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Keypoint Matches Filtering in Computer Vision: Comparative Analysis of RANSAC and USAC Variants

ANDRIY FESIUK, YURIY FURGALA
Optoelectronics and Information Technologies, Ivan Franko National University of Lviv, Lviv, 79005, Ukraine

Corresponding author: Andriy Fesiuk (e-mail: Andrii.Fesiuk@lnu.edu.ua)

ABSTRACT In this study, a detailed analysis is conducted to evaluate the efficiency of various keypoint matching filtering methods, including RANSAC and its USAC variations, namely, USAC-DEFAULT, USAC-FAST, USAC-ACCURATE, USAC-MAGSAC, and USAC-PROSAC. Keypoints are detected and described using the SIFT, SURF, ORB, and BRISK methods. This work aims to assess the impact of filtering methods on the accuracy, stability, and processing speed of image analysis. The results show that while RANSAC has the slowest performance, it provides the highest stability, with a similarity coefficient deviation of 0.5%. RANSAC with modified parameters demonstrates higher accuracy and significantly faster processing compared to standard RANSAC, outperforming it by approximately 2.5 times and achieving a 4% accuracy improvement over USAC-DEFAULT. The most rapid methods are USAC-PROSAC and USAC-FAST, whereas USAC-MAGSAC has the longest execution time among all USAC variations. Accuracy analysis of the different detectors shows that SIFT achieved the highest similarity coefficient values. SURF demonstrated slightly lower accuracy than SIFT, while BRISK showed results inferior to SURF. ORB is found to be the least effective among the evaluated detectors. This work emphasizes the importance of an adaptive approach when selecting keypoints matching filtering methods to achieve high accuracy, stability, and processing speed in various computer vision applications. The findings of this study will assist developers and researchers in choosing optimal filtering methods and improving the efficiency of image processing algorithms for specific tasks.

KEYWORDS SIFT; SURF; ORB; BRISK; RANSAC; USAC; detection; description; keypoints.

I. INTRODUCTION

In the modern world, digital technologies play a crucial role across various fields where images and videos are utilized for decision-making and process automation. Computer vision enables machines to "see" and understand the surrounding environment, unlocking new opportunities for innovation and advancement in domains such as autonomous vehicle control, medical diagnostics, industrial automation, and others [1-5].

The development of these technologies relies on image processing methods, with a significant focus on the detection and description of keypoints - distinctive features in images that remain robust against changes in lighting, scale, viewpoint, etc. These features are essential for constructing 3D models, motion tracking, and change detection [6-8].

SIFT (Scale-Invariant Feature Transform) [9] remains one of the most reliable methods for keypoint detection due to its ability to maintain accuracy even under significant image variations. However, the substantial computational cost of this method has driven researchers to seek faster solutions. Alternative methods such as SURF (Speeded-Up Robust Features) [10], ORB (Oriented FAST and Rotated BRIEF) [11], and BRISK (Binary Robust Invariant Scalable Keypoints) [12] offer various trade-offs between computational speed and invariance to geometric transformations, as well as robustness against noise and changes in illumination. The choice of method depends on the specific task and system constraints.

Therefore, even the most reliable keypoint detection and description methods encounter challenges in ensuring the accuracy of matches between images. The presence of outliers can significantly degrade analysis results, necessitating diverse approaches capable of mitigating these adverse effects. Notable strategies in this domain include voting-based approaches like the Hough Transform [13], local analysis methods such as k-Nearest Neighbors, and various filtering methods like RANSAC [14] and advanced RANSAC variants.

RANSAC (Random Sample Consensus) [14] is a classical algorithm for filtering; however, its effectiveness diminishes under challenging conditions, such as varying lighting, viewpoints, scales, and other factors.

Advanced variations such as USAC (Universal Sample Consensus) [15] methods were developed to address the described limitations. These methods employ adaptive parameter selection approaches, including inlier selection based on their probability of correct matches and local optimization to refine the model. These techniques improve the accuracy and robustness of filtering under high noise levels and complex geometric conditions while increasing processing speed [16].

For example, in autonomous transportation, the accuracy and speed of image processing are critical factors for ensuring road safety. Even minor improvements in keypoint detection and filtering methods can significantly enhance system performance, preventing accidents and ensuring smooth operation [1]. Similarly, high accuracy of results and the ability to process images in real time are essential in medical diagnostics for making quick and well-founded decisions [2, 3].

