ACIP

Activity 3

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1 Introduction

From our previous activities, we identified the Scale Invariant Feature Transform (SIFT) and Binary Robust Invariant Scalable Keypoints (BRISK) as promising feature detection methods. This activity focuses on using MATLAB's 'matchFeatures' function to match features detected by SIFT and BRISK in transformed images. We will adjust the 'MaxRatio' parameter and analyze the statistical results. The findings from this comparison will help decide the preferred method for future activities.

The function 'matchFeatures' provides us with 'indexPairs' and 'matchMetrics', where 'matchMetrics' quantifies the Euclidean distance between matched feature vectors, serving as an indicator of match closeness and accuracy. By evaluating the number of matches, mean score, median score, and standard deviation of scores at different 'MaxRatio' settings, we aim to conduct a thorough quantitative analysis. This analysis will complement our visual assessments, helping us to determine the most effective feature detection method.

2 First Transformation (Shearing) - SIFT

In this activity, first, the previous codes from Activity 2 are implemented again to detect and extract the features (SIFT method) from the original and transformed image. Then, the matchFeatures function is used to match the two sets of control points. This function takes the feature descriptors from the two sets, and calculates the similarity between each pair of features based on a distance metric; meaning it measures how close two feature descriptors are in their multi-dimensional space. With the 'Unique' set to true, the function makes sure that each feature in the first set is matched with at most one feature in the second set and vice versa.

The 'MaxRatio' parameter which will be used later to fine-tune the parameter, is used to accept a match only if the ratio of "the distance of the nearest neighbor" to "the distance of the second-nearest neighbor" is below a certain threshold. This helps to take out weak matches. A lower ratio means stricter matching. We will use this parameter in the following sections to reject ambiguous matches. The default value of this parameter is 0.6; by increasing this value the function returns more matches, and vice versa.

Next, the showMatchedFeatures function is used. This function displays lines connecting matching pairs of features between two images, which makes it easier to assess the quality of the matches. The 'montage' option places the images side by side with matching features connected by lines.

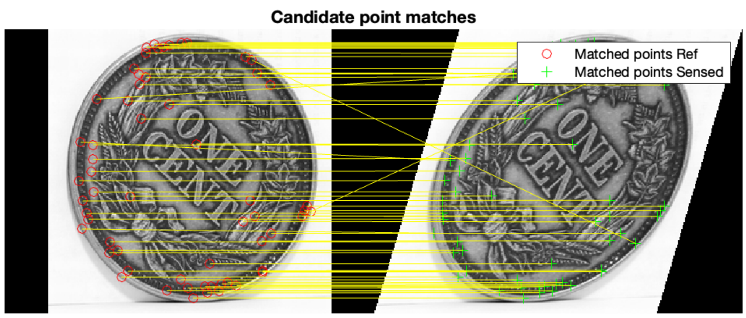

Figure 1: Original and the first transformed images, with all of their matched features - SIFT.

As can be seen in the image, we have two or three pairs of features that seem to be incorrect matches as the lines cross each other. Further tuning was needed to delete these features.

2.1 Adjusting MaxRatio Parameter

The MaxRatio parameter was set to multiple numbers to take out incorrect matches. We experimented with different numbers (0.9, 0.7, 0.5, 0.4) and finally set this number to 0.4, as with this number it was evident in the matching figure that we got rid of the incorrect matches. Again, as it was said the default value for this parameter is 0.6 so by using values more than this we are expecting to have more matches compared to Figure 1, which is evident in Figure 2. Figure 2 shows the final matched features and their corresponding MaxRatio parameter.

