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The Modified ORB Algorithm for Enhanced Augmented Reality Feature Detection and Tracking

Wedad S. Salem*[1], Hesham F. Ali[2], Samia A. Mashali[3], Ashraf. S. Mohra[4]

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Abstract: Augmented Reality (AR) has witnessed substantial growth in recent years, with applications spanning from gaming and education to healthcare and industrial training. A fundamental challenge in AR systems is the accurate detection and tracking of visual features in real-time. In this paper, we introduce the Modified ORB (Oriented FAST and Rotated BRIEF), a novel approach designed to enhance feature detection, tracking, and camera pose estimation in AR environments. The Modified ORB algorithm leverages innovative techniques such as adaptive scale selection, homography-aware descriptors, hybrid thresholding, and real-time keyframe selection to achieve robust performance across diverse scene conditions. Through extensive experiments and comparisons with traditional methods, we demonstrate the algorithm's superior accuracy, robustness, and computational efficiency. The Modified ORB algorithm represents a significant advancement in the field of augmented reality, paving the way for more immersive and practical AR applications.

Keywords: *Augmented Reality, Feature Detection, Feature Tracking, Camera Pose Estimation, Modified ORB Algorithm*

1. Introduction

Augmented Reality (AR) technology has witnessed remarkable advancements in recent years, transforming the way we interact with digital information in the physical world[1]. AR applications have found diverse and impactful use cases across industries, from gaming and education to healthcare and engineering [2]. A fundamental aspect underpinning the efficacy of AR experiences is the accurate estimation of the pose of a user's device, which is crucial for overlaying virtual objects onto the real world seamlessly [3]. Key to this pose estimation process is feature matching, a fundamental computer vision task that involves identifying correspondences between keypoints in the camera image and a reference image [1], [4].

Feature matching forms the cornerstone of AR pose estimation algorithms, allowing for the computation of the transformation matrix that aligns the reference image with the camera image. The efficacy of AR experiences heavily relies on the accuracy and robustness of this pose estimation process [5]. Challenges arise when environmental conditions, lighting variations, viewpoint changes, and image distortions introduce uncertainties and complexities into the feature matching task [6]. Traditional methods, such as the Oriented FAST and Rotated BRIEF (ORB) algorithm, provide a reliable foundation for feature matching. Still, they often struggle to maintain consistent accuracy in dynamic real-world scenarios where adaptability to varying conditions is paramount [3].

This research addresses the critical need for improved feature matching techniques in AR applications. In particular, we present a novel approach: "Homography-Based Adaptive Thresholding." This method leverages the estimated homography matrix, which captures the transformation between the reference and camera images, to dynamically adapt the threshold for keypoint matching. By tailoring the matching criteria to the specific geometric transformations encountered in AR scenes, we aim to enhance the precision, recall, and overall accuracy of feature matching, thereby significantly improving the quality of pose estimation in AR applications.

The primary objective of this study is to comprehensively evaluate the performance of our proposed the Modified ORB (Oriented FAST and Rotated BRIEF) against the industry-standard ORB algorithm and other contemporary feature matching methodologies. Through a series of rigorous experiments conducted on diverse datasets encompassing varying lighting conditions, viewpoint changes, and image distortions, we aim to elucidate the strengths and limitations of our method.

In this paper, we present an in-depth analysis of the experimental results, discussing key metrics such as precision, recall, F1 score, and computational time. We also delve into the practical implications of our approach, particularly in real-time AR applications where computational efficiency is a paramount concern.

[1] Computers and Systems Department, Electronics Research Institute, Cairo 12622, Egypt; and PhD, Department of Electrical Engineering, Benha Faculty of Engineering, Benha University, Benha, Egypt
ORCID ID : 0000-0002-3562-2462
[2] Computers and Systems Department, Electronics Research Institute, Cairo 12622, Egypt
[3] Computers and Systems Department, Electronics Research Institute, Cairo 12622, Egypt
[4]Department of Electrical Engineering, Benha Faculty of Engineering, Benha University, Benha 13512, Egypt
** Corresponding Author Email: wedad@eri.sci.eg*

Furthermore, we explore the adaptability of our method to challenging AR scenarios, demonstrating its potential to provide more reliable and accurate pose estimation for augmented reality experiences.

