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Enhanced Image Retrieval using Hybrid ORB Algorithm

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Abstract: Achieving precise feature matching is a critical challenge in the field of computer vision, with applications ranging from image stitching and 3D reconstruction to image retrieval. This research paper presents an in-depth comparative analysis of the Hybrid ORB algorithm in conjunction with the widely recognized basic ORB and SIFT algorithm for image feature matching. The study meticulously evaluates the performance of these algorithms, encompassing aspects of accuracy, speed, and robustness, under various rotation and scaling scenarios. Furthermore, the research explores the distinct advantages of Hybrid ORB, an amalgamation of Canny Edge and Mean blur techniques, which enhances feature detection and matching. This work sheds light on the essential roles that these algorithms play in modern computer vision applications and lays the groundwork for future innovations in advanced image retrieval.

Keywords: *Canny Edge, Computer Vision, Feature Detection, Feature Matching, Hybrid ORB, Image Processing, Mean Blur, ORB, Performance Evaluation, SIFT*

1. Introduction

In recent years, the field of computer vision has seen remarkable progress, increasing the demand for robust and efficient feature-matching algorithms. These algorithms play a vital role in tasks such as object recognition, augmented reality, and automated visual analysis. Achieving a balance between precision and processing time efficiency has become the cornerstone of algorithmic innovation, driven by the ever-growing need for automation. In the domain of image matching, selecting the most suitable algorithm is a persistent challenge. No single option, whether it's ORB, SIFT, Canny, or blur-based techniques, offers the perfect equilibrium between precision and processing efficiency. This challenge requires a comprehensive comparative analysis to guide algorithm selection.

This research paper aims to bridge this gap by introducing a novel approach – the integration of Canny Edge and Mean Blur techniques with ORB, termed as Hybrid ORB, to enhance feature matching capabilities. The primary objectives include a detailed examination of the Hybrid ORB algorithm, an exploration of its strengths and limitations, and a meticulous evaluation of its performance in various dimensions. It also compares the performance of Hybrid ORB with the well-established traditional ORB and SIFT algorithm.

Through an exhaustive assessment of Hybrid ORB and its integration with these techniques, this paper enriches the existing knowledge base by providing valuable insights into its merits. The outcomes of this research are expected to empower practitioners in selecting the most suitable algorithm for specific application scenarios, thereby inspiring further research in the dynamic field of computer vision and pattern recognition.

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2. Literature Review

The continuous evolution of computer vision and image processing has witnessed substantial progress in recent years, fuelled by the demand for robust and efficient pattern-matching and feature-matching algorithms. These algorithms individually play a pivotal role in various applications, including object recognition, image registration, scene analysis, IOT based application [1], and cloud-based systems [2]. We review the pertinent literature that underpins the development and evaluation of the ORB, SIFT, Canny edge detection, and Mean (Box) Blurring techniques, as well as their combination with each other.

ORB, introduced by Rublee et al. [3], has garnered attention for its computational efficiency and robustness in detecting and matching key points within images. By combining FAST corner detection with BRIEF binary descriptors, ORB achieves real-time performance without compromising accuracy. Previous studies have demonstrated its applicability in diverse scenarios, ranging from robotics to mobile applications. However, its limitations, such as sensitivity to scale variations and orientation changes, have led researchers to explore hybrid approaches to enhance its adaptability [4][5].

SIFT, proposed by Lowe [6], revolutionized feature-based object recognition with its scale-invariant key point detection and description. The algorithm's ability to withstand transformations such as rotation, scaling, and changes in viewpoint has made it a cornerstone in computer vision. Subsequent research has contributed to refining SIFT's performance and addressing its computational complexity. While SIFT's accuracy is commendable, its computation-intensive nature has prompted the exploration of faster alternatives, driving the comparative analysis presented in this paper [7].

The integration of ORB and SIFT has been explored in recent studies to capitalize on their individual strengths. Chen et al. [8] proposed a hybrid approach that leverages ORB's speed and SIFT's robustness for object recognition in challenging environments. Similar work [9] highlights the synergistic benefits of combining these algorithms, showcasing improved performance over their standalone counterparts. The integration approach lays the groundwork for our investigation into the joint utilization of ORB and SIFT in conjunction with Canny edge detection for enhanced pattern-matching capabilities.