The application of computer vision for process automation in retail, particularly for product recognition and analysis, is an active area of research. Keypoint detection and description methods are used for product identification, quality assessment, and inventory control [17-21]. RANSAC was successfully applied to filter matches in product detection on shelves and to identify product shortages [17, 18]. However, the diversity of products, changes in imaging conditions, lighting, reflections, and limited datasets pose challenges to the effective use of computer vision methods in this domain [20, 21].

Nevertheless, selecting the optimal combination of keypoint detection and filtering methods for specific applications remains a pressing issue. Each technology has advantages and limitations, such as sensitivity to external factors, computational complexity, erroneous matches, etc. [22].

This study focuses on a comparative analysis of keypoint detection and description methods and matching filtering techniques in the context of their ability to provide accuracy, speed, and result stability. The performance of SIFT, SURF, ORB, and BRISK methods with varying keypoint quantities is analyzed in combination with different matching filtering approaches, including the classical RANSAC and advanced techniques such as USAC-DEFAULT, USAC-FAST, USAC-ACCURATE, USAC-MAGSAC, and USAC-PROSAC [16].

The findings provide valuable insights into the interaction between keypoint detection and description methods with RANSAC and USAC-based techniques. These results contribute to a better understanding of the interplay between detection and filtering methods, enabling the identification of suitable combinations for solving image similarity assessment tasks - an important step in developing efficient and reliable computer vision systems.

Section 2 describes the keypoints detection and filtering methods, experimental methodology, and research parameters. Section 3 presents the experimental results and their discussion. Section 4 concludes the paper with insights and suggestions for future research directions.

II. MATERIALS AND METHODS

This study utilized four widely known methods for detecting image keypoints: SIFT, SURF, ORB, and BRISK. The parameters used to control the number of detected keypoints for each method and their respective ranges are shown in Table 1. These adjustments allowed for an analysis of their impact on the effectiveness of match filtering.

Table 1. Parameters and ranges for keypoint detection

Method	Control Parameter	Range
SIFT	Number of keypoints	100-1000
SURF	hessianThreshold	300-2700
ORB	Number of keypoints	100-1000
BRISK	thresh	46-88

Brute-Force matcher with cross-check validation was used for feature matching between two images [23]. In this method, each descriptor from the first image's keypoints was compared with all descriptors from the second image to find the closest pairs. Cross-check validation helped to reject ambiguous matches where the distance to the nearest descriptor was not significantly smaller than the distance to the second nearest one [24].

The following distance norms were applied for each feature detection method [25, 26]:

- Euclidean distance (NORM_L2) for SIFT and SURF.
- Hamming distance (NORM_HAMMING) for ORB and BRISK.

The classical RANSAC method and its modern modifications grouped under USAC were utilized to filter potential matches between keypoints.

RANSAC is an iterative method that randomly selects the minimum number of points required to estimate a model containing the largest number of inliers - points that fit the model within a defined threshold [14]. While RANSAC is a powerful tool, it has certain limitations, including the need for manual parameter tuning and sensitivity to a high number of outliers.

To study the impact of RANSAC parameters [25] on its performance, the maximum number of iterations was reduced to 700, the confidence level was changed to 0.97, and the threshold distance for defining inliers was set to 5. This configuration is referred to as RANSAC_M in this work.

USAC is an advanced extension of RANSAC that introduces several improvements to enhance the accuracy and efficiency of model estimation in the presence of outliers [22]. The following USAC variants available in OpenCV [16, 25, 26] are analyzed in this study:

- USAC_DEFAULT: Combines classical RANSAC with LO-RANSAC (Locally Optimized RANSAC) [27] and degeneracy checks.
- USAC_FAST: Optimized for speed, employing fewer LO-RANSAC iterations and early stopping based on RANSAC consensus evaluation.
- USAC_ACCURATE: Prioritizes accuracy over speed using GC-RANSAC (Graph-Cut RANSAC) [28] for local optimization. GC-RANSAC considers the spatial coherence of points and optimizes the model by incorporating the global structure of the data, enhancing both accuracy and robustness against outliers.
- USAC_MAGSAC: Utilizes MAGSAC++ (Maximum Agreement Sample Consensus with PROSAC and Progressive Sample Consensus) [29] for robust model estimation and automatic threshold selection for inliers. It integrates PROSAC (Progressive Sample Consensus) [30] for efficient point sampling and Progressive NAPSAC [31] for improved model accuracy, making it

highly effective when dealing with noisy and outlier-rich data.