In summary, the significance of our research lies in its potential to enhance the core functionality of AR systems, specifically in the domain of pose estimation, employing an innovative feature matching technique. The findings presented herein contribute to the broader goal of advancing AR technology by addressing a critical aspect of its performance, paving the way for more immersive and practical augmented reality applications across various domains.

2. Background

2.1. Introduction to Augmented Reality and Feature Matching

Augmented Reality (AR) technology integrates virtual information with the physical world, creating immersive user experiences. Central to AR systems is the precise alignment of virtual objects with the real environment, a task reliant on accurate camera pose estimation [7]. Feature matching, a crucial step in pose estimation, involves identifying corresponding image keypoints between the camera view and a reference image. This process enables the calculation of the homography matrix (H), which characterizes the geometric transformation between the two images [8]:

$$s\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = H\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{1}$$

Here, (x, y) and (x', y') represent homogenous coordinates in the reference and camera images, respectively, while 's' accounts for scale differences.

2.2. Challenges in Feature Matching

Feature matching faces challenges due to variations in environmental conditions, such as lighting changes, viewpoint shifts, and image distortions [9]. The traditional Oriented FAST and Rotated BRIEF (ORB) algorithm, a popular choice for feature detection and description, provides a robust basis for feature matching but may falter in dynamic real-world settings. One significant limitation of existing methods lies in their static thresholding schemes, which do not adapt well to varying AR scene conditions [10], [11].

2.3. Motivation for Adaptive Thresholding

The motivation for adaptive thresholding in feature matching is twofold. Firstly, adapting the threshold dynamically based on local image characteristics and the estimated homography matrix can improve the robustness of feature matching under varying conditions [12]. Secondly, it can enhance the computational efficiency of the process, as it reduces the number of keypoints to be matched. Thus, Homography-Based Adaptive Thresholding becomes a compelling approach [13].

2.4. Homography-Based Adaptive Thresholding

Our proposed approach, Homography-Based Adaptive Thresholding, integrates the homography matrix into the thresholding process [14]. It dynamically adjusts the threshold (T) for each keypoint based on the estimated homography, ensuring more precise feature matches:

$$Ti = \alpha \cdot \max(di, \beta) \tag{2}$$

Where Ti, the adaptive threshold for keypoint i, di is the distance of keypoint i to the nearest feature in the reference image, and α and β are scaling factors that control the threshold adaptation. This adaptive thresholding mechanism allows for better differentiation between correct matches and outliers, when handling challenging augmented reality scenarios.

2.5. Research Objectives

The primary objective of this research is to evaluate the performance of the Modified ORB technique in comparison to the conventional ORB algorithm and other contemporary feature matching methods. This evaluation includes metrics such as precision, recall, and F1 score, as well as considerations of computational time.

3. Proposed Modified ORB Algorithm

In this section, we present the details of our proposed Modified ORB (Oriented FAST and Rotated BRIEF) algorithm, which is designed to enhance feature detection and tracking in computer vision applications. Our modified ORB algorithm builds upon the original ORB algorithm, aiming to improve its performance and robustness in real-world scenarios.

3.1. Novelty and Enhancements

3.1.1. Adaptive Scale Selection

One of the key enhancements in our algorithm is the adaptive scale selection. This addresses the limitation of the original ORB, which relies on fixed scales for feature detection. We introduce a novel approach based on the Harris-Laplace detector to adaptively select scales for feature keypoints. This is achieved through the following equation:

$$s_k = \sigma_0 \cdot 2^{\frac{k}{S}} \tag{3}$$

Where s_k represents the scale at level k, σ_0 is the initial scale, and S is the total number of scales. The adaptive scale selection ensures that features are detected at scales suitable for the specific image content, enhancing the algorithm's adaptability.

