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An Enhancement of Oriented Fast and Rotated Brief (Orb) Algorithm for Feature Extraction in Retinal Images

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Abstract

The extraction of descriptive features from retinal images is a significant challenge to computer vision algorithms due to textures and different intensity variations. While the Oriented Fast and Rotated Brief (ORB) algorithm is rotation invariant, its application in retinal imaging is often constrained by its existing algorithmic processes. This study proposes an enhancement of the ORB algorithm for retinal feature extraction to address the limitations of traditional approaches. Significant limitations of the existing algorithm include the use of a fixed threshold that results in non-uniform keypoint distribution and reliance of feature descriptors on intensity comparisons that leads to incorrect feature matching. These problems lead to biased feature representations that fail to capture the crucial anatomical information in the retina. To overcome these challenges, a two-fold enhancement is introduced: an adaptive thresholding mechanism based on local pixel intensities and the incorporation of intensity difference information to enrich feature descriptors. Experimental evaluation using standard performance metrics demonstrates that the enhanced ORB algorithm significantly outperforms the standard implementation, achieving a 33.8% improvement in keypoint distribution evenness and a 14.8% increase in precision with a 42.9% reduction in RMSE. These results indicate that the proposed method effectively improves the performance of the algorithm for feature extraction in retinal images.

Keywords: Oriented Fast and Rotated Brief, feature extraction, retinal images, adaptive threshold.

1. Introduction

1.1. Background of the Study

The human eye allows us to see the world around us. Deep within the eye lies the retina that holds intricate and complex structure of blood vessels that forms a distinctive pattern with critical information that is unique to each individual. Beyond its biometric structure, a study conducted by Abràmoff et al. (2010) stated that the retina is anatomically designed to be optically transparent and vascular, as it serves as a unique “window” that is capable of manifesting abnormalities that indicate both ocular and systemic diseases.

Feature extraction focuses on finding the most descriptive and informative set of features to address a problem as noted by Guyon et al. (2006, p. ix), a process that is crucial when dealing with high-dimensional and complex data in images. According to Ping Tian (2013), feature extraction is a challenging problem in computer vision since it sometimes does not capture the whole features in an image completely. Such failure of capturing the entire features could lead to incorrect representations and biased results, a limitation that is critical when applied in retinal images. These images have distinct patterns that make up unique information from the blood vessels that represent visual data, but these create sharp intensity variations where detection of features is challenging.

ORB is a type of feature extraction algorithm commonly used in the field of computer vision. It extracts features based on each pixel of the image unlike other methods that process only specific regions to perform the task (Shabbir et al., 2021). Due to ORB's ability to capture features, it is efficient to use because of its speed to detect key features in retinal images.

Despite the ORB algorithm's advantages, it also has its drawbacks. First, because it only relies on fixed intensity threshold across the image, it places too much weight on high-contrast areas and ignores places where the contrast is low causing non-uniform keypoint distribution (Ma et al., 2021). This bias reduces the heterogeneity of the features, making it more difficult to detect critical retinal structures that have subtle intensity variations. ORB is also sensitive to light changes, which renders key points unstable, and image-to-image feature matches unreliable. It also uses binary feature descriptors based on pixel brightness rather than actual gray level difference which sacrifices information from the image.

Furthermore, this study aims to address the limitations of the traditional ORB algorithm in feature extraction by developing a more efficient method in capturing characteristics in retinal images. The proposed enhancement seeks to improve the limitations discussed by offering a balanced solution to the algorithm's existing shortcomings.

1.2. Statement of the Problem

1.2.1. General Statement of the Problem

The Oriented FAST and Rotated BRIEF (ORB) algorithm is limited by its fixed thresholding and binary intensity comparisons, which lead to uneven keypoint distribution and inaccurate matching in retinal images. These constraints result in biased feature extraction that fail to capture the subtle textures and critical anatomical structures in retinal images.

1.2.2. Specific Statement of the Problem

1. ORB produces a non-uniform distribution of keypoints in retinal images, leading to dense clustering in certain regions while failing to detect sufficient features in low-contrast areas.
2. ORB's binary feature descriptors rely solely on intensity comparisons rather than actual gray-level differences resulting in loss of subtle textural information.

1.3. Objective of the Study

1.3.1. General Objective

This study aims to develop a retinal-aware enhancement of the Oriented FAST and Rotated BRIEF (ORB) algorithm tailored for retinal imaging applications. The goal is to improve the quality and reliability of feature extraction by addressing the key limitations of standard ORB, specifically its fixed intensity threshold and loss of gray-level information in binary descriptors.