- USAC_PROSAC: Employs the PROSAC [30] method for point selection during model construction but requires pre-sorting input point pairs based on distance.

The homography matrix was used to evaluate image similarity, which describes the projective transformation between two planes [32]. Homography allows assessing how well one image can be projected onto another, making it a valuable measure of their similarity. The number of inliers, i.e., the points consistent with the computed homography, was used as the measure of similarity between two images. The method cv2.findHomography from OpenCV [25, 26] was applied to estimate the homography between image pairs.

The effectiveness of the various keypoint matching filtering methods was evaluated using a similarity coefficient, consistent with approaches in our work [33]. This coefficient was defined as the ratio of the number of inlier matches, determined as those keypoint correspondences consistent with the homography matrix, to the total number of initially detected keypoints.

Experiments were conducted on a dataset of 100 images of beer cans, divided into ten groups according to their brand, as detailed in our previous work [33]. Each image was processed using SIFT, SURF, ORB, and BRISK to extract keypoints and their descriptors, followed by match filtering using various RANSAC and USAC variations.

The results were evaluated using several key metrics:

- Accuracy: Measured using similarity coefficients.
- Stability: Assessed by analyzing the ratio of mean similarity coefficients and standard deviation.
- Speed: Measured as the execution time of each filtering method.

The stability metric is used to quantify the consistency of the outcome from a specific matching or subsequent filtering stage. The stability is calculated as the standard deviation of the similarity coefficients divided by their mean value. While the inherent characteristics of the keypoints provided by the detector/descriptor method influence all processing stages, by keeping the detector and initial matching strategy constant for comparative analysis, the measured stability primarily reflects the consistency of the stage being analyzed.

III. RESULTS AND DISCUSSION

Figure 1 illustrates the average execution speed of filtering methods across different keypoint detection and description approaches. A similar pattern was observed in all plots. The RANSAC method was the slowest, lagging significantly behind other methods by approximately 150 seconds. RANSAC_M ranked second in execution time, taking twice as long as the third slowest method - USAC_MAGSAC. The remaining USAC methods demonstrated similar speeds, with only slight differences of a few seconds.

USAC_PROSAC emerged as the fastest filtering method for SIFT, ORB, and BRISK. Its superior efficiency is directly linked to its strategy of pre-sorting matches based on distance. Following it, USAC_FAST secured the second-fastest spot, with USAC_ACCURATE taking third and USAC_DEFAULT ranking fourth.

Conversely, for SURF, USAC_FAST proved to be the fastest method. USAC_ACCURATE was a close second, trailing by only a second. USAC_PROSAC was the third fastest, and USAC_DEFAULT again placed fourth.

It is important to note that the processing time was inconsistent throughout the experiments. Specifically, when using SIFT with over 100 keypoints, processing time increased by nearly 100 seconds for RANSAC and about 25 seconds for RANSAC_M. BRISK generally followed the overall processing pattern, with the key difference being in its RANSAC performance, where time deviations were observed for varying numbers of keypoints. ORB also exhibited time deviations, though not as severe as BRISK, and its performance was less linear than that of SURF.

Figure 2 shows the average similarity coefficient values after filtering using different methods for similar images. Higher similarity coefficient values indicate better method performance, as the goal is to achieve maximum similarity between identical images.

The choice of detection and description methods also influenced the average similarity coefficient. The RANSAC_M method demonstrated the highest average values, surpassing USAC_DEFAULT by approximately 4%. Next were USAC_MAGSAC and USAC_FAST, with only slight differences between them. USAC_ACCURATE showed slightly lower results, lagging behind USAC_FAST, while USAC_PROSAC trailed USAC_ACCURATE by a few tenths of a percent. The worst results were observed for the RANSAC method, which fell short of USAC_PROSAC by approximately 0.5%.