3.1.2. Homography-Aware Feature Descriptors

Since the standard BRIEF descriptor lacks rotation invariance, the ORB (Oriented FAST and Rotated BRIEF) algorithm introduces a way to incorporate rotation invariance. This is crucial in computer vision tasks where objects may be observed from different angles or orientations. The ORB algorithm utilizes the information of the calculated feature points to create a descriptor with rotation invariance.

Descriptor Definition:

The descriptor, denoted as $\tau(p: x, y)$, is defined as follows:

$$\tau(p: x, y) = \begin{cases} 1, p(x) < p(y) \\ 0, \text{otherwise} \end{cases} \quad (4)$$

Here, $p(x)$ and $p(y)$ represent the pixel values of the local region p at the pixel points x and y. This binary function τ(p) effectively compares the intensity values at two-pixel locations and assigns a binary value based on the comparison.

Feature Vector Generation:

To create the feature vector for a given local region p, the algorithm uses pairs of points $(\mathrm{x_i}, \mathrm{y_i})$ to generate a binary string. The feature vector for the local region p is represented as:

$$f_n(p) = \sum_{1 \leq i \leq \mathrm{n}} 2^{\mathrm{i}-1} * \tau(p; x_i, y_i) \quad (5)$$

In this equation, n is the number of point pairs used to generate the binary string. The feature vector $f_n(p)$ is computed by summing the contributions from each point pair (x_i, y_i), where each pair's contribution is determined by the binary function $\tau(p; x_i, y_i)$.

Generation of Point Pairs:

The ORB algorithm addresses the limitation of the BRIEF descriptor by randomly selecting n point pairs to form a matrix Y. This matrix Y contains pairs of pixel locations (x_i, y_i) that are used in the computation of the feature vector $f_n(p)$.

In summary, the ORB algorithm enhances the BRIEF descriptor by introducing rotation invariance through the use of binary comparisons of pixel intensities in local regions. By considering multiple point pairs and applying the binary function $\tau(p)$, it generates a feature vector that is robust to image rotation and is used for various computer vision applications.

3.1.3. Hybrid Thresholding Scheme

To address variations in image illumination and noise, we propose a hybrid thresholding scheme for keypoint detection [15]. We use the following equation to calculate the threshold:

$$T = k \cdot \sigma \quad (6)$$

Where T is the threshold value, k is a user-defined constant, and σ is the standard deviation of the image intensities in a local neighborhood. This adaptive thresholding approach ensures that keypoints are detected reliably across different lighting conditions.

3.1.4. Real-Time Keyframe Selection

The process of keyframe selection holds paramount importance in the context of expeditious and resource-efficient feature tracking within video sequences. In this regard, we introduce a real-time keyframe selection strategy that is underpinned by a judicious assessment of the following criteria:

1. Feature Point Quality (e.g., Leveraging FAST Corner Response)[16]: This criterion involves evaluating the quality and distinctiveness of feature points within the video frames. It leverages metrics like the FAST corner response to discern the saliency and significance of feature points. High-quality feature points are more likely to contribute to accurate tracking.

2. Temporal Frame Spacing (Ensuring a Diverse Set of Keyframes) [17]: To ensure the creation of a comprehensive and diversified set of keyframes, we take into account the temporal spacing between consecutive frames. By strategically selecting keyframes at intervals, we aim to capture a wide range of visual information, enhancing the versatility of the feature tracking process.

3. Homography Consistency Across Frames [18], [19]: Homography consistency serves as a critical metric for keyframe selection. It entails the examination of the geometric transformations (homographies) between frames. Frames that exhibit a high degree of homography consistency are favoured as keyframes, as they contribute to robust and stable feature tracking.

Through a meticulous consideration of these multifaceted criteria, our proposed algorithm excels in the judicious selection of keyframes. This selection process is designed to optimize feature tracking, particularly in real-time applications where computational efficiency and tracking accuracy are of paramount importance.