1.3.2. Specific Objectives

1. To ensure a more uniform keypoint distribution in ORB, enabling better representation of low-contrast retinal regions while preventing over-detection in high-contrast areas.
2. To strengthen ORB's feature descriptor to better represent subtle retinal intensity variations for more robust feature matching.

1.4 Scope and Limitations

This research is concerned with improving the Oriented FAST and Rotated BRIEF (ORB) algorithm by suggesting solutions to issues in feature extraction of retinal images, such as, fixed threshold and comparing pixel brightness instead of gray value differences. The proposed enhancements are exclusively applied to a publicly available retinal image dataset from Kaggle. The effectiveness of the enhanced ORB algorithm will only be tested on retinal images, and does not cover other types of images.

The study is only limited to feature extraction and does not cover classification, disease diagnosis, and detection. The study is confined to the aspects mentioned above and does not cover any additional problems surrounding the ORB algorithm that may arise.

1.5 Definition of Terms

This section of the study specifically defines the key terms that are used within the study. The following terms are:

Evenness. A metric used to evaluate the spatial distribution of keypoints. This checks whether the distribution of keypoints is spread uniformly across the image. A lower evenness value means that the features are well distributed.

Feature Descriptor. Mathematical representation of the key points of an image, that is used to compare and match images and also to classify and recognize patterns.

Feature Extraction. Keypoint and pattern detection and description procedure in an image to facilitate identification.

Grayscale. In ORB algorithm images are converted to grayscale before feature extraction. Since ORB performs based on the intensity of variations rather than color information, this process makes it to be computationally inexpensive.

Key points. The separate points in an image like edges or corners, that serve as the point of reference in pattern recognition and computer vision tasks feature extraction.

ORB (Oriented FAST and Rotated BRIEF). A feature detection and description algorithm used in computer vision.

Precision. Measures the ratio of correctly matched feature pairs to the total number of detected matches. It quantifies the ability of the descriptor to distinguish true correspondences from false matches during the feature matching process.

Root Mean Square Error (RMSE). A metric that checks how far matched keypoints move from their actual locations after the image has been transformed.

Scale Invariance. It is the capability of an algorithm to recognize features in an input image regardless of size differences.

Threshold. This pertains to the parameter applied in FAST corner detection to determine which key points are detected.

2. Review of Related Literature

2.1. Feature Extraction in Computer Vision

Computer vision systems process images from data created by electronic devices such as cameras. It acts as an electronic counterpart of the human vision system. Computer vision techniques are widely used in different applications such as food quality inspection, biometrics, and human recognition.

Basic features that can be extracted normally from an image without any shape information are called low-level features. These features are fundamental data points that can be extracted from an image without any complex model in order to understand the context of the image. These help computers easily identify them by simply looking at the raw values (intensity and gradient) of an individual or group of pixels (Nixon & Aguado, 2019, p. 213).

According to Niyonkuru (2025), the traditional feature extractions such as Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), and Oriented FAST and Rotated BRIEF (ORB) were the initial computer vision systems developed that helped in the improvement of computer visions today. These algorithms extract features from the local properties of an image finding keypoints and descriptors as they do not check the bigger picture but processes information only by a small group of pixels in finding edges, corners, etc. For this reason, some features may be difficult to extract due to its complexity, scalability, and sometimes lack semantic context.

2.2 Challenges in Retinal Image Analysis

Image processing is performed by extracting features to identify, classify, diagnose, recognize and detect raw images. The extraction of features chosen is crucial as it can influence the interpretation, and can lead to bias, which can distort the results. (Mutlag et al., 2020).

According to a study conducted by Shen et. al., (2020), retinal fundus images captured by clinical cameras mostly capture uneven lighting distribution and low local contrast Due to the special optical beam of fundus imaging and structure of the retina, which is why natural enhancement is not possible to directly enhance it as it can lose crucial features.

Meanwhile, a study conducted by Lee et. al. (2009) stated that fundus cameras often produce vignetting in retinal images as it tends to make the center bright and darker corners. This is caused by the light projection and the challenge of illuminating the surface of the retina because of its curved structure which is why some regions cannot be illuminated uniformly. For this reason, global thresholding techniques relying on one single, static intensity value fail to accurately determine these images. A single threshold cannot determine whether it is a low intensity pathological feature in a bright region or a healthy region that appears to be dark due to poor lighting conditions (Aziz et. al., 2021)

In retinal image, feature extraction is important to detect anatomical features such as blood vessels, lesions, and optic disc in checking disease progression. Computer Aided Diagnostic (CAD) systems have difficulty in identifying retinal diseases as retinal images have lower contrast and intricate small vessels which make it harder to distinguish due to small and thin features such as the blood vessels (Gojić et al., 2023). In addition to that, Saffarzadeh et al. (2014) stated that detection of vessels in retinal images is difficult because of the variation of bright and dark lesions.