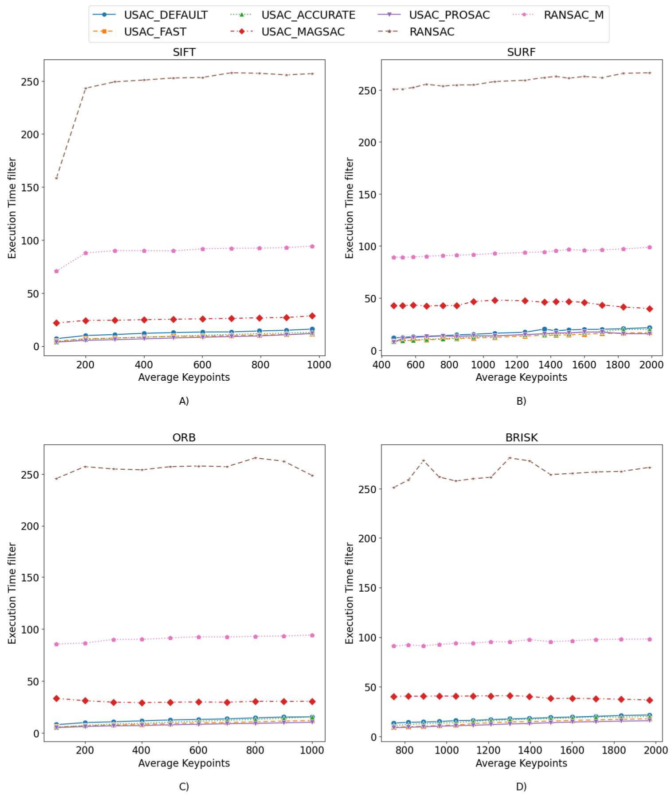

Figure 1. Average execution speed of filtering methods: A) SIFT; B) SURF; C) ORB; D) BRISK.

The analysis of the results shows that the behavior of filtering methods depends on the selected detection/description method and the number of keypoints. For instance, with SIFT, when the number of keypoints was up to 200, all filtering methods provided an increase in the similarity coefficient of about 1%. As the number of keypoints increased, the results deteriorated, with a loss of about 2%. However, when the number of keypoints exceeded 700, the rate of decline slowed. In the case of SURF, the results consistently declined as the number of keypoints increased from 400 to approximately 2000, with a loss of about 6% for each filtering method. BRISK demonstrated a similar degradation trend as the number of keypoints increased, though the losses were around 3%.

The ORB method exhibited behavior distinct from the others: with up to 500 keypoints, the average similarity coefficient increased by approximately 2%, after which a decrease of about 0.5% was observed.

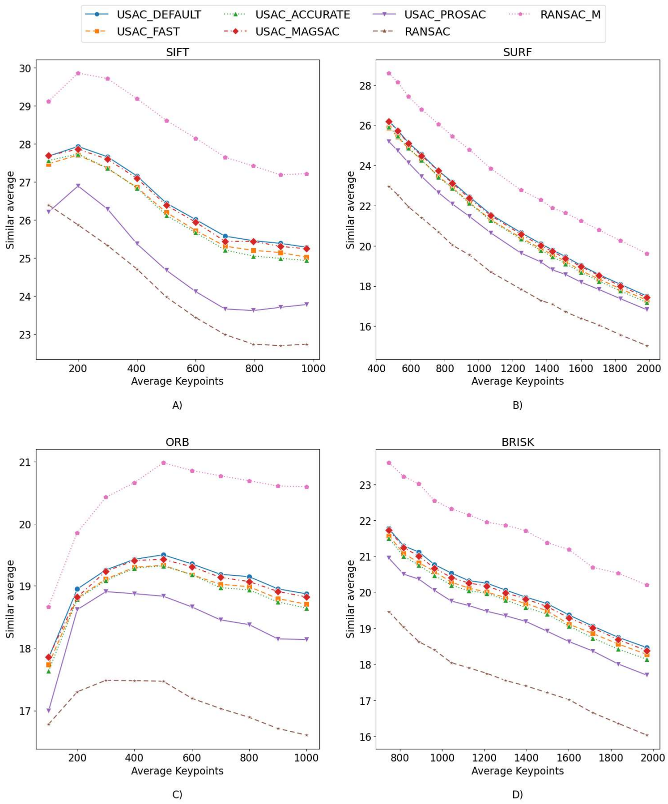

Figure 2. Average similarity coefficient values after filtering for similar images: A) SIFT; B) SURF; C) ORB; D) BRISK.