Canny edge detection, introduced by Canny, is renowned for its capability to extract edge information from images. Its role in pattern matching lies in accentuating salient features and aiding in the localization of key points. Prior research [10] has showcased the effectiveness of combining Canny edge detection with other algorithms for improved feature extraction and image registration. The potential of integrating Canny's edge information with ORB and SIFT presents an unexplored avenue for enhancing pattern matching performance, as we delve into in the subsequent sections of this paper.The integration of these algorithms with Canny edge detection represents a novel and promising approach to address the limitations and further elevate the capabilities of pattern-matching techniques.

In the context of computer vision and image processing [11], the integration of blur techniques, particularly Gaussian blur preprocessing, has emerged as a noteworthy strategy for enhancing edge detection accuracy Enhanced blurring techniques has presented a new framework which firstly learns how to transfer sharp images to realistic blurry images via a learning-to-blur GAN (BGAN) module. The paper discussed a framework that trains a learning-to-deblur GAN (DBGAN)module to learn how to recover a sharp image from a blurry image [12]. In this paper, the author proposes an approach called blurring and sharpening based three-way clustering (BS3WC) which constructs the three-way clusters without the need for determining the thresholds. The BS3WC is motivated by observing that the blurring and sharpening operations can produce a three-way representation for a typical object in an image consisting of a core inner, outer blurry, and part not belonging to the object [13].

3. Methodology

3.1. Hybrid ORB Algorithm

```
# Algorithm: Hybrid ORB

# Input: Source Image, Scaling Factors, Rotation Angles

#Output: Results, Performance Metrics, and Visualizations


# Step 1: Define Variables
    #The source image for matching
    source_image = load_image("source_image_path")
    # Scaling factors for resizing images
    scaling_factors = [0.3, 0.6, 0.9, 1.0, 1.2, 1.5, 1.8]
    # Rotation angles for creating rotated images
    rotation_angles = [0, 60, 120, 180, 240, 300]


# Step 2: Preprocess Source Image (Hybrid ORB)
    # Apply Canny edge to the source image
    canny_edges = apply_canny(source_image)


# Step 3: Generate Candidate Images for Hybrid ORB
for scale_factor in scaling_factors:
    for rotation_angle in rotation_angles:
        scaled_image = scale_image(source_image, scale_factor)
        rotated_image = rotate_image(source_image, rotation_angle)
        canny_scaled = apply_canny(scaled_image)
        canny_rotated = apply_canny(rotated_image)
# Step 4: Feature Matching and Analysis for Canny
for candidate_image in [canny_scaled, canny_rotated]:
    #Hybrid ORB Implementation
    orb_matches = match_features(canny_edges, candidate_image, method='ORB')
    curated_orb_matches = curate_matches(orb_matches)
    orb_precision=calculate_metrics(curated_orb_matches, orb_matches)
    total_matching_time_orb=calculate_total_matching_time(orb_start_time, orb_end_time)
    save_matching_results(candidate_image, orb_matches)
    visualize_metrics(candidate_image,orb_precision)
    record_metrics(candidate_image,orb_precision, total_matching_time_orb, 'ORB')


# Step 5: Preprocess Source Image (Hybrid ORB)
    # Apply blur to the source image
```

```
    blurred_image = apply_blur(source_image)


# Step 6: Generate Candidate Images for Hybrid ORB
for scale_factor in scaling_factors:
    for rotation_angle in rotation_angles:
        scaled_image = scale_image(source_image, scale_factor)
        rotated_image = rotate_image(source_image, rotation_angle)
        blurred_scaled = apply_blur(scaled_image)
        blurred_rotated = apply_blur(rotated_image)


# Step 7: Feature Matching and Analysis for Blur
for candidate_image in [blurred_scaled, blurred_rotated]:
    #Hybrid ORB Implementation
    orb_matches=match_features(blurred_image, candidate_image, method='ORB')
    curated_orb_matches = curate_matches(orb_matches)
    orb_precision=calculate_metrics(curated_orb_matches, orb_matches)
    total_matching_time_orb=calculate_total_matching_time(orb_start_time, orb_end_time)
    save_matching_results(candidate_image, orb_matches)
    visualize_metrics(candidate_image, orb_precision)
    record_metrics(candidate_image,orb_precision,total_matching_time_orb, 'ORB')
# Step 8: Create Result Tables and Visualizations
    # Create data tables with matching metrics
    create_result_tables(metrics_data)
    # Generate visualizations based on matching metrics
    generate_visualizations(metrics_data)
# Step 9: Cleanup and End
    # Close any open resources or windows
    close_resources()
```

