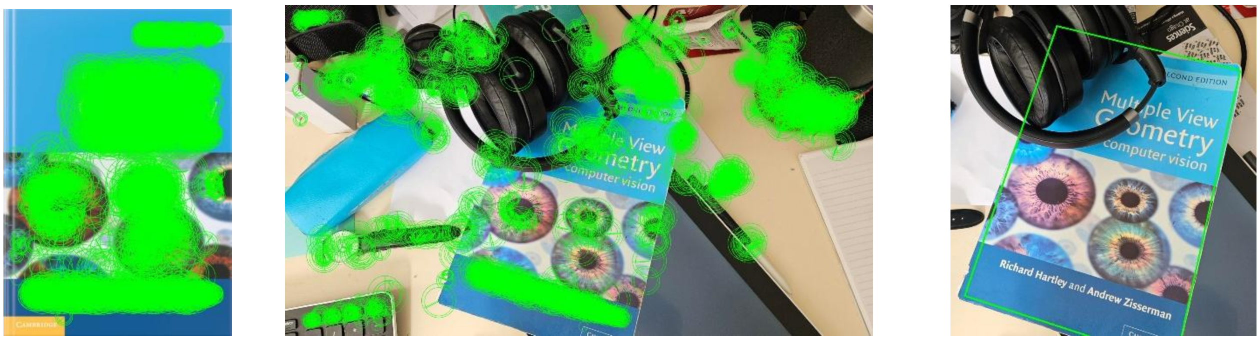


Figure 4 Object and Scene KeyPoints with Boundary Box drawn using the ORB detector and FLANN matcher

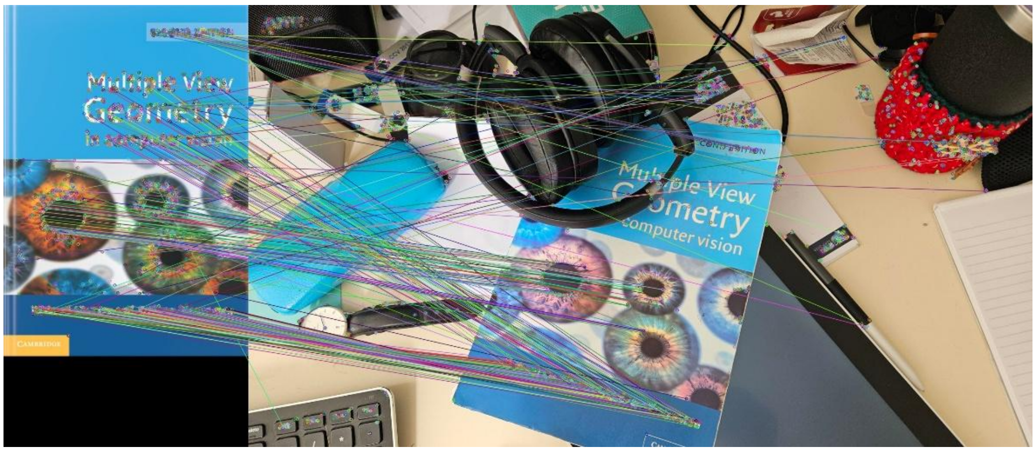


Figure 6 Feature Matching using OpenCV and ORB KeyPoints

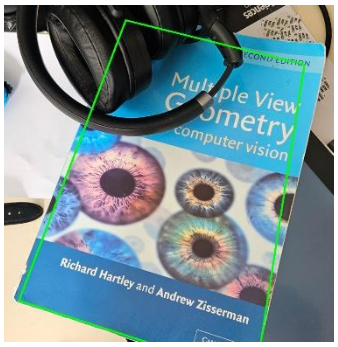


Figure 5 SIFT with a Lowe Ratio of 0.8

Conclusion:

- SIFT's higher accuracy output with detecting robust KeyPoints and considerable inlier output outweighed its slower speed performance compared to ORB.
- Testing with a SIFT feature cap of 1000 yielded unsatisfactory results (see Figure 1). Loosening Lowe's ratio from 0.8 to 0.6 slightly improved coverage but remained visually inaccurate (see Figure 2).
- I ended up keeping the feature cap at its default '0', which allows the algorithm to detect as many KeyPoints as possible based on its internal criteria. This gave a higher degree of accuracy, I tried to refine this further by adjusting the Lowes ratio, keeping the feature cap at 0 (INF) I adjusted the ratio to compare the number of inliers each result produced. While looking at the test data the ratio of 0.6 produced the best ratio of inliers from the matches, the ratio that produced the greater number of inliers was selected.