2.3. Feature Extraction Algorithms

According to Wu et. al (2013), Scale-invariant Feature Transform (SIFT) is a local-based feature description algorithm. Local keypoints with large amounts of information are detected due to their stability and invariance. The procedure includes keypoint detection, establishing of descriptors, and image feature matching. However, SIFT relies on complex floating-point mathematics, making it computationally expensive, which is crucial for real time systems (Rublee et. al., 2011).

For this reason, to address the computationally intensive limitation of SIFT, Bay et al. (2006) introduced Speeded-Up Robust Features (SURF) as a more robust alternative. SURF uses integral images and a Hessian matrix-based detector to make its speed performance better compared to SIFT's performance. While SURF greatly improved in processing time, it still relies on floating point descriptors which makes it computationally heavy compared to other binary alternatives.

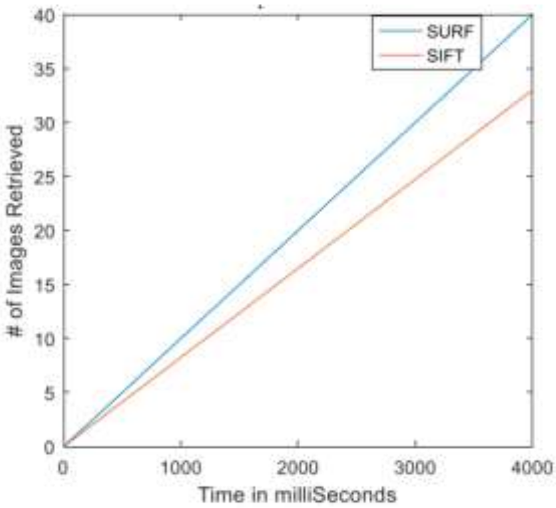


Figure 2.1. Response time of SURF and SIFT

2.4. Oriented FAST and Rotated BRIEF Algorithm

Designed as a high-speed, open-source alternative to heavier algorithms like SIFT and SURF, ORB was introduced by Rublee et al. (2011) to address the needs of real-time computer vision. Fundamentally, the system functions as a binary descriptor by merging the speed of the FAST detector (Features from Accelerated Segment Test) with the efficiency of the BRIEF descriptor (Binary Robust Independent Elementary Features). Luo et al. (2019) describe the ORB workflow as a three-stage pipeline: extracting feature points, generating descriptors, and finally, matching images.

To transform these older components into a modern, robust tool, ORB implements two critical enhancements:

1. Oriented FAST (oFAST): While the original FAST algorithm excels at speed, it suffers from a lack of orientation awareness. ORB bridges this gap by calculating the "intensity centroid" of a detected corner. By determining this centroid, the algorithm can assign a precise angle to each keypoint, adding vital directional data that standard FAST ignores (Li et al., 2021).
2. Rotated BRIEF (rBRIEF): Similarly, the standard BRIEF descriptor is sensitive to rotation; if an image is turned, the descriptor often fails to match. ORB resolves this by "steering" the BRIEF pattern to align with the specific angle calculated by oFAST. This alignment ensures that the binary descriptor remains stable and consistent, regardless of how the image is rotated (Li et al., 2021).

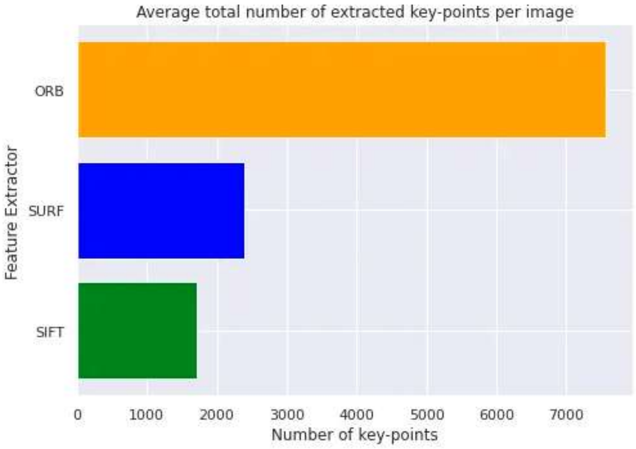


Figure 2.2. Comparison in average total number of extracted keypoints per image in ORB, SIFT, and SURF.