3.2. Hybrid ORB Algorithm Implementation

1. Source Image Enhancement: Utilize either Canny edge detection or Mean blur for preprocessing the source image.
2. Candidate Image Generation: Create a set of candidate images by scaling and rotating the pre-processed source image.
3. Hybrid ORB Feature Detection and Matching: Implement Hybrid ORB algorithm for feature detection and matching between the source image and each candidate transformed image. Employ a threshold-based mechanism (an optimal curation threshold of 40 for Hybrid ORB) to eliminate incorrectly matched features, ensuring accuracy.
4. Performance Evaluation: Assess the results by computing precision, recall, and matching time metrics for the Hybrid ORB and compare the results with ORB and SIFT feature matching.
5. Iterative Process: Iterate through steps 1-5 for both Canny edge detection and Mean blur enhancements.

3.3. Experimental Setup

In this paper, we have devised an innovative approach to assess Hybrid ORB in diverse real-world scenarios. This involves comprehensive testing, including image rotation and scaling, to evaluate the algorithm performance under varying conditions. For the comparison process, the candidate image is systematically rotated in 60-degree increments, spanning a complete 360-degree rotation. Simultaneously, the image is scaled across a range from 30% to 180% of the source image, with increments of 30%. These specific choices stem from the observation that significant alterations in feature matches manifest within these parameter boundaries. This rigorous testing approach allows for a comprehensive understanding of the algorithms' effectiveness in image retrieval tasks.

3.4. Dataset Selection

To ensure a comprehensive evaluation of the proposed approach and the compared algorithms, a diverse dataset spanning various object types, scales, and environments is selected. The dataset comprises both synthetic and real-world images, incorporating scenarios with varying degrees of noise, occlusion, and illumination changes. Eight base images of the Oxford Visual Geometry Group (VGG) dataset. @Oxford_VGG is a Computer Vision group from the University of Oxford. We have used image retrieval dataset Affine Covariant Features Dataset and Building Dataset. A small dataset containing 8 scenes with sequence of 6 images per scene. Preprocessing steps involve resizing images to a standardized resolution, grayscale conversion, and noise reduction using Gaussian blurring to simulate realistic conditions.

3.5. Performance and Statistical Analysis

The performance of the algorithms is quantitatively assessed using two parameters of precision and matching time. The minimum average for features is considers the average performance across all precision operating points. Qualitative analysis is also conducted by visualizing matched key points and descriptors on sample images.

$$precision = TP / (TP + FP)$$

where TP=True Positive and FP=False Positive. To establish the significance of the results, the total matching time will be calculated as follows:

$$t5\_fin = t1\_fin + t2\_fin + t3\_fin + t4\_fin$$

where, t5_fin=total matching time, t1_fin=time taken to detect feature points in the base image, t2_fin=time taken to detect feature points in the candidate image, t3_fin=time taken to match the features between the two images, and t4_fin=time taken to eliminate wrongly matched features based on a threshold.

4. Hybrid - ORB Implementation

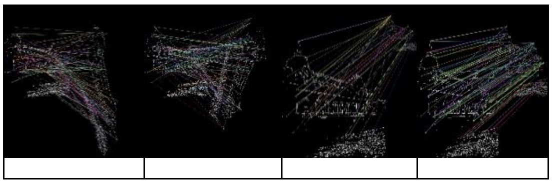

Fig. 1 Feature Detection and Matching for with different angles and scales for Hybrid ORB – C [Canny Edge].

In Fig. 1, the first two columns have a Canny-edge base image and is presented alongside the edged candidate images rotated at angles 60 and 120 and the next two columns corresponding the edged candidate images scaled at percentages 30% and 60%.

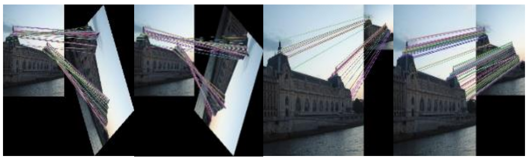

Fig. 2 Feature Detection and Matching for with different angles and scales for Hybrid ORB – B [Box Blur].