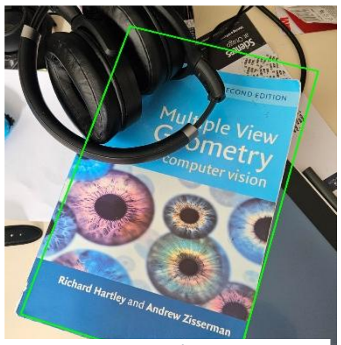


Figure 7 SIFT with a Lowe Ratio of 0.6

Parameters	Inliers	Good Matches	Ratio
SIFT INF Lowe0.6	300	463	0.65
SIFT INF Lowe0.7	332	573	0.58
SIFT INF Lowe0.8	420	720	0.58

Figure 8 Test Results with Lowe Ratio Experimentation

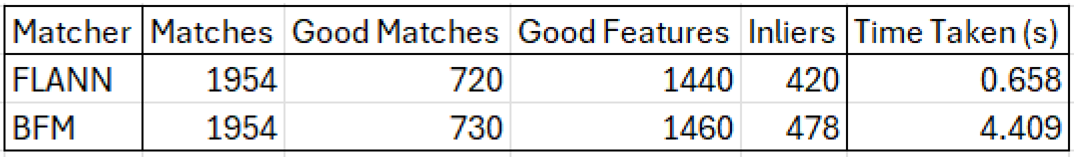
Matcher and Feature Extraction

Approach:

Fast Library for Approximate Nearest Neighbours (FLANN) and Brute-Force Matching (BFM) were tested using k-nearest neighbours matching with *k = 2*. A Lowe's ratio of 0.8 was applied to filter matches, ensuring only strong matches contributed to homography computation. For consistency, SIFT was chosen as the detection method for the test

Test Results:

Running the test under the same desired conditions as before, with a Lowe Ratio of 0.8, both matchers gave an identical number of matches, but BFM produced a slightly higher output of good matches and features from them after filtering using the Lowes ratio test. This resulted in a higher number of inliers but not by a wide margin.



Matcher	Matches	Good Matches	Good Features	Inliers	Time Taken (s)
FLANN	1954	720	1440	420	0.658
BFM	1954	730	1460	478	4.409

Figure 9 Matcher Test Results using SIFT

Observations:

While FLANN and BFM produced similar match counts, the Lowe's ratio test yielded better results with BFM—though BFM was 6.7x slower than FLANN. In later accuracy tests with varied images, FLANN provided more accurate match filtering with SIFT compared to BFM. FLANN handles high-dimensional float descriptors efficiently using approximate nearest neighbour search, making it significantly faster and more scalable than BFM. Although BFM is accurate, it becomes computationally expensive with the large number of features SIFT generates, especially on larger images. Overall, FLANN struck the best balance between speed and accuracy, making it the preferred matcher for these test cases.

2.5 Build and Run Instructions

Compilation:

The project is built using CMake and compiled in Visual Studio. The source code values have not been altered much from the provided skeleton code aside from these changes.

- CMakeLists.txt: changed CMAKE_TOOLCHAIN_FILE path to "C:\\vcpkg\\scripts\\buildsystems\\vcpkg.cmake" for my own system.
- Launch.vs.json: Commented out preset arguments in favour of a terminal menu for selecting methods.

Execution:

The skeleton code was significantly modified to create a robust testing environment with a terminal menu for variable configuration and test selection.

- **Option 1:** Runs object detection with the chosen parameters using the provided object and scene images, providing the output given the chosen parameters I deemed best for this project; this uses the provided object and scene images for object detection.
- **Option 2:** Displays usage by printing current settings (default values for the assignment).
- **Settings Menu:** Allows changing the object and scene filenames (from the working directory) and switching the detector and matcher types.

- Additionally, the other menu options are for testing data I noted in this report, while the Speed Test will work with the provided set of object and scene, the Accuracy Test will need disabling the "default" Boolean and changing filenames, additionally these files are available in my public repo noted at bottom. *Note these two methods are not needed for the assignment*

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3. Experiment Design

3.1 Test Data

Speed Test

- The provided object and scene images ("Multiple View Geometry" book on a cluttered desk) were used.