2.5 Problems of the ORB Algorithm

Although ORB shows promise in its performance, there are several limitations that hinder its full potential. In a study entitled, "Overview of Image Matching Based on ORB Algorithm" conducted by Luo et al. (2019), the image matching process of the ORB algorithm is divided into three steps: feature point extraction, producing feature point descriptors, and feature point matching. Since the algorithm utilizes FAST (features from accelerated segment test) in detecting features, if the pixel in an image is relatively different compared to adjacent pixels, then that is considered a corner point. The FAST algorithm focuses only on the brightness differences between pixels, which means it overlooks any directional information. A pixel gets labeled as a feature point just based on the brightness difference with surrounding pixels, even if it is not a unique or important feature in the image.

A study published in 2021 titled as, "Homogenized ORB Algorithm Using Dynamic Threshold and Improved Quadtree" by Ma et al., since the ORB algorithm adopts FAST point extraction algorithm, this compares the grayscale values of pixels around the surrounding pixels and selects the distinctive ones as feature points. However, due to the global fixed threshold, this results in overly clustered or overlapping key points especially in areas where minimal variation happens. Consequently, while a higher number of key points leads to a better result in terms of image matching accuracy, the uneven distribution of this reduces the reliability of feature descriptors in certain areas.

In the same study by Ma et al. (2021), the limitations of the BRIEF algorithm in feature description are also highlighted. BRIEF produces binary descriptors by randomly choosing pairs of pixels in a window around each feature point and comparing their gray values. Though this is computationally fast, this approach only looks at the relative relationship between pixel intensities whether or not one pixel is brighter than another. But it fails to consider the real value of the intensity difference, for example, useful image information contained in the grayscale variations is discarded.

As stated by Luo et al. (2019), BRIEF is used to calculate the feature descriptors by comparing the grayscale values between pairs of pixels within a local patch (9x9) around a key point. A fixed length binary string is generated to describe the local features of the feature point. For each pair, it outputs a 1 if one pixel is brighter than the other and 0 if otherwise.

Mur-Arta et al. (2017) created a study, "ORB-SLAM: A versatile and accurate monocular SLAM system" that combined the FAST feature point extraction with double threshold and feature point management and optimization method using quadtree. The said method significantly improved the uniformity of feature point distribution. However, it still relies on manually defined threshold and does not consider variations of conditions the pixel neighborhood of an image is in. As a result, it falls short of achieving better feature extraction. As a result, the researchers proposed the use of dynamic local threshold where it is computed according to the characteristic of each pixel's surrounding image block. This enhances the ORB algorithm's ability to detect feature points in areas with subtle image or light changes, improving detection accuracy in low texture conditions.

Furthermore, a study entitled, "ALGD-ORB: An improved image feature extraction algorithm with adaptive threshold and local gray difference" by Chu et al. (2023), stated that while a fixed global simplifies the calculations and reduces processing time, it still lacks in meeting the requirements for feature point extraction, especially in situations where the image quality is poor or significant changes occur in the external environment, the number of extracted feature points can sharply decrease leading to inaccurate image information.

Xie et al. (2022), in their study "Fast Target Recognition Based on Improved ORB Feature", emphasized the ORB algorithm's preference for pixels with relatively high contrast. The ORB algorithm, which combines the FAST corner detection and the BRIEF descriptor, identifies feature points by comparing the intensity of a pixel to its surrounding pixels. This process favors pixels located in regions with strong local intensity variation—such as contour lines, bright spots in dark regions, or dark spots in bright areas. As a result, ORB performs well in images with clear contrast but struggles under poor lighting conditions, such as underexposed or overexposed scenes, where distinctive features may not be easily detected.

3. Design and Methodology

3.1. Research Design

Quantitative experimental research design was applied by manipulating the components of the standard ORB algorithm, specifically, the threshold, feature descriptor, and keypoint selection, to evaluate their effects on the performance of feature extraction. The standard ORB algorithm was the control setup, while the Enhanced ORB served as the experimental setup. Both of the algorithms were evaluated under the same conditions by using the same retinal image dataset, same preprocessing steps, and the same evaluation metrics for fair and objective comparison.