In Fig. 2, the first two columns have a Mean-blur base image and are presented alongside blurred candidate images rotated at angles 60 and 120 and the next two columns blurred candidate images scaled at percentages 30% and 60%.

5. Results for Hybrid ORB

5.1. Tables

Table 1. Precision and Matching Time with different angles

Angles	*Precision-ORB*	*Precision-Hybrid ORB-C*	*Precision-Hybrid ORB-B*	*Time-ORB*	*Time-Hybrid ORB-C*	*Time-Hybrid ORB-B*
0	0.986	0.872	0.978	0.031	0.04384	0.049451
60	0.884	0.39	0.904	0.046	0.0481	0.060263
120	0.878	0.36	0.912	0.031	0.047	0.056988
180	0.95	0.404	0.958	0.034	0.03157	0.050227
240	0.894	0.374	0.92	0.047	0.05117	0.059865
300	0.888	0.35	0.89	0.035	0.05058	0.063041

In Table 1, At 0 degrees, all variants exhibit high precision, with Hybrid ORB-C [Canny] slightly trailing behind. However, the time efficiency of Hybrid ORB-B is noticeably higher. As the angle increases, Hybrid ORB-B [Blur] demonstrates impressive precision, outperforming the others at 60 and 120 degrees. Interestingly, at 180 degrees, ORB and Hybrid ORB-B maintain precision, while Hybrid ORB-C sees a slight drop.

Table 2. Precision and Matching Time with different scales

Scales	*Precision-ORB*	*Precision-Hybrid ORB-C*	*Precision-Hybrid ORB-B*	*Time-ORB*	*Time-Hybrid ORB-C*	*Time-Hybrid ORB-B*
30	0.168	0.104	0.176	0.024	0.0323	0.0299
60	0.634	0.306	0.642	0.023	0.03093	0.0358
90	0.946	0.352	0.948	0.61	0.03344	0.1902
100	0.986	0.872	0.978	0.032	0.04375	0.0503
120	0.88	0.43	0.892	0.027	0.04601	0.0521
150	0.744	0.278	0.736	0.048	0.05586	0.0664
180	0.61	0.248	0.634	0.051	0.075	0.0768

Examining Table 2, the precision analysis indicates that Hybrid ORB-C tends to have lower precision compared to both ORB and Hybrid ORB-B. While Hybrid ORB-B consistently demonstrates commendable precision across scales, Hybrid ORB-C exhibits a trade-off between precision and efficiency. Notably, at smaller scales (30 and 60), Hybrid ORB-C lags in precision. On the other hand, Hybrid ORB-B maintains a balance, providing reliable precision without compromising on efficiency.

Table 3. Precision and Matching Time with different angles

Angles	*Precision-SIFT*	*Precision-Hybrid ORB-C*	*Precision-Hybrid ORB-B*	*Time-SIFT*	*Time-Hybrid ORB-C*	*Time-Hybrid ORB-B*
0	0.839373	0.872	0.978	0.47	0.04384	0.04945
60	0.570029	0.39	0.904	0.58	0.0481	0.06026
120	0.58668	0.36	0.912	0.581	0.047	0.05699
180	0.770813	0.404	0.958	0.48	0.03157	0.05023
240	0.571009	0.374	0.92	0.568	0.05117	0.05987
300	0.590597	0.35	0.89	0.589	0.05058	0.06304

Table 3 presents a comparative analysis of precision and processing time for SIFT, Hybrid ORB with Canny preprocessing (Hybrid ORB-C), and Hybrid ORB with Mean blur preprocessing (Hybrid ORB-B) at various angles. While SIFT initially exhibits higher precision, both

Scales	*Precision-SIFT*	*Precision-Hybrid ORB-C*	*Precision-Hybrid ORB-B*	*Time-SIFT*	*Time-Hybrid ORB-C*	*Time-Hybrid ORB-B*
30	0.105779	0.104	0.176	0.2509	0.0323	0.0299
60	0.286974	0.306	0.642	0.3216	0.03093	0.0358
90	0.502449	0.352	0.948	0.4057	0.03344	0.1902
100	0.839373	0.872	0.978	0.4849	0.04375	0.0503
120	0.606268	0.43	0.892	0.5278	0.04601	0.0521
150	0.589618	0.278	0.736	0.744	0.05586	0.0664
180	0.5857	0.248	0.634	0.8925	0.075	0.0768

Hybrid ORB variants surpass it in precision, with Hybrid ORB-B leading. Notably, Hybrid ORB-B achieves excellent precision at the cost of slightly increased processing time compared to SIFT.