The ranges of similarity coefficient values, sorted in descending order of the best result, are as follows:

- SIFT: from 30% to 23%
- SURF: from 28.3% to 15.8%
- BRISK: from 23.3% to 16%
- ORB: from 21% to 16.5%

SIFT demonstrated the highest similarity coefficient values among all methods. SURF and BRISK were at approximately the same level. However, SURF showed slightly higher potential with the best result of 28.3% but also exhibited a more significant decline as the number of keypoints increased. The results for the ORB method had the lowest similarity coefficient values in all scenarios. It is worth noting that SIFT and ORB exhibited the smallest ranges of similarity coefficient variation, at 7% and 4.5%, respectively. Thus, this indicates that they demonstrate higher stability in comparison with SURF and BRISK, whose ranges were 12.5% and 7.3%, respectively.

Figure 3 shows the average similarity coefficient values after filtering using various methods for different images. In this case, lower similarity coefficient values indicate better method performance, as the goal was to minimize similarity between different images. These data show that the choice of keypoint detection and description methods influenced the average similarity coefficient values after filtering for different images. Overall, the RANSAC_M demonstrated the highest average values, slightly surpassing RANSAC, which ranked second. Other methods did not exhibit a clear pattern that repeated across all detection and description methods. However, a general trend was observed: the rate of change in average similarity values decreased as the number of keypoints increased.

All filtering methods showed similar behavior within a single detection and description method: the average similarity coefficient decreased as the number of keypoints increased for different images. For SIFT, the average value ranged from 6% to 0.7%. A notable characteristic was the behavior of the USAC_PROSAC method, which exhibited the lowest values up to 400 keypoints but outperformed other USAC methods afterward.

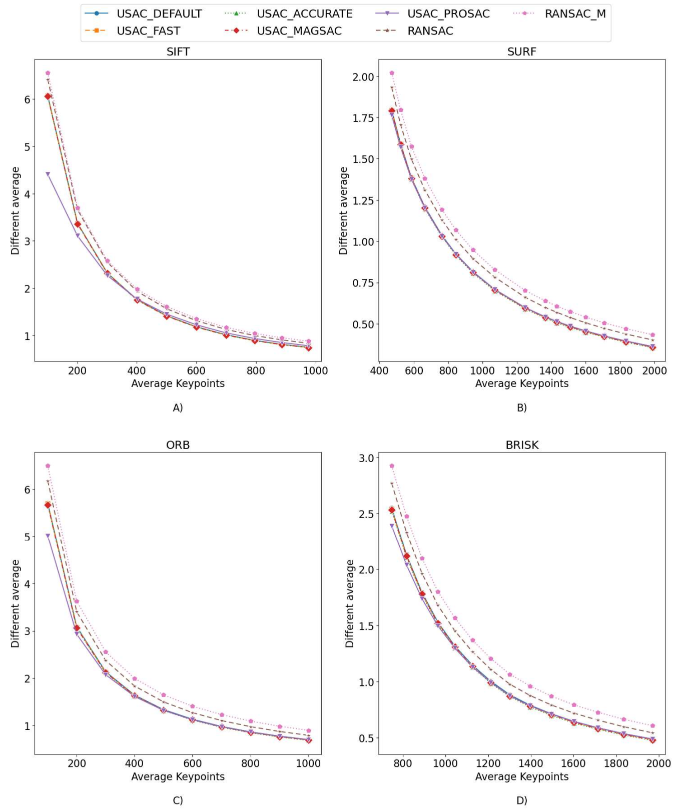

Figure 3. Average similarity coefficient values after filtering for different images: A) SIFT; B) SURF; C) ORB; D) BRISK.

For SURF, the change in the average value ranged from 2% to 0.25%, with all USAC methods demonstrating similar dynamics, with variations of only a few hundredths of a percent. The BRISK method showed identical behavior, but its values ranged from 3% to 0.5%. In this case, USAC_PROSAC exhibited the lowest results up to approximately 1000 keypoints, after which USAC_ACCURATE demonstrated the lowest values, although the difference between them was minor.

Finally, for ORB, the filtering methods showed behavior and values similar to those observed for SIFT, with the difference that after 400 keypoints USAC_PROSAC aligned with the other USAC methods.

The observed tendency for the similarity coefficient to decrease as the number of detected keypoints increases is consistent with the expectation that a larger initial pool of keypoints may also contain a higher proportion of outliers. When such outliers are not eliminated by the filtering process, a reduction in the similarity coefficient can be anticipated, consequently lowering its calculated value.