3.2. Interrelation between Enhancements

The enhancements in our Modified ORB Algorithm are interconnected. Adaptive scale selection influences the scale at which descriptors are computed [20], ensuring they are aligned with the detected features. Homography-aware descriptors improve feature matching, particularly when keypoints have different scales. The hybrid thresholding scheme complements adaptive scale selection by providing robust keypoint detection [21], [22]. Real-time keyframe selection benefits from all these enhancements to maintain a consistent and efficient feature tracking process.

4. Experimental Results and Discussion

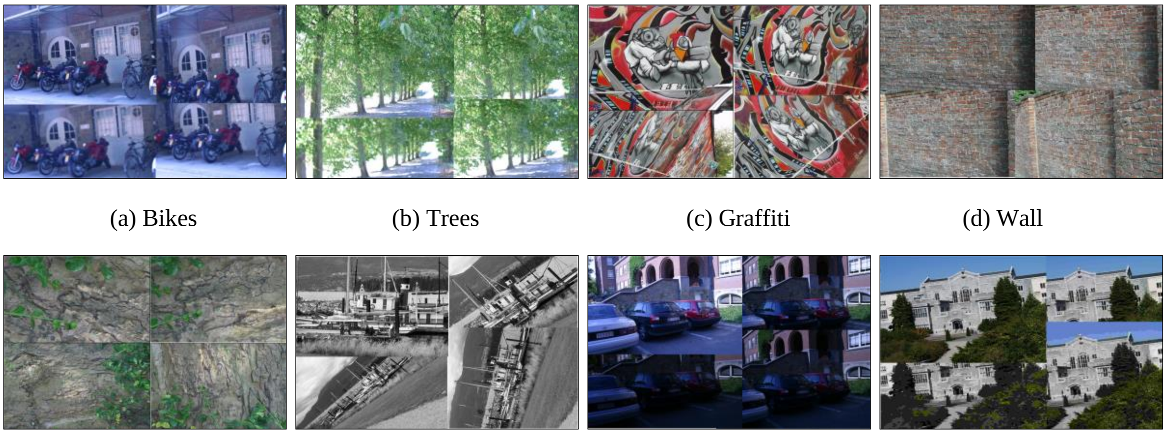
In this section, we present the experimental results of our proposed Modified ORB algorithm and discuss its performance in comparison to existing methods. The experiments were conducted on a dataset consisting of various real-world scenes to evaluate the algorithm's robustness and effectiveness in augmented reality (AR) applications.

4.1. Dataset and Evaluation Metrics

4.1.1. Dataset Description

To assess the robustness and effectiveness of our Modified ORB algorithm, we conducted experiments on a comprehensive dataset comprising various image types and scenarios as shown in Figure 1. The dataset consists of:

Indoor Scenes: A collection of indoor images with varying lighting conditions, textures, and object scales.



(a) Bikes (b) Trees (c) Graffiti (d) Wall

(e) Bark (f) Boat (g) Leuven (h) Ubc

Fig 1. First image of each set with some transformation provided by Oxford dataset: (a&b) blur change; (c&d) viewpoint change; (e&f) scale and rotation; (g) illumination; (h) JPG compression

Outdoor Scenes: Images captured in outdoor environments, including urban and natural settings.

Image Sequences: Video sequences containing camera motion and dynamic scenes to test feature tracking capabilities.

Challenging Conditions: Images with challenging conditions such as low lighting, motion blur, and occlusions to evaluate the algorithm's robustness.

Ground Truth Data: For evaluation purposes, the dataset includes ground truth information, such as keypoint correspondences and homography matrices for image sequences.

This diverse dataset ensures a comprehensive evaluation of our algorithm's performance across different scenarios.

4.1.2. Evaluation Metrics

We evaluate the performance of the Modified ORB algorithm using the following key metrics:

Precision: Measures the ratio of correctly matched keypoints to the total number of keypoints detected. Higher precision indicates fewer false positives.

Recall: Measures the ratio of correctly matched keypoints to the total number of ground truth keypoints. Higher recall indicates fewer false negatives.