3.2. Overview of Oriented Fast and Rotated Brief Algorithm

ORB detects key points using the FAST algorithm, which relies on a fixed intensity threshold to decide if a pixel is a keypoint. In addition, ORB uses BRIEF to create feature descriptors by comparing pixel brightness in pairs and encoding the result as a binary string (1 if one pixel is brighter than the other, 0 otherwise). This method is fast and memory-efficient but loses important intensity and color details because it only cares about relative brightness, not absolute intensity differences

3.2.1. Pseudocode of the Oriented Fast and Rotated Brief Algorithm

```
START
Step 1: Data collection
●   Import the retinal image.
    Step 2: Data preprocessing
●   Convert the image to grayscale for feature detection.
    Step 3: Image Pyramid Construction
```

- Build an image pyramid with multiple layers.
- Each layer is a scaled-down version of the previous one.

Step 4: Detect key points

- At each pyramid level, apply the FAST corner detection algorithm.
- For each pixel, evaluate whether it's a corner by comparing it to its neighbors in a circular region.
- A pixel is classified as a corner if at least 12 contiguous pixels in the circle are all brighter than the center pixel by a fixed threshold T, or all darker than the center pixel by T.

Step 5: Orientation Assignment

- For each keypoint, calculate the gradient (dx, dy) at its surrounding region.
- Compute the orientation as the angle of the gradient using the arctangent function.

Step 6: BRIEF Descriptor Extraction

- For each keypoint, create a patch centered around it.
- For each pair of pixels in the patch, compare their intensities.
- Set a bit in the descriptor if one pixel is brighter than the other.

END

SOP 1: Relies on a fixed intensity threshold to identify keypoints, extracting all high-contrast regions resulting in non-uniform keypoint distribution

SOP 2: ORB relies on relative brightness not absolute intensity differences resulting in feature mismatching.

3.2.2. Simulation of the Problem in the Initial Oriented Fast and Rotated Brief Algorithm

Problem 1: ORB produces a non-uniform distribution of keypoints in retinal images, leading to dense clustering in certain regions while failing to detect sufficient features in low-contrast areas.

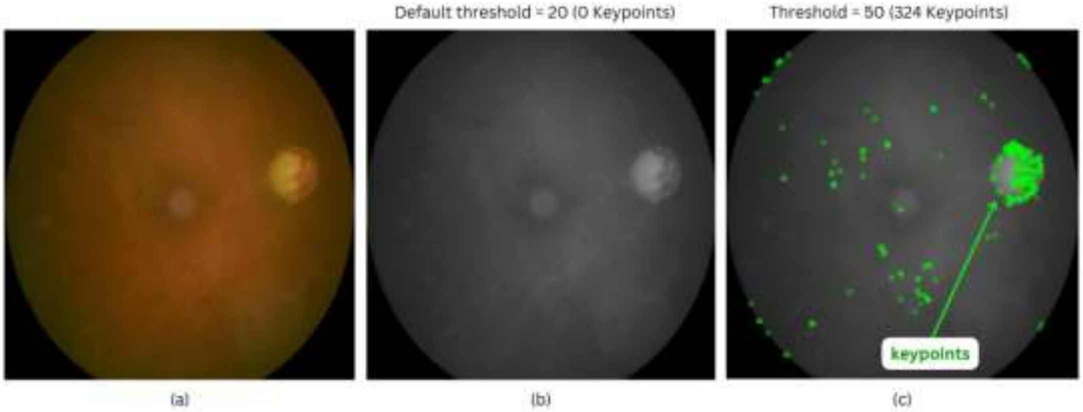


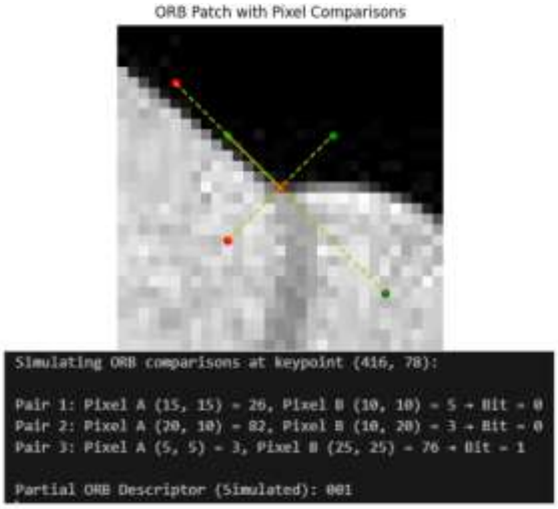
Figure 3.1. (A) Fundus image, (B) ORB using default threshold of 20, (c) using 50 as a threshold

Analysis:

ORB detects key points using the FAST algorithm, which relies on a fixed intensity threshold to decide if a pixel is a keypoint. Since ORB uses the same threshold across the entire image, it struggles with the uneven contrast in fundus images. In Figure 3.1, image B demonstrates the effect of using ORB's default FAST threshold of 20 for keypoint detection. Since the fundus image has low contrast, ORB fails to detect any key points because the pixel intensity differences do not exceed the threshold. However, in Image C, the threshold was increased to 50, allowing ORB to detect contrast changes more effectively.