Table 4. Precision and Matching Time with different scales

Table 4 presents a comparison of precision and processing time for SIFT, Hybrid ORB with Canny preprocessing (Hybrid ORB-C), and Hybrid ORB with Mean blur preprocessing (Hybrid ORB-B) across different scales. Precision varies with scale, with Hybrid ORB-B consistently outperforming the others in precision. However, this increase in precision is accompanied by an increase in processing time.

5.2. Graph

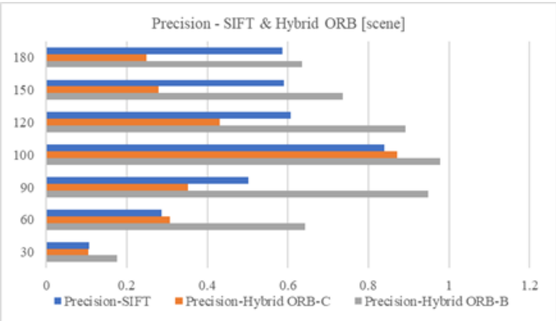

Fig. 3 Precision for different angles vs ORB.

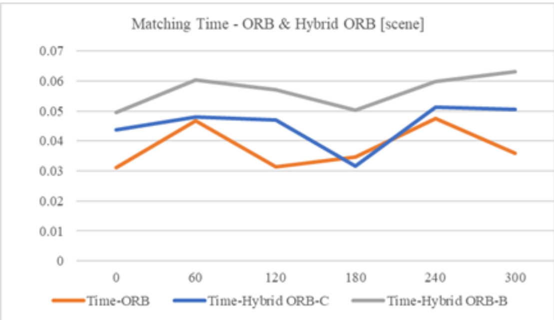

Fig. 4 Matching Time for different angles vs ORB.

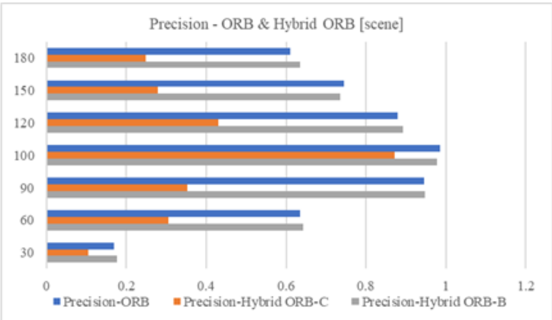

Fig. 5 Precision for different scales vs ORB.

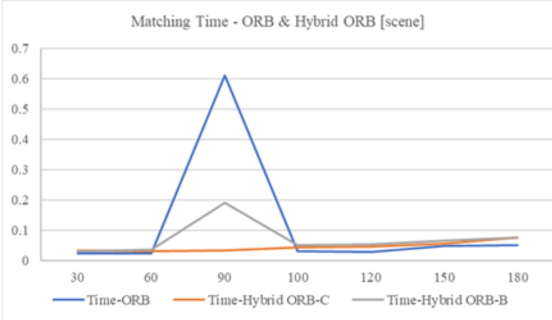

Fig. 6 Matching Time for different scales vs ORB.

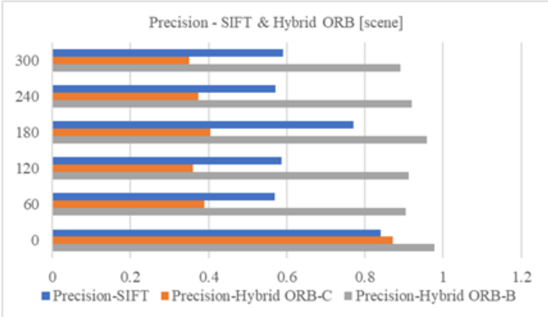

Fig. 7 Precision for different angles vs SIFT.

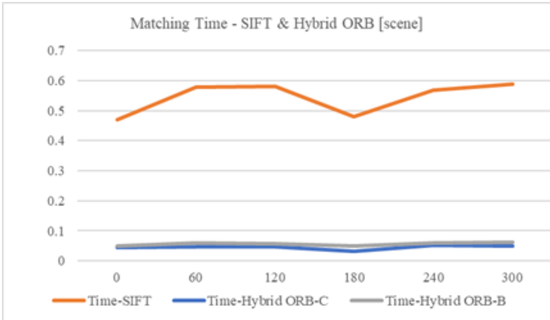

Fig. 8 Matching Time for different angles vs SIFT.