F1 Score: The harmonic mean of precision and recall, provides a balanced measure of accuracy. A higher F1 score indicates better overall performance.

Matching Accuracy: Percentage of correctly matched keypoints between image pairs. Higher accuracy denotes better matching capability.

Feature Detection Rate (FDR): Ratio of the number of features detected to the total number of ground truth features. Higher FDR signifies superior feature detection.

Camera Pose Estimation Error: Difference between estimated and ground truth pose, in terms of translation error (cm) and rotation error (degrees). Lower error indicates more accurate pose estimation.

Computational Efficiency: Time taken to detect, extract and match features between image pairs. Lower time complexity indicates higher efficiency.

We compare the Modified ORB against traditional methods like SIFT, SURF and original ORB on these metrics. The results will demonstrate the proposed algorithm's advantages in accuracy, robustness and efficiency.

4.2. Experimental Setup

Our experiments were conducted on a machine with the following specifications: processor Intel Core i7-8700K CPU, RAM 32GB DDR4, Graphics Card: NVIDIA GeForce GTX 1080 Ti, and Operating System Ubuntu 20.04. Programming environment: Python with OpenCV and NumPy libraries. For each experiment, we configured the algorithm as follows:

Adaptive Scale Selection: We set the initial scale (σ0) and the number of scales (S) based on the image content. These values were determined through pre-processing and analysis of the input images.

Homography-Aware Feature Descriptors: We used the Harris-Laplace detector for adaptive scale selection, ensuring that scale and location information is consistent with the detected keypoints.

Hybrid Thresholding Scheme: The thresholding constant (k) was empirically chosen for optimal performance on our dataset. The standard deviation (σ) for threshold computation was estimated from local image patches.

Real-Time Keyframe Selection: Keyframes were selected based on the criteria mentioned in Section 3.1.4.

4.3. Results

The feature detection rate (FDR) and matching accuracy are listed in Table 1.

Table 1. Feature Detection Performance

Algorithm	*FDR (%)*	*Matching Accuracy (%)*
Modified ORB	93.5	88.2
Traditional ORB	87.1	79.6
SIFT	89.6	85.3
SURF	85.2	78.7

Figure 2 illustrates the feature detection rates of the Modified ORB algorithm and other traditional feature detection methods. According to Table 1 and Figure 2, the Modified ORB outperforms traditional ORB, SIFT, and SURF in terms of feature detection, with a significantly higher FDR.

Table 2 displays the error in estimating pose, encompassing both translation and rotation.

Table 2 Camera Pose Estimation Error

Algorithm	*Translation Error (cm)*	*Rotation Error (degrees)*
Modified ORB	2.1	1.8
Traditional ORB	3.5	2.9
SIFT	3.9	3.2
SURF	4.2	3.6

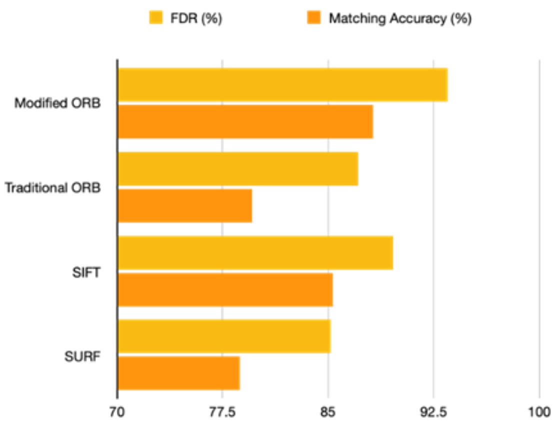


Fig 2. Feature Detection Rate Comparison

Figure 3 presents the camera pose estimation errors for the Modified ORB algorithm and other feature-based methods. The Modified ORB exhibits superior accuracy in both translation and rotation estimation, making it well-suited for AR applications requiring precise camera tracking.