The issue with this approach is that not all fundus images have the same contrast levels. Some images may require a lower threshold (e.g., 20) to detect subtle features, while others may need a higher threshold (e.g., 50 or more) to capture significant structures.

Problem 2: ORB's binary feature descriptors rely solely on intensity comparisons rather than actual gray-level differences resulting in loss of subtle textural information.



```
Simulating ORB comparisons at keypoint (416, 78):

Pair 1: Pixel A (15, 15) = 26, Pixel B (10, 10) = 5 → Bit = 0
Pair 2: Pixel A (20, 10) = 82, Pixel B (10, 20) = 3 → Bit = 0
Pair 3: Pixel A (5, 5) = 3, Pixel B (25, 25) = 76 → Bit = 1

Partial ORB Descriptor (Simulated): 001
```

Figure 3.2. ORB Binary Descriptor Simulation

Analysis:

ORB uses BRIEF to create feature descriptors by comparing pixel brightness in pairs and encoding the result as a binary string (1 if one pixel is brighter than the other, 0 otherwise). Figure 3.2 demonstrates how ORB generates binary descriptors at a keypoint by comparing pairs of pixel intensities. Each bit is set to 1 if one pixel is brighter than another, or 0 otherwise. In this simulation, three pixel pairs around the keypoint were compared:

- In the first pair, Pixel A (15,15) had intensity 26, and Pixel B (10,10) had intensity 5, resulting in 0 because A > B.
- The second pair also returned 0.
- Only the third pair (with A = 3 and B = 76) returned 1.
- This yields a partial descriptor of 001.

Although efficient, this binary approach discards how much brighter one pixel is than the other. The difference between 3 and 76 is large, yet it's treated the same as a much smaller difference. This loss of intensity magnitude limits ORB's ability to capture gradual transitions or subtle texture patterns, leading to less distinctive feature descriptions and weaker feature matching performance in retinal images.

3.2.3. Pseudocode of the Proposed Enhancement of the Oriented Fast and Rotated Brief Algorithm

START

Step 1: Data collection

- Import the retinal image.

Step 2: Data preprocessing

- Extract the green channel and apply CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance local contrast.
- Generate an adaptive circular mask using Otsu's thresholding and morphological operations to isolate the retinal region and remove black borders.

Step 3: Image Pyramid Construction

- Construct an image pyramid with 3–4 layers.Each layer is scaled by a factor of ~1.2.
- Compute the number of required key points per layer.

Step 4: Adaptive Keypoint Detection

- Divide each pyramid layer into a grid (20 × 20 blocks).
- For each block:
  - Compute the mean intensity (μ) of the block.
  - Compute the standard deviation (σ) of the block.
  - Set FAST threshold as:
    $T = T_{base} + \alpha * \sigma$ ($\alpha \approx 0.25$)
- Apply the FAST algorithm in that block using T as the threshold.
- Repeat this process for each block in the grid.

SOLUTION TO PROBLEM 1

Step 5: Apply Orientation to the Key points

- For each keypoint, the image gradients (dx, dy) in its local patch are calculated.
- Compute the orientation as the angle of the gradient using the arctangent function.

Step 6: Enhanced BRIEF Descriptor Extraction

- For each oriented keypoint, extract a patch centered on the keypoint and rotate it according to the assigned orientation.
- Select n pairs of pixel blocks (not just pixels) randomly per pyramid level, and apply it to all key points within that level.
- For each block pair (A_i, B_i):
  - Standard BRIEF test (~70% of pairs):
    - Assign 1 if intensity(A_i) > intensity(B_i), else 0.
  - Intensity-difference test (~30% of pairs):
    - Compute the absolute intensity difference H_i for each block pair.
    - Compute standard deviation σ_p of pixel intensities in the entire keypoint patch.
    - Normalize each H_i: $H_{normi} = H_i \sigma_p$
    - Compute adaptive threshold $T_{avg} = \text{mean}(H_{normi})$
    - Assign 1 if $H_{normi} > T_{avg}$ else 0. OBJECTIVE 2

SOLUTION TO PROBLEM 2

- Mix both types of tests into a single fixed-length binary descriptor (e.g., 256 bits, ~70% standard, ~30% intensity-difference).
- Use the descriptor set for feature matching.