Figures 4 and 5 present the ratio of the standard deviation of similarity coefficient values to their average for both similar and different images. Lower values of this ratio indicate a smaller spread in possible similarity coefficient values, which reflects higher stability and predictability of the method's performance.

When comparing similar images, high similarity coefficient values and stability are desirable, as they ensure the algorithm reliably identifies identical or very similar images, even in the presence of minor changes in lighting, perspective, etc. Low similarity coefficient values and stability are critical when comparing different images, as they enable the algorithm to distinguish dissimilar images clearly, minimizing the risk of false positives.

The stability of initial matches obtained directly from the Brute-Force matcher with cross-check validation (named as BF_DATA) was analyzed to provide a comprehensive baseline for result consistency. The stability of BF_DATA represents the consistency of the output from the initial keypoint detection and raw matching stages before applying any robust geometric filtering techniques.

It may be observed from Figures 4 and 5 that the stability for BF_DATA can be lower, indicating higher numerical stability than that of some RANSAC or USAC-filtered results. The Brute-Force matching with cross-check validation inherently performs a preliminary filtering step, potentially leading to a relatively consistent count of initial matches, especially if the underlying keypoint detector's output is also stable. Subsequently, while RANSAC and USAC variants aim to enforce geometric correctness, the number of inliers they identify can exhibit greater variability relative to their mean. This increased variability can occur if the geometric model fitting is sensitive to scene-specific nuances or the filtering process substantially reduces the mean number of matches. A significant reduction in the mean, even with a standard deviation that is not proportionally smaller, often results in a higher stability for the filtered set.

Therefore, while a lower stability for BF_DATA suggests higher numerical consistency in the number of initial matches, the stability of the filtered methods must be interpreted in conjunction with their primary objective: to ensure the geometric validity of correspondences. The BF_DATA line serves as an essential reference for assessing the impact of the filtering techniques on the consistency of results, beyond just the retention of geometrically sound matches.

According to Figure 4, the choice of detection and description method influenced the stability of the filtering results. For SIFT, a decrease in the ratio of standard deviation to the mean was observed with an increasing number of keypoints, indicating improved stability. For SURF and BRISK, this ratio consistently increased as the number of keypoints grew, suggesting reduced stability with more features. Most filtering methods for ORB showed a general increase in the ratio with some fluctuations. An exception was RANSAC_M, where the ratio initially increased but decreased after reaching 200 keypoints.

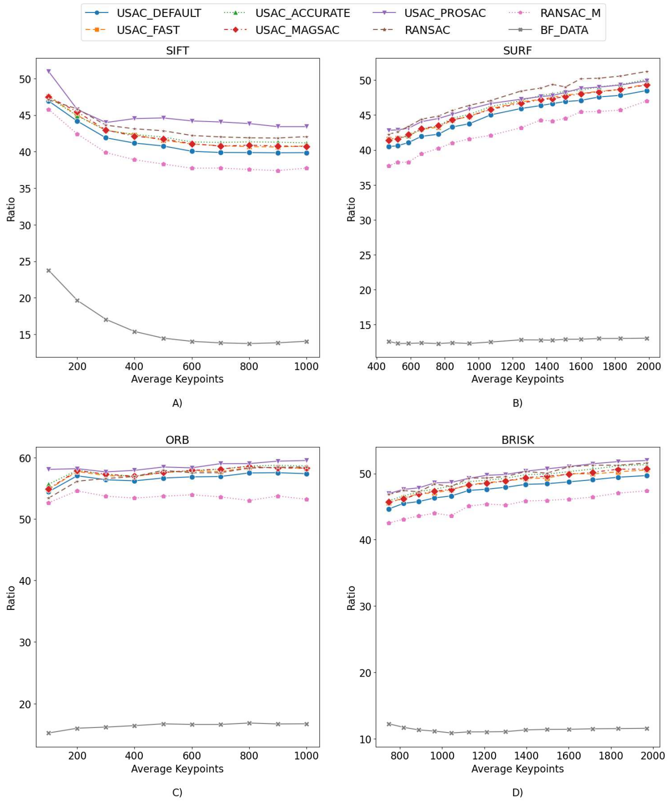

Figure 4. The ratio of standard deviation to the average value for similar images: A) SIFT; B) SURF; C) ORB; D) BRISK.