Accuracy Test

- A photo of a card playing game "Monopoly Deal" was used in conjunction with;

  Two scene images (md-scene1 & md-scene2) of the game on a desk with clutter, both scene identical with one being closer to the table (md-scene2), resulting in a larger in-scene object presence.

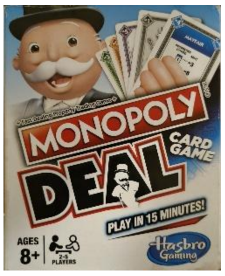


Figure 10 Monopoly Deal (md)

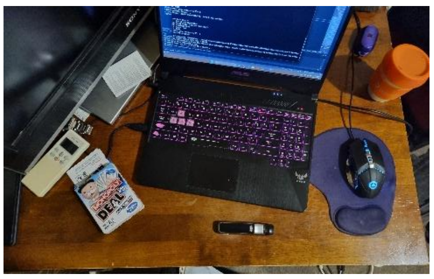


Figure 11 md-scene1

- A photo of a book "Asterix: The Champion" was used in conjunction with;
  - A scene image of books laid in a grid formation, denoted b-scene1. (*see figure 14*)
  - A scene image of books scattered around, covering ~50% of the object, denoted b-scene2. (*see figure 15*)
  - A darker image of the b-scene1 with its brightness scaled down, denoted b-sceneD

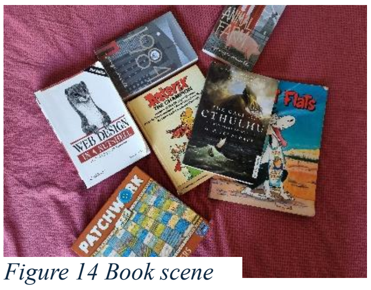
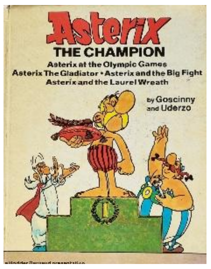


Figure 14 Book scene cluttered.


Asterix
THE CHAMPION
Asterix at the Olympic Games
Asterix The Gladiator • Asterix and the Big Fight
Asterix and the Laurel Wreath
by Goscinny and Uderzo
Figure 13 Asterix

3.2 Hypotheses and Experimental Questions

Speed Test:

- While ORB is faster than SIFT, I compared both detection methods to assess if the speed gain justifies any loss in accuracy by comparing their matches and feature detection.

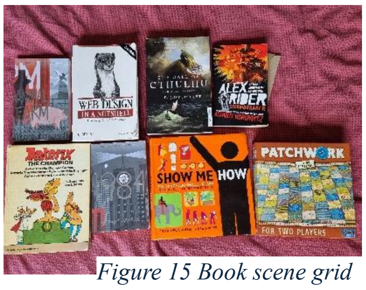


Figure 15 Book scene grid

Accuracy Test:

- It was hypothesized that despite SIFT's longer processing time, its ability to accurately detect the object is significantly better. The test aimed to quantify this accuracy using a defined metric. Additionally, lab observations suggested that BFM yields superior matching results, this was something I wanted to test across a broader range of images.

3.3 Benchmarking Approaches

Method for Testing Speed:

Each detector/matcher combination was executed twenty times. ORB detector used NORM_HAMMING for the BFM and used the index parameters for the tables, key size, and multi probe levels as 12, 20, 2 respectively, for the FLANN matcher. Detectors had a feature cap of 5000, and used the Lowes Ratio test of 0.8. Performance was measured by averaging the execution times. Total elapsed time over twenty tests divided by 20.

Key performance metrics included:

- Execution time for feature detection.
- Execution time for descriptor matching.
- Number of KeyPoints detected and matches produced.

Method for Testing Accuracy:

To determine the true object size in the scene, OpenCV features were used to present the user with a reference photo and corresponding scene image, then manually selected the object's visible corners. These “ground truth” corners (with a 5-pixel user error margin) allowed the detected bounding box corners—computed via the homography matrix—to be compared using Euclidean distance between the vectors. Default corners were defined to minimize user error and maintain consistency across tests. Five tests using different object and scene combinations were conducted for each detector to compute the average pixel error per corner and per test.

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4. Test Results

4.1 Detection Execution Times

Test Results:

The test was conducted to determine the average time it took for each detector matcher combination to find features, and find the good matches from them.