END

3.3. Methodology

The aim of this study is to improve the quality and reliability of feature extraction by addressing the key limitations of standard ORB, specifically its fixed intensity threshold and loss of gray-level information in binary descriptors.

3.3.1. Data Collection

A publicly available retinal image dataset from Kaggle was utilized for testing. To ensure fair comparison of results, a constant set of fifteen images was chosen to be evaluated in all test conditions. All images were preprocessed using Contrast Limited Adaptive Histogram Equalization (CLAHE) and an adaptive circular masking technique based on Otsu's thresholding and morphological operations. This masking process automatically isolates the retinal field of view (FOV), removes border artifacts, and prevents keypoint detection outside the retinal region before feature extraction.

3.3.2. Evaluation Metrics

The effectiveness of the enhanced ORB algorithm was evaluated both quantitatively and qualitatively through the objectives. The adaptive thresholding mechanism was assessed using the Evenness metric to determine the uniformity of keypoint distribution across retinal images. Meanwhile, the enhanced feature descriptor was evaluated using Precision and Root Mean Square Error (RMSE) metrics to measure its ability to preserve intensity information and improve feature matching accuracy. Each evaluation was conducted in direct comparison with the standard ORB algorithm under identical experimental conditions, following the same preprocessing steps of CLAHE enhancement and adaptive circular masking. This approach provided a comprehensive and objective assessment of the proposed enhancements in terms of keypoint distribution uniformity and feature matching reliability. The following are the specifics of each evaluation used:

- **Evenness:** A smaller Evenness value indicates a more uniform distribution of feature points across all regions, signifying improved representation of both high- and low-contrast retinal areas. Conversely, a higher value implies clustering or uneven spatial distribution of keypoints.
- **Precision (%):** As defined by Ma et al. (2025), precision measures the ratio of correctly matched feature pairs to the total number of detected matches. It quantifies the ability of the descriptor to distinguish true correspondences from false matches during the feature matching process. A higher precision value indicates that the descriptor generates more consistent and reliable feature correspondences across transformations.
- **Root Mean Square Error (RMSE, px):** According to Ma *et al.* (2025), RMSE measures the average pixel distance between matched keypoints in transformed images and their corresponding points in the original images. This metric reflects the spatial consistency of the descriptor under geometric or photometric transformations. Lower RMSE values show that matched points are closer to their true spatial locations, which indicates a more accurate localization of features. Reduced RMSE shows that the enhanced descriptor preserves the correct positions of keypoints even under transformations, improving matching accuracy.

3.4. Requirements Analysis

The enhancement of Oriented Fast and Rotated Brief (ORB) Algorithm for feature extraction in retinal images was developed using AMD Ryzen 5 with NVIDIA Geforce RTX 3050. The algorithm was implemented in Python, utilizing OpenCV (cv2) for core computer vision and image processing tasks, NumPy for numerical array computations, Matplotlib for visualizing the image data and feature matches, and the standard time module to benchmark computational efficiency.

4. Results and Discussion

4.1. Enhanced ORB General Performance

The metrics, Evenness, Precision, and RMSE, were computed as the mean results from 15 retinal images. These collectively evaluate the algorithm’s ability to achieve uniform keypoint distribution and an accurate and reliable feature matching selection.

Table 4.1 Summary of average metric results comparing Standard ORB and Enhanced ORB

Metric	**Standard ORB**	**Enhanced ORB**	**Improvement**
Evenness	44.876	28.716	+33.8%

Precision (%)	85.768	97.612	+14.8%
RMSE	0.856	0.474	+42.9%

Table 4.1 presents the average results for both the Standard and Enhanced ORB implementations. The Enhanced ORB consistently outperformed the Standard ORB in all evaluated criteria, indicating that the proposed modifications effectively addressed ORB’s main limitations in retinal image analysis. Specifically, the improvement in Evenness (+33.8%) demonstrates better uniformity of keypoint distribution across varying contrast regions, while the increase in Precision (+14.8%) and decrease in RMSE (+42.9%) confirm higher matching accuracy and spatial consistency of detected features. These results collectively confirm that the integration of adaptive thresholding and intensity-difference-based descriptor enhancement significantly improves the robustness and reliability of ORB in retinal image feature extraction tasks.

4.2. Results per Objective

Objective 1: To develop an adaptive thresholding mechanism for ORB that ensures more uniform keypoint distribution, improving representation of low-contrast retinal regions while preventing over-detection in high-contrast areas.