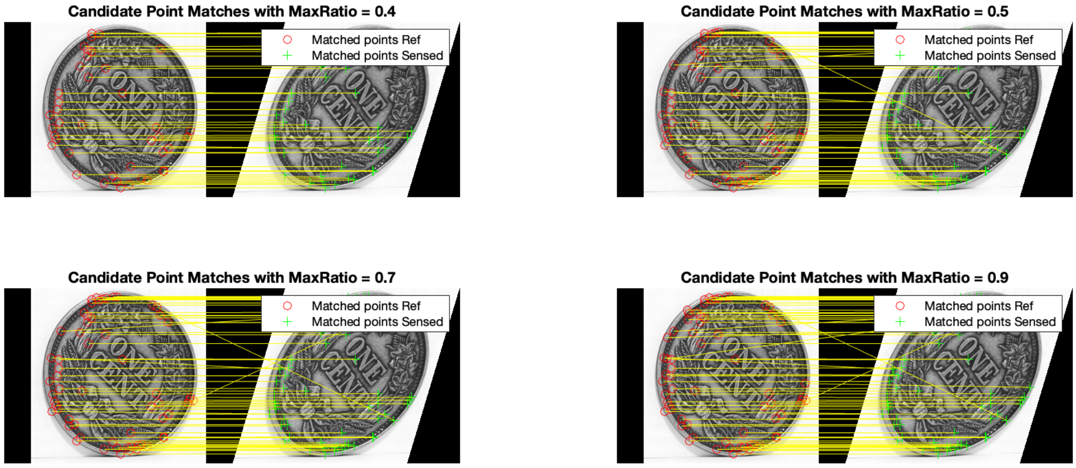

Figure 2: Original and the first transformed images with refined parameters.

2.2 Statistical Analysis

The table shows the statistical analysis of using different MaxRatio and getting the values from matchMetrics for the first transformation using the SIFT method. Mean Score is the average Euclidean distance between matched feature vectors. Lower values suggest closer and potentially more accurate matches. The Standard Deviation of Scores measures the spread or variability of the match scores around the mean. Lower values indicate more consistency in match quality.

MaxRatio	Number of Matches	Mean Score	Standard Deviation
0.9	71	0.0212	0.0106
0.7	64	0.0211	0.0106
0.5	55	0.0213	0.0104
0.4	44	0.0231	0.0105

Table 1: Statistical analysis of using different MaxRatio for the first transformation using the SIFT method.

We observe that a MaxRatio of 0.9 yields a higher number of matches but includes some incorrect matches, as evidenced by visual inspection. On the other hand, a MaxRatio of 0.4, while providing fewer matches, results in a bit more accurate pairings, as we can see from Figure 2, where the incorrect matches dissapeared with MaxRatio = 0.4.

Furthermore, while the mean score slightly increases to 0.0231 at a MaxRatio of 0.4, this minor increase is insignificant compared to its effectiveness in filtering out incorrect matches, thereby enhancing the overall accuracy of the pairings. This suggests a trade-off between the number of matches and their accuracy, highlighting the need for a balanced approach in practical applications.

3 First Transformation (Shearing) – BRISK

Similar to the SIFT method, the BRISK method was also used to evaluate feature matching. Below are the initial matches observed using the BRISK method.

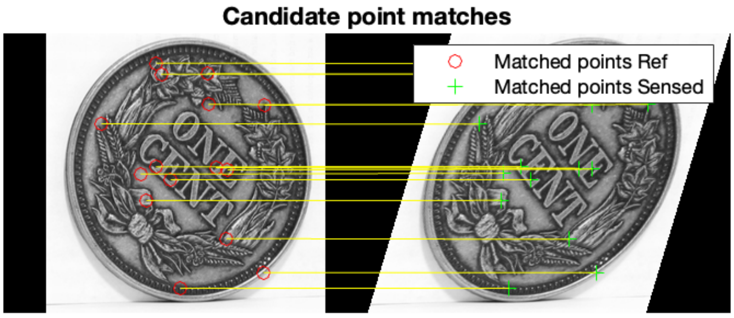

Figure 3: Original and the first transformed images with all of their matched features - BRISK.

Same as with the SIFT method, the MaxRatio parameter was adjusted to refine the matching results for BRISK as well. As with SIFT, making the MaxRatio stricter resulted in fewer matches, but it effectively filtered out incorrect matches, as evidenced in the figures below.