Detector/Matcher	Total Features object+scene	Good Matches	Average Execution Time (s)
SIFT/FLANN	6955	646	5.15
SIFT/BFM	6955	629	10.52
ORB/FLANN	9998	404	1.56
ORB/BFM	9998	343	1.26

Observations:

- ORB was much faster than SIFT in terms of raw execution time, taking around 18% of the total time SIFT executes in; however, SIFT’s output was significantly more accurate, outputting more good matches with fewer total features.

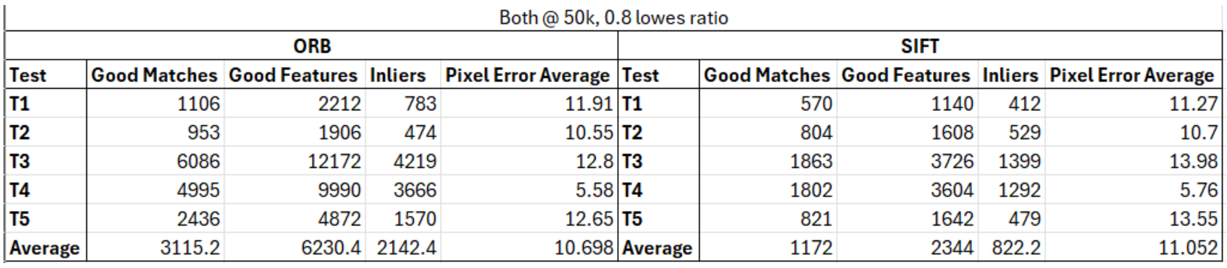
- Despite BFM typically yielding better inliers, its count of "good matches" was lower than FLANN's. This is because BFM, being exact, finds the true closest and second-closest matches, resulting in smaller distance gaps and fewer matches passing Lowe's ratio test. In contrast, FLANN's approximate search often inflates these gaps, allowing more matches to pass and resulting in a higher count.

- BFM performs slower with SIFT yet faster with ORB, this would be because while BFM operates by comparing each descriptor in image A to *every* descriptor in image B using Euclidean distance, obviously slowing down matching with large data sets (big images), so It’s O(n^2) and doesn’t scale well with large numbers of KeyPoints which SIFT provides. But ORB uses BFM with Hamming distance between binary strings, meaning that even though its complexity is still O(n^2) its bitwise operations are hardware accelerated.

4.2 Detection Accuracy

Test Results:

I initially ran the program to manually define object corners in each scene, establishing consistent defaults for averaging tests. The results below show the detected corners, with abbreviated data for clarity. A summary table presents the average pixel errors;



Both @ 50k, 0.8 lowes ratio

ORB					SIFT				
Test	**Good Matches**	**Good Features**	**Inliers**	**Pixel Error Average**	**Test**	**Good Matches**	**Good Features**	**Inliers**	**Pixel Error Average**
T1	1106	2212	783	11.91	**T1**	570	1140	412	11.27
T2	953	1906	474	10.55	**T2**	804	1608	529	10.7
T3	6086	12172	4219	12.8	**T3**	1863	3726	1399	13.98
T4	4995	9990	3666	5.58	**T4**	1802	3604	1292	5.76
T5	2436	4872	1570	12.65	**T5**	821	1642	479	13.55
Average	3115.2	6230.4	2142.4	10.698	**Average**	1172	2344	822.2	11.052

Figure 12 Initial Accuracy Test with a feature cap of 50,000 for both detectors

ORB Detector Accuracy Test Results:

Test 1: md + md-scene1 Default Corners TopL: (675, 1736) TopR: (1024, 1478) BotR: (1328, 1883) BotL: (961, 2154) Number of inliers: 783 out of 1106 good matches. Detected Object Corners: [679.5, 1732.14] [1024.02, 1486.65] [1311.18, 1884.42] [946.574, 2146.72] Pixel Errors; TopL: 5.93037 pixels TopR: 8.65482 pixels BotR Error: 16.8757 pixels BotL Error: 16.1601 pixels Avg. Error: 11.9 pixels	Test 2: md + md-scene2 Default Corners TopL: (961, 1849) TopR: (1454, 1430) BotR: (1972, 2044) BotL: (1471, 2463) Number of inliers: 474 out of 953 good matches. Detected Object Corners: [969.494, 1848.99] [1451.07, 1435.09] [1962.21, 2037.25] [1455.35, 2460.1] Pixel Errors; TopL: 8.49439 pixels TopR: 5.8753 pixels BotR Error: 11.8944 pixels BotL Error: 15.9193 pixels Avg. Error: 10.5 pixels	Test 3: book + b-scene1 Default Corners TopL: (41, 1576) TopR: (978, 1549) BotR: (957, 2754) BotL: (16, 2800) Number of inliers: 4219 out of 6086 good matches. Detected Object Corners: [48.7008, 1572.02] [971.441, 1554.2] [932.914, 2744.39] [10.611, 2806.22] Pixel Errors; TopL: 8.66895 pixels TopR: 8.37035 pixels BotR Error: 25.9336 pixels BotL Error: 8.22852 pixels Avg. Error: 12.8 pixels	Test 4: book + b-scene2 Default Corners TopL: (1372, 1085) TopR: (2132, 654) BotR: (2735, 1638) BotL: (1987, 2094) Number of inliers: 3666 out of 4995 good matches. Detected Object Corners: [1368.7, 1088.44] [2134.5, 660.802] [2736.19, 1641.63] [1992.65, 2097.16] Pixel Errors; TopL: 4.76814 pixels TopR: 7.2462 pixels BotR Error: 3.82283 pixels BotL Error: 6.47348 pixels Avg. Error: 5.6 pixels	Test 5: book + b-sceneD Default Corners TopL: (41, 1576) TopR: (978, 1549) BotR: (957, 2754) BotL: (16, 2800) Number of inliers: 1570 out of 2436 good matches. Detected Object Corners: [48.0941, 1572.3] [971.059, 1554.08] [933.399, 2744.19] [11.0263, 2806.82] Pixel Errors; TopL: 8.00329 pixels TopR: 8.60062 pixels BotR Error: 25.5572 pixels BotL Error: 8.44303 pixels Avg. Error: 12.6 pixels

SIFT Detector Accuracy Test Results:

Test 1: md + md-scene1 Default Corners TopL: (675, 1736) TopR: (1024, 1478) BotR: (1328, 1883) BotL: (961, 2154) Number of inliers: 412 out of 570 good matches. Detected Object Corners: [678.189, 1732.36] [1024.19, 1485.51] [1311.53, 1885.01] [946.308, 2147.24] Pixel Errors; TopL: 4.83615 pixels TopR: 7.50978 pixels BotR Error: 16.5899 pixels BotL Error: 16.1724 pixels Avg. Error: 11.3 pixels	Test 2: md + md-scene2 Default Corners TopL: (961, 1849) TopR: (1454, 1430) BotR: (1972, 2044) BotL: (1471, 2463) Number of inliers: 529 out of 804 good matches. Detected Object Corners: [966.016, 1848.62] [1451.38, 1435.76] [1958.97, 2037.28] [1454.55, 2459.66] Pixel Errors; TopL: 5.03015 pixels TopR: 6.32687 pixels BotR Error: 14.6614 pixels BotL Error: 16.7858 pixels Avg. Error: 10.7 pixels	Test 3: book + b-scene1 Default Corners TopL: (41, 1576) TopR: (978, 1549) BotR: (957, 2754) BotL: (16, 2800) Number of inliers: 1499 out of 1992 good matches. Detected Object Corners: [48.7821, 1573.23] [968.973, 1556.39] [935.002, 2745.12] [9.3464, 2809.16] Pixel Errors; TopL: 8.26169 pixels TopR: 11.6682 pixels BotR Error: 23.7236 pixels BotL Error: 11.3192 pixels Avg. Error: 13.7 pixels	Test 4: book + b-scene2 Default Corners TopL: (1372, 1085) TopR: (2132, 654) BotR: (2735, 1638) BotL: (1987, 2094) Number of inliers: 1360 out of 1820 good matches. Detected Object Corners: [1367, 1088.04] [2134.24, 660.96] [2731.22, 1640.15] [1992.59, 2096.82] Pixel Errors; TopL: 5.85317 pixels TopR: 7.31213 pixels BotR Error: 4.3527 pixels BotL Error: 6.25972 pixels Avg. Error: 5.9 pixels	Test 5: book + b-sceneD Default Corners TopL: (41, 1576) TopR: (978, 1549) BotR: (957, 2754) BotL: (16, 2800) Number of inliers: 479 out of 821 good matches. Detected Object Corners: [47.8987, 1572.47] [969.7, 1555.63] [933.833, 2743.56] [9.9246, 2808.44] Pixel Errors; TopL: 7.74744 pixels TopR: 10.6211 pixels BotR Error: 25.4124 pixels BotL Error: 10.401 pixels Avg. Error: 13.5 pixels