To quantitatively assess how uniformly the detected keypoints are distributed across the retinal image, the Evenness metric proposed by Ma et al. (2020) was adopted. This metric evaluates the spatial distribution of keypoints by dividing the image into ten regions from five directional perspectives (vertical, horizontal, 45°, 135°, internal, and external). The number of detected keypoints within each region is counted to form a dataset, from which the variance (V) is computed. The Evenness value is then calculated as: 100 * log(V).

Table 4.2 Comparison of Evenness between standard ORB and enhanced ORB across 15 retinal image

Evenness - Lower is Better						
File Name	**Standard ORB**			**Enhanced ORB**		**Improvement (%)**
	(threshold = 5)	**(threshold = 20)**	**Mean**	**Adaptive Threshold**	**Mean**	
2508_right.jpg	49.416	37.888	43.652	11.4	35.692	+18.2%
2394_left.jpg	45.925	19.358	32.644	10.88	33.348	-2.2%
10116_right.jpeg	49.772	48.643	49.208	12.36	25.971	+47.2%
2349_right.jpg	49.565	45.848	47.707	12.13	31.143	+34.7%
1123_left.jpeg	49.843	47.590	48.717	11.8	26.345	+45.9%

1146_right.jpeg	49.987	46.788	48.388	11.76	20.097	+58.5%
1096_left.jpeg	45.589	43.280	44.435	11.99	30.241	+31.9%
10078_left.jpeg	46.093	38.358	42.226	11.62	35.440	+16.1%
10109_left.jpeg	48.552	48.106	48.329	12.33	21.567	+55.4%
2403_right.jpg	50.020	48.658	49.339	11.98	29.872	+39.5%
2463_right.jpg	48.339	47.424	47.882	12.27	25.633	+46.5%
2438_right.jpg	47.108	41.533	44.321	11.79	33.133	+25.2%
2427_left.jpg	51.258	44.783	48.021	11.49	25.353	+47.2%
2486_right.jpg	45.527	32.836	39.182	11.59	27.622	+29.5%
2444_right.jpg	50.391	27.797	39.094	10.89	33.302	+14.8%
Mean Result:	**48.492**	**41.259**	**44.876**	**11.777**	**28.716**	**+33.89%**

As shown in Table 4.2, the enhanced ORB achieved lower evenness values across nearly all images, with an average improvement of 33.89% compared to the standard ORB. This result confirms that the adaptive thresholding mechanism significantly improved the balance of keypoint distribution across retinal regions. In particular, images that previously exhibited strong clustering in vessel areas now display a more uniform spread of keypoints, capturing both bright and dim retinal structures. The threshold per retinal image was also calculated by getting the threshold of each block in an image and taking its average. We can see that the threshold varies depending on the retinal image, having a mean threshold of 11.77 across the 15 retinal images.

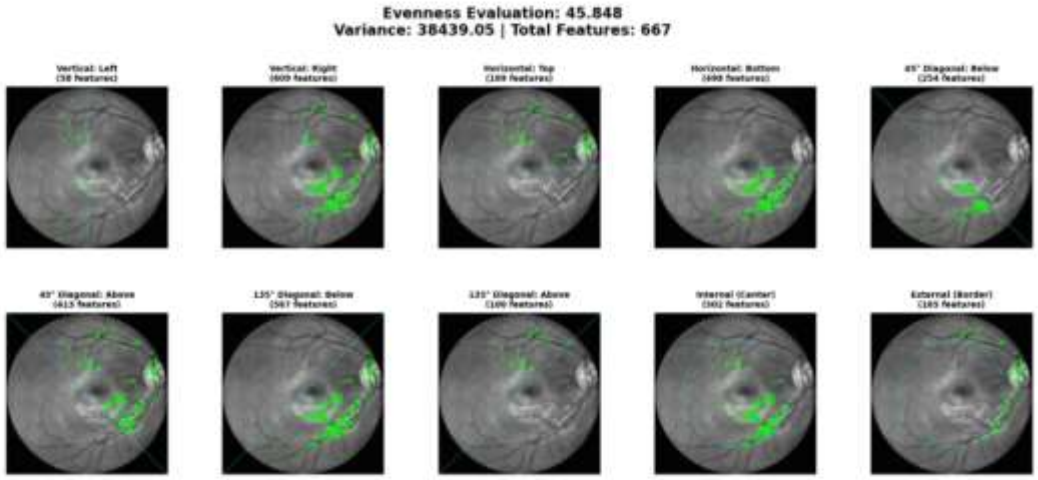


Figure 4.1 Regional keypoint distributions for Standard ORB divided into ten directional regions.