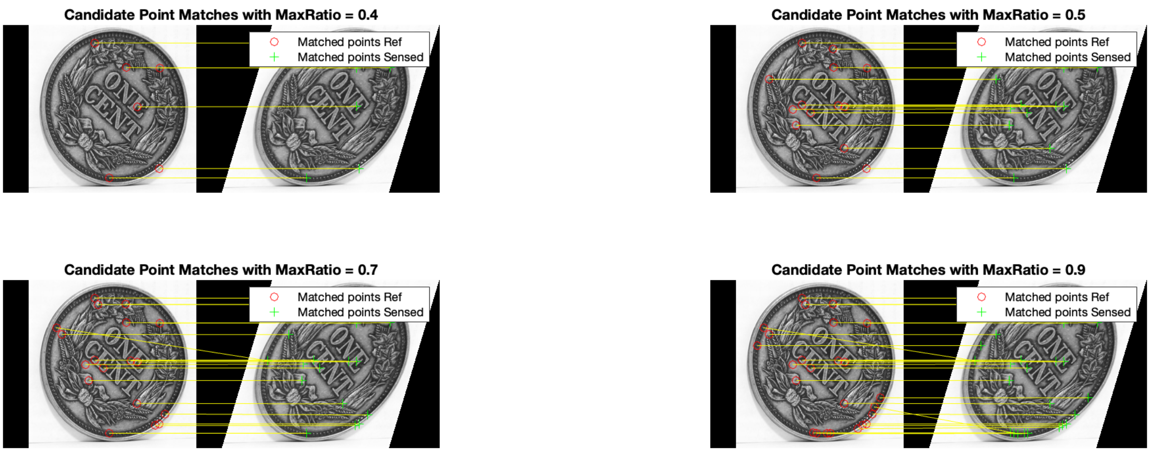

Figure 4: Original and transformed images with refined parameters - BRISK.

3.1 Statistical Analysis for BRISK Method

The table shows the statistical analysis of using different MaxRatio for the first transformation using the BRISK method.

MaxRatio	Number of Matches	Mean Score	Standard Deviation
0.9	25	42	8.63
0.7	18	41.5	9.65
0.5	14	42.07	10.34
0.4	6	36	13.62

Table 2: Statistical analysis of using different MaxRatio for the first transformation using the BRISK method.

4 Comparison of the First Transformation (Shearing) Between SIFT and BRISK

Compared to the SIFT method, the statistical analysis of the BRISK method shows a significant increase in both the mean scores and the standard deviations. For instance, the mean score with a MaxRatio of 0.4 for BRISK is significantly higher than its counterpart in SIFT, indicating less similarity between matched features. Similarly, the standard deviations are much larger, suggesting greater variability in the quality of matches. This variation in mean and standard deviation underscores the distinct characteristics of BRISK, particularly its sensitivity to variations in image features and matching criteria.

Furthermore, the number of matches obtained using BRISK is consistently lower across all MaxRatio settings compared to SIFT. This observation aligns with the nature of BRISK, which is designed for faster computation at the expense of some matching precision. For applications where speed is prioritized over match accuracy, BRISK may offer a suitable compromise. However, for tasks requiring high precision in feature matching, the increased mean scores and variability suggest that SIFT might be more appropriate. The table comparisons clearly show these differences, with BRISK typically achieving fewer matches of lower similarity, emphasizing its trade-off between speed and precision.

5 Second Transformation (Rigid) – SIFT

The SIFT method was also applied for the second transformation to compare with the BRISK method. Initial and refined matches are shown below:

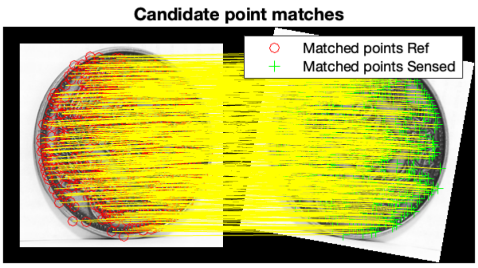

Figure 5: Original and the second transformed images with all of their matched features - SIFT.