Observations:

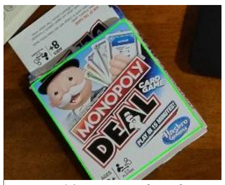


Figure 13 Detected with workaround

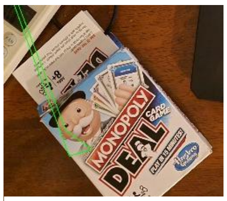


Figure 14 Failed Detection Scene1

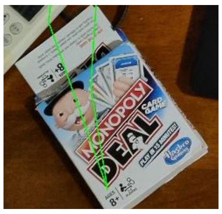
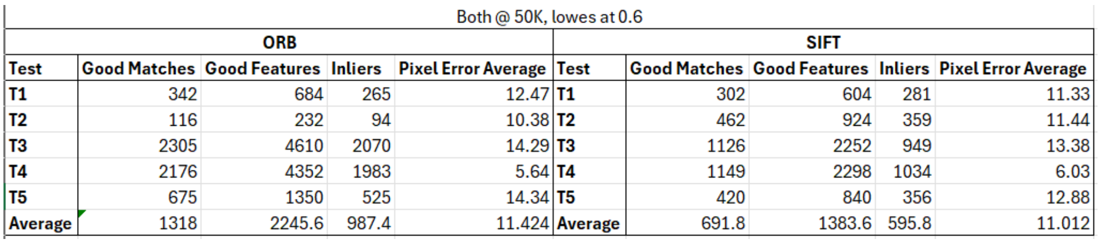


Figure 15 Failed Detection Scene 2

Initial tests showed ORB struggled to detect the object in Test 1 and Test 2 (Figures 14 & 15), likely due to the large scale difference between the object image (2171×2648) and its scene size (~446×505). Since ORB is not as robust to scale variance as SIFT, this discrepancy hindered accurate detection.
Raising ORB's feature cap to 50,000 improved results slightly. Additionally, scaling the object image down by 0.4× was the minimum required adjustment for reliable detection (Figure 13).

At this high cap, SIFT produced more, though potentially less robust, features. A lenient Lowe's ratio of 0.6 combined with 50K features yielded a slightly lower average pixel error for SIFT and a higher error for ORB (Figure 15). Lowering the cap to 5000 had minimal effect on SIFT (less than 1% error decrease) but caused ORB's error to jump over 23% (Figure 16).
Further testing with lower caps—1,000 for ORB and 500 for SIFT—intended to favour robustness over quantity, backfired. SIFT's error rose by 25% and ORB's by over 84% compared to the original 50K-cap test (Figure 18).

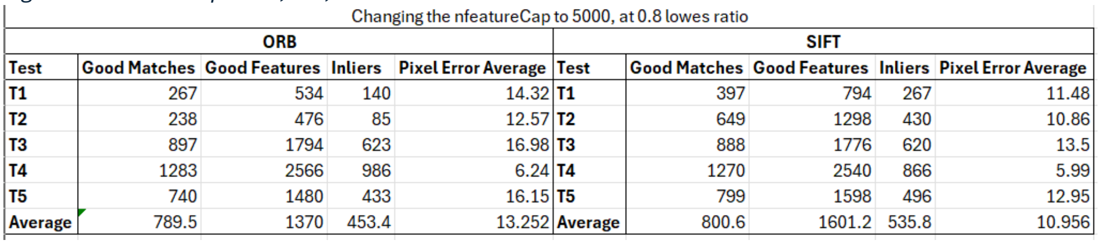
Additional Test Results:



Both @ 50K, lowes at 0.6

ORB					SIFT				
Test	Good Matches	Good Features	Inliers	Pixel Error Average	Test	Good Matches	Good Features	Inliers	Pixel Error Average
T1	342	684	265	12.47	T1	302	604	281	11.33
T2	116	232	94	10.38	T2	462	924	359	11.44
T3	2305	4610	2070	14.29	T3	1126	2252	949	13.38
T4	2176	4352	1983	5.64	T4	1149	2298	1034	6.03
T5	675	1350	525	14.34	T5	420	840	356	12.88
Average	1318	2245.6	987.4	11.424	Average	691.8	1383.6	595.8	11.012