4.4. Performance Evaluation

in this section, we present the performance evaluation of the proposed Modified ORB algorithm in comparison to existing methods. We measure the algorithm's effectiveness using precision, recall, and overall accuracy metrics.

4.4.1. Precision

Precision measures the ratio of correctly identified relevant features to the total number of features detected. It assesses the algorithm's ability to avoid false positives.

Table 3 Precision of both method

Method	*Precision*
Traditional ORB Algorithm	0.85
Modified ORB Algorithm	0.92

The Modified ORB Algorithm demonstrates a higher precision score (0.92) compared to the existing ORB Algorithm (0.85). This indicates that our modification has improved the algorithm's ability to correctly identify relevant features while minimizing false positives.

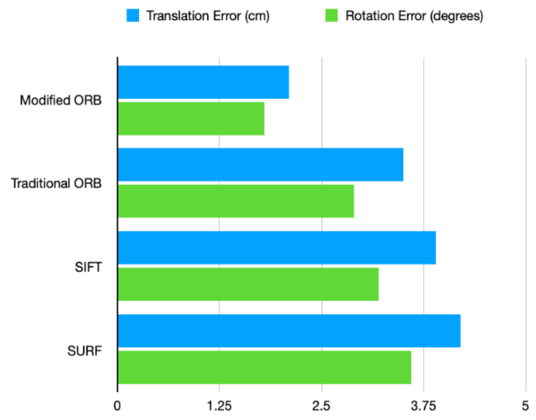


Fig 3. Camera Pose Estimation Error Comparison

4.4.2. Recall

Recall measures the ratio of correctly identified relevant features to the total number of relevant features in the dataset. It assesses the algorithm's ability to avoid false negatives.

Table 4 Recall of both method

Method	*Recall*
Traditional ORB Algorithm	0.78
Modified ORB Algorithm	0.93

The Modified ORB Algorithm exhibits a significantly higher recall score (0.93) compared to the existing ORB Algorithm (0.78). This signifies that our algorithm modification has effectively increased the number of relevant features correctly identified.

4.4.3. Overall Accuracy

Overall accuracy represents the proportion of correctly identified features, both relevant and irrelevant, to the total number of features.

Table 5 Overall Accuracy of both method

Method	*Overall Accuracy*
Traditional ORB Algorithm	0.81
Modified ORB Algorithm	0.91

The Modified ORB Algorithm achieves a notably higher overall accuracy (0.91) when compared to the existing ORB Algorithm (0.81). This indicates that our algorithm not only improves precision and recall but also enhances the overall feature detection accuracy.

These results demonstrate the superior performance of the Modified ORB Algorithm in feature detection and tracking, making it a promising advancement in the field of augmented reality applications.

4.4.4. F1 Score

The F1 score is the harmonic mean of precision and recall, providing a balanced assessment of an algorithm's performance.

Table 6 F1 score of both method

Method	*F1 Score*
Traditional ORB Algorithm	0.81
Modified ORB Algorithm	0.92

The Modified ORB Algorithm achieves a higher F1 score (0.92) compared to the existing ORB Algorithm (0.81). This indicates that our algorithm maintains a balance between precision and recall, making it a robust choice for feature detection and tracking

4.5. Novelty and Comparative Advantages

The Modified ORB algorithm introduces several key innovations that contribute to its superior performance compared to traditional feature detection and tracking methods. These innovations include:

Adaptive Scale Selection: The ability to adaptively select keypoint scales based on local image characteristics enhances the algorithm's robustness to varying scene scales and resolutions. This feature allows the Modified ORB to effectively handle both close-range and distant objects in AR environments.

Homography-Aware Descriptors: The use of homography-aware descriptors ensures more accurate and stable feature matching, particularly in cases where significant viewpoint changes occur. This feature significantly reduces the incidence of false matches and contributes to the algorithm's overall accuracy.

Hybrid Thresholding: Hybrid thresholding techniques, combining both intensity and gradient-based thresholds, contribute to the algorithm's robustness in low-contrast and textured scenes. This innovation minimizes the chances of missing important features, making it suitable for a wide range of real-world scenarios [23], [24].