Regardless of the detection and description method, RANSAC_M provided the lowest ratio of standard deviation to the mean, indicating the highest stability. It was followed by USAC_DEFAULT, which also demonstrated high stability, except for ORB with fewer than 300 keypoints, where RANSAC yielded better results. The highest ratios were observed for USAC_PROSAC with SIFT, BRISK, and ORB, while for SURF, RANSAC demonstrated the worst results.

The USAC_FAST, USAC_ACCURATE, and USAC_MAGSAC methods exhibited similar results with some variations. For instance, with SURF, USAC_ACCURATE showed reduced stability as the number of keypoints increased compared to USAC_PROSAC. Conversely, for ORB, USAC_ACCURATE outperformed other USAC methods.

The following observations were made after the range of the standard deviation-to-mean ratio for similar images analyses:

- For SIFT, the ratio ranged from 50% to 38%, indicating increased stability with more keypoints.
- For SURF, the ratio increased from 38% to 50%, suggesting reduced stability as the number of keypoints grew.
- For BRISK, the ratio also increased, from 42% to 52%, showing a similar trend of declining stability.
- The ratio varied from 53% to 60% for ORB, generally indicating reduced stability, though with some fluctuations.

Figure 5 illustrates the ratio of the standard deviation of similarity coefficients to their mean values for various images, highlighting the influence of the detection and description method on this ratio.

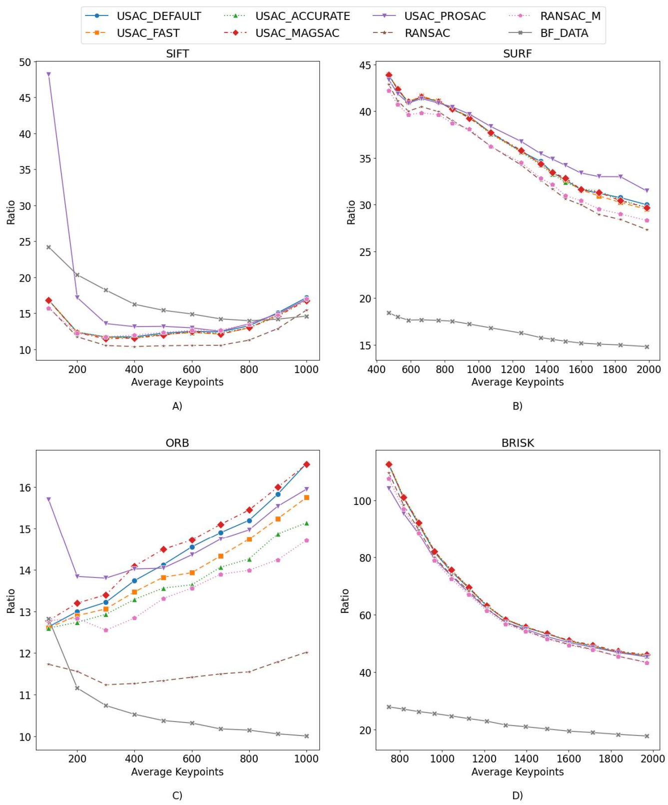

Figure 5. The ratio of the standard deviation to the mean value for different images: A) SIFT; B) SURF; C) ORB; D) BRISK.

In the case of SIFT, the ratio initially decreased overall, but after reaching 300 keypoints, it gradually increased. For SURF, the ratio consistently decreased as the number of keypoints increased, indicating a steady improvement in the stability of the results. A similar trend was observed for BRISK. For ORB, most filtering methods exhibited a general increase in the ratio, with various fluctuations, except for USAC_PROSAC, whose results initially decreased and then gradually increased after 200 keypoints.

For all detection and description methods except BRISK, RANSAC was the filtering method that provided the lowest standard deviation-to-mean ratio among all methods, indicating the highest stability. For BRISK, the most stable method was RANSAC_M. In most cases, the following best method after RANSAC was RANSAC_M, except for SIFT with more than 200 keypoints, where USAC_MAGSAC demonstrated better results.

The USAC_PROSAC method had the highest ratio values when using SIFT and SURF, whereas the USAC_MAGSAC method showed the worst results for BRISK. For ORB, USAC_PROSAC had the worst performance up to 400 keypoints, after which USAC_MAGSAC exhibited the highest ratio values.