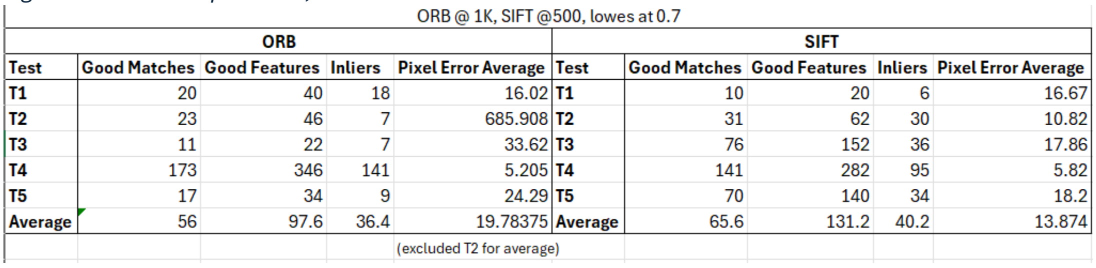
Figure 16 Feature cap of 50,000, Lowes Ratio of 0.6



Changing the nfeatureCap to 5000, at 0.8 lowes ratio

ORB					SIFT				
Test	Good Matches	Good Features	Inliers	Pixel Error Average	Test	Good Matches	Good Features	Inliers	Pixel Error Average
T1	267	534	140	14.32	T1	397	794	267	11.48
T2	238	476	85	12.57	T2	649	1298	430	10.86
T3	897	1794	623	16.98	T3	888	1776	620	13.5
T4	1283	2566	986	6.24	T4	1270	2540	866	5.99
T5	740	1480	433	16.15	T5	799	1598	496	12.95
Average	789.5	1370	453.4	13.252	Average	800.6	1601.2	535.8	10.956

Figure 17 Feature cap of 5000, Lowes Ratio of 0.8



ORB @ 1K, SIFT @500, lowes at 0.7

ORB					SIFT				
Test	Good Matches	Good Features	Inliers	Pixel Error Average	Test	Good Matches	Good Features	Inliers	Pixel Error Average
T1	20	40	18	16.02	T1	10	20	6	16.67
T2	23	46	7	685.908	T2	31	62	30	10.82
T3	11	22	7	33.62	T3	76	152	36	17.86
T4	173	346	141	5.205	T4	141	282	95	5.82
T5	17	34	9	24.29	T5	70	140	34	18.2
Average	56	97.6	36.4	19.78375	Average	65.6	131.2	40.2	13.874
				(excluded T2 for average)					

Figure 18 Feature cap of 1K for ORB, 500 for SIFT, Lowes Ratio of 0.7

Final Observations:

- Preprocessing was necessary in Test 1 for ORB due to its poor performance with large scale differences between object and scene sizes—an issue not present with SIFT, which handled scale variance well. Reducing ORB's feature cap below 5000 caused failure in Test 2, reinforcing this limitation.
- In Test 4 (book.jpg + b-scene.jpg), both detection methods produced a lower average pixel error compared to other tests, despite the object's corner not being visibly present in the scene. To compensate, I estimated the corner positions using on-screen rulers. This outcome highlights the strength of the homography calculation, which effectively infers object geometry based on matched KeyPoints. Interestingly, the method appears to perform better when approximating corners through overall geometry rather than relying solely on clearly defined visible corners.

6. Conclusion

This project successfully implemented an object-in-scene detection program using C++ and OpenCV. The SIFT and FLANN combination, while slower, delivered the accuracy needed to detect the object reliably. The experiments emphasized the trade-off between speed and accuracy across varying images and conditions.

Although not required, I thoroughly enjoyed this assignment and experimenting with different parameters out of interest, structuring my program to support future personal experimentation with more robust and adaptable detection methods.

Due to the extensive test data collected, some results were omitted to keep the report reasonably concise. Despite the 9-page length. For instance, tests with non-planar objects were excluded, as they added two extra pages. Additional testing notes and the full project are available in a public GitHub repository.

https://github.com/BrooklynT101/ObjectDetection

7. Disclaimer

This version of the report is a shortened copy of the original long version, with help from ChatGPT used only to condense certain paragraphs. No data, results, or conclusions were altered in the process.