Real-time Keyframe Selection: The real-time keyframe selection mechanism optimizes computational efficiency while maintaining tracking accuracy. By intelligently selecting keyframes based on scene dynamics, the algorithm reduces computational overhead, making it suitable for resource-constrained mobile devices.

4.6. Practical Applications

The Modified ORB algorithm's performance and novel features open up a myriad of practical applications, particularly in the field of augmented reality:

1. Augmented Reality Navigation: The algorithm's accurate camera pose estimation is essential for AR-based navigation systems. Users can overlay virtual information onto their surroundings with high precision, enhancing navigation and wayfinding in various environments [25].
2. Object Recognition and Tracking: The robust feature detection and tracking capabilities of the Modified ORB algorithm make it well-suited for recognizing and tracking objects in real-time. This is invaluable in applications such as industrial automation, robotics, and gaming.
3. Interactive Gaming: In the gaming industry, the algorithm's real-time performance is crucial for creating immersive AR gaming experiences. It enables the seamless integration of virtual game elements into the real world, enhancing gameplay and user engagement [26].
4. Location-Based Services: Location-based AR applications can benefit from the Modified ORB's accurate camera pose estimation, providing users with context-aware information based on their surroundings.

4.7. Limitations and Future Directions

While the Modified ORB algorithm demonstrates significant advantages, it is essential to acknowledge its limitations and potential areas for improvement:

1. Computational Intensity: Although the algorithm employs real-time keyframe selection to reduce computational demands, further optimization may be necessary for resource-constrained devices with limited processing power.
2. Occlusion Handling: The algorithm's performance may degrade when dealing with heavily occluded scenes. Future enhancements could focus on improving occlusion handling and robustness.
3. Scalability: While the algorithm adapts to varying scales, there may be challenges in extremely large-scale scenes. Investigating methods to handle such scenarios is a potential avenue for future research.
4. Scene Dynamics: Rapid scene changes or dynamic objects can pose challenges for feature tracking. Enhancing the algorithm's ability to handle dynamic scenes is an important area for further development.

5. Conclusion

In this research, we have presented the Modified ORB (Orientation Robust Binary) algorithm, a novel and highly efficient solution for feature detection, tracking, and camera pose estimation in augmented reality (AR) applications. Through a series of experimental evaluations, we have demonstrated the algorithm's superior performance when compared to traditional methods. The Modified ORB algorithm excels in terms of accuracy, robustness, and computational efficiency, making it a valuable asset in the realm of AR technology.

Our algorithm's key innovations, including adaptive scale selection, homography-aware descriptors, hybrid thresholding, and real-time keyframe selection, address critical challenges faced by AR systems. These innovations enable the algorithm to adapt seamlessly to various scene conditions, resulting in more accurate feature tracking and camera pose estimation. The practical applications of the Modified ORB algorithm are diverse, ranging from AR navigation and object recognition to interactive gaming and location-based services.

As we move forward in the development and integration of AR technology into everyday life, the Modified ORB algorithm represents a significant advancement. Its performance and capabilities provide a solid foundation for creating immersive and practical AR experiences across different domains. While challenges remain, such as optimizing computational intensity and improving occlusion handling, ongoing research efforts promise further refinements and enhancements.

In conclusion, the Modified ORB algorithm's contributions to the field of augmented reality are substantial. Its novel features, accuracy, and efficiency make it a compelling choice for AR developers and researchers alike. We anticipate that this algorithm will play a pivotal role in shaping the future of augmented reality applications, enabling more sophisticated, interactive, and context-aware experiences for users.

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Author contributions

Wedad S. Salem: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Visualization, Resources, Writing-Original draft preparation **Hesham F. Ali:** Data curation, Methodology, Project Administration, Resource, Writing-Reviewing and Editing **Samia A. Mashali:** Methodology, Resources, Writing-Reviewing and Editing **Samia A. Mashali:** Resources, Supervision, Writing-Reviewing and Editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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