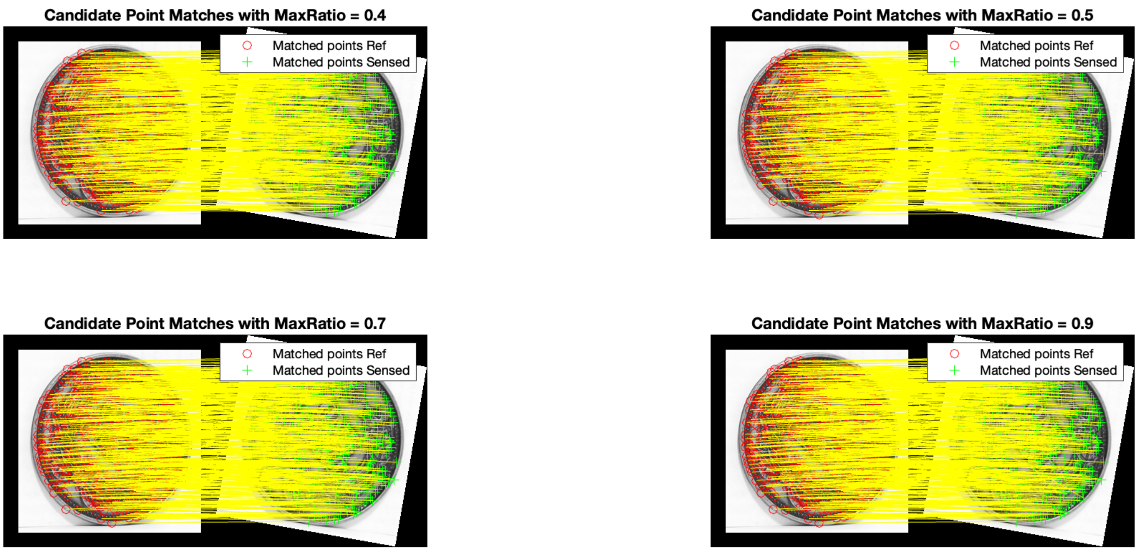

Figure 6: Original and the second transformed images with refined parameters - SIFT.

5.1 Statistical Analysis of Second Transformation Using SIFT

The table shows the statistical analysis of using different MaxRatio for the first transformation using the SIFT method.

MaxRatio	Number of Matches	Mean Score	Standard Deviation
0.9	556	0.011	0.008
0.7	553	0.0109	0.009
0.5	550	0.0108	0.009
0.4	547	0.0108	0.009

Table 3: Statistical analysis of using different MaxRatio for the second transformation using the SIFT method.

For the rigid transformation, SIFT seems to work exceptionally well, as evidenced by high numbers of matches and low average and standard deviation values. Interestingly, variations in MaxRatio settings do not significantly affect these metrics, indicating robust performance across different strictness levels in matching criteria.

6 Second Transformation (Rigid) – BRISK

The BRISK method was applied again for the second transformation. Initial matched features are shown below:

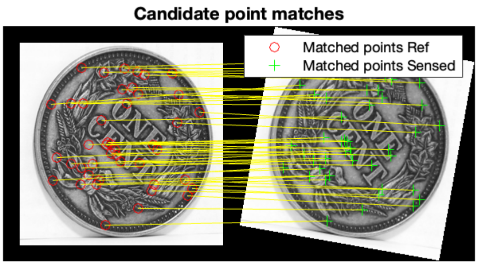

Figure 7: Original and the second transformed images with all of their matched features - BRISK.

Adjustments to the MaxRatio parameter were made similarly to the first transformation to improve the quality of the matches. As was said before, the default value is 0.6, therefore using higher values will result in higher number of matches. The results are presented below:

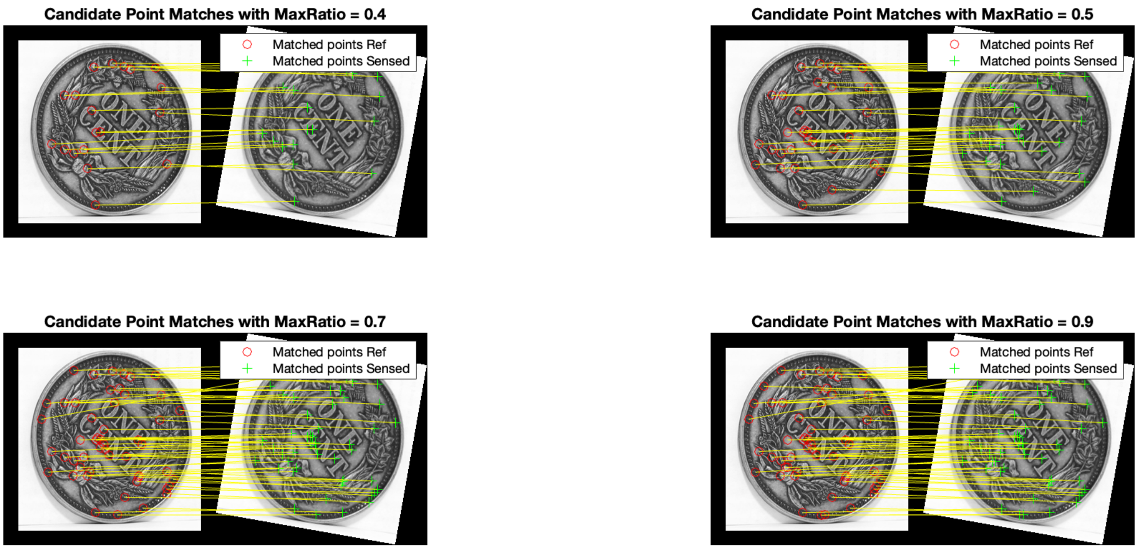

Figure 8: Original and transformed images with refined parameters - BRISK.

6.1 Statistical Analysis of Second Transformation

The table shows the statistical analysis of using different MaxRatio for the second transformation using the BRISK method. As with the first transformation, a stricter MaxRatio leads to fewer matches but generally results in slightly lower mean scores, suggesting an incremental improvement in match accuracy. However, the higher standard deviations indicate a greater variability in match quality compared to SIFT, reinforcing BRISK's characteristic trade-off between speed and precision.

MaxRatio	Number of Matches	Mean Score	Standard Deviation
0.9	54	43.74	6.45
0.7	51	43.43	6.48
0.5	31	42.06	6.99
0.4	19	39.89	7.68

Table 4: Statistical analysis for the second transformation using the BRISK method.

This analysis indicates that although the mean score decreases as the MaxRatio becomes stricter, which typically suggests better matching accuracy, the overall high values and increased standard deviations highlight BRISK's limitations in ensuring consistent match quality, especially in rigid transformation scenarios.

7 Comparison of the Second Transformation (Rigid) Between SIFT and BRISK

Just like in the first transformation, the second rigid transformation shows clear differences between SIFT and BRISK methods. The SIFT method stands out for its high precision in feature matching, consistently producing lower mean scores and smaller standard deviations.

In contrast, BRISK offers faster processing but at the cost of accuracy, as seen in its higher mean scores and greater variability in standard deviations. The number of matches it produces also tends to be fewer, especially with stricter MaxRatio settings, underlining its trade-off between speed and match quality. While BRISK may be appropriate for situations where quick results are more important than exact precision, SIFT is better suited for applications that demand high accuracy, particularly in scenarios involving rigid transformations.

8 Overall Comparison of SIFT and BRISK Methods

8.1 Method Performance

We compared the SIFT and BRISK methods across various transformations to determine their effectiveness in feature matching. The BRISK method, while faster, tends to produce less precise matches compared to SIFT.

8.2 Visual and Quantitative Metrics

We incorporated both visual inspection and quantitative metrics to evaluate the performance of each method. The quantitative data include mean scores, median scores, and standard deviations of match scores, which provide insight into the consistency and reliability of the matches.

9 Conclusion

Based on the analysis, we conclude that the SIFT method provides more reliable and accurate matches compared to BRISK. Although SIFT is computationally more intensive, it is preferable for applications where match accuracy is critical. We select SIFT for subsequent activities, prioritizing quality over computational speed.

References

[1] Lowe D. G., "Distinctive image features from scale-invariant keypoints," in International journal of computer vision, 60, 91-110., 2004.

[2] Leutenegger, S., Chli, M., Siegwart, R. Y., "BRISK: Binary robust invariant scalable keypoints," in International conference on computer vision, pp. 2548-2555, IEEE, 2011.