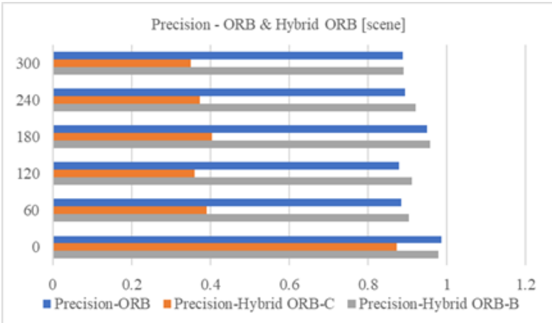

Fig. 9 Precision for different scales vs SIFT.

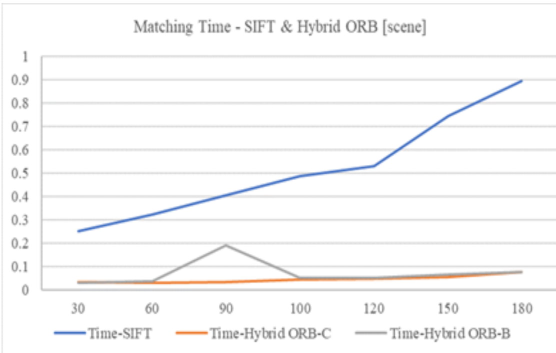

Fig. 10 Matching Time for different scales vs SIFT

6. Discussion

In our study, the integration of Box blur and Canny Edge with ORB and SIFT algorithms consistently demonstrated superior results in terms of precision and matching time when compared to using ORB and SIFT in isolation. Our extensive experimentation and analysis revealed a substantial improvement in feature matching accuracy and efficiency across a range of scenarios.

The results of the Hybrid ORB integration of Canny edge provided a remarkable illustration of its potential. Precision and Matching time data indicated a noticeable enhancement in precision, striking a favorable balance between accurate detection and robustness. Upon the Hybrid ORB integration of Blur technique, our findings revealed significantly improved performance. Precision and Matching time data demonstrated a notable enhancement in precision, effectively balancing accurate detection and robustness. In the fusion Hybrid ORB, the hybrid model adeptly addresses rotations and scales. SIFT proves sensitive to angles, while Hybrid ORB remains steadfast. Scaling introduces dynamism, with SIFT revealing nuances, and Hybrid ORB standing resilient.

In my research, we have deeply studied ORB, Hybrid ORB-C, and Hybrid ORB-B at different angles and scales. To make my work even better, we suggest a Hybrid integration strategy to boost ORB's performance. This approach involves smartly adjusting scales based on image features, using Hybrid ORB-C for efficiency, and including Hybrid ORB-B for precision. The goal is to strike a perfect balance between speed and accuracy, which should lead to much better results in image processing. This means our approach will work well in various situations and offer improved performance. By optimizing the input data with Canny edge and Box blur, we have effectively struck a balance between noise reduction and feature preservation, leading to more robust and timely feature matching results.

7. Conclusion

In conclusion, the comparative analysis reveals the nuanced strengths and trade-offs of ORB and SIFT. ORB, recognized for its precision and computational efficiency, stands as a formidable choice for real-time applications. Conversely, SIFT, while offering commendable precision, incurs a marginally higher computational cost. Notably, the integration of innovative techniques like Hybrid ORB, which combines Canny edge detection and Mean blur preprocessing, presents a compelling solution. It not only enhances precision but also opens new avenues for feature matching proficiency. The selection between ORB and SIFT, as well as the adoption of advanced approaches like Hybrid ORB, should be driven by the specific requisites of the application, offering a dynamic and adaptable framework for image retrieval tasks. This enhancement is especially noteworthy in situations where image data is noisy or contains fine details that could otherwise hinder feature-matching accuracy While further research is needed to explore the full extent of the advantages and potential limitations of this integration, our findings offer a compelling case for its adoption in real-world image processing tasks. Our research underscores the practical utility of this integrated approach in computer vision applications, such as object recognition, image stitching, and 3D reconstruction, where precision and efficiency are critical factors.

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