It is worth noting that the ratio values differed only slightly when using SIFT, SURF, and BRISK for other filtering methods. In the case of ORB, other methods consistently showed an increase in the ratio, with differences between them amounting to a few percentage points.

The following observations were made after the range of the standard deviation-to-mean ratio values for different images analyses:

- For SIFT, the ratio values varied from 18% to 10%, then rose to 18%, indicating an initial improvement in stability followed by its deterioration as the number of keypoints increased. An exception was the USAC_PROSAC method, where the ratio sharply decreased from 48% to 17%.
- In the case of SURF, the ratio values decreased from 42.5% to 27.5%, demonstrating consistent stability improvement with an increasing number of keypoints.
- The most significant stability improvement for BRISK was observed, with the ratio values decreasing from 110% to 45%.
- ORB exhibited the smallest variation in values, ranging from 12% to 17%, indicating relatively stable behavior. An exception was the USAC_PROSAC method, which initially showed improved stability, with a reduction from 15.7% to 13.8%, but later stability declined, similar to other methods.

The efficiency of filtering depends on the quality of the detected and described keypoints [22]. Therefore, careful tuning of the detector and descriptor parameters is vital in achieving optimal results. Proper parameter selection can significantly impact the accuracy and stability of the outcomes. These conclusions align with our previous studies [33, 34], which analyzed the influence of Lowe's ratio parameters and limitations on the number of keypoints on the performance of SIFT, SURF, ORB, and BRISK methods.

The obtained results are consistent with the conclusions of other studies [35, 36], which also emphasize the importance of an adaptive approach to selecting keypoint matching filtering methods. The efficiency of each method depends on numerous factors, such as the number of keypoints, image quality, noise level, scene complexity, and requirements for accuracy and speed.

IV. CONCLUSIONS

This study provides a detailed analysis of the effectiveness of keypoint matching filtering methods, specifically RANSAC and its USAC variations. Keypoint detection and description were performed using SIFT, SURF, ORB, and BRISK methods.

It should be acknowledged that certain methodological decisions define the scope of the presented comparative analysis. The investigation was centered on a specific selection of keypoint detection, description, and filtering techniques. Furthermore, the experimental outcomes were generated using a dataset with particular visual attributes, while image similarity was assessed using the homography model. The performance benchmarks reported also correspond to the specific parameter configurations chosen for the algorithms under evaluation. These factors naturally delineate the current study's scope and offer valuable perspectives for guiding future research endeavors.

The SIFT method demonstrated high accuracy and stability, confirming its effectiveness in tasks where recognition precision is a priority. However, its computational complexity can be a limiting factor in applications where processing speed is critical. The SURF and BRISK methods offered a compromise between accuracy and speed, making them suitable for applications requiring a balance between these parameters. Although ORB lagged in accuracy, it exhibited high speed, which is advantageous for resource-constrained applications.

The results of this study highlight the importance of an adaptive approach to selecting keypoint matching filtering methods. USAC_PROSAC and USAC_FAST demonstrated the highest processing speeds, making them attractive for applications where speed is essential. Among the USAC variations, USAC_MAGSAC had the longest execution time.

At the same time, RANSAC provided the highest stability, although it lagged in terms of speed. Notably, parameter tuning for RANSAC significantly impacted its performance. Reducing the number of iterations, lowering the confidence level, and adjusting the inlier distance threshold improved its accuracy compared to USAC_DEFAULT without sacrificing stability.

Future research will expand the analysis by using additional matching filtering methods, such as MLESAC, LMedS, SCRAMSAC FSASAC, and others. Furthermore, studies will explore different approaches for evaluating image similarity. The FLANN method will also be considered to determine its impact on match search accuracy and speed. These efforts aim to provide a more comprehensive understanding of the efficiency of various filtering approaches and develop recommendations for their selection in specific applications.

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***ANDRIY FESIUK** is a PhD student and an assistant at the Department of Optoelectronics and Information Technologies, Faculty of Electronics and Computer Technologies, Ivan Franko National University of Lviv. His research interests include image processing and pattern recognition.*

***YURIY FURGALA** is the Dean of the Faculty of Electronics and Computer Technologies and an Associate Professor at the Department of Optoelectronics and Information Technologies, Ivan Franko National University of Lviv. His research interests include optoelectronics, signal and image processing, pattern recognition, and control theory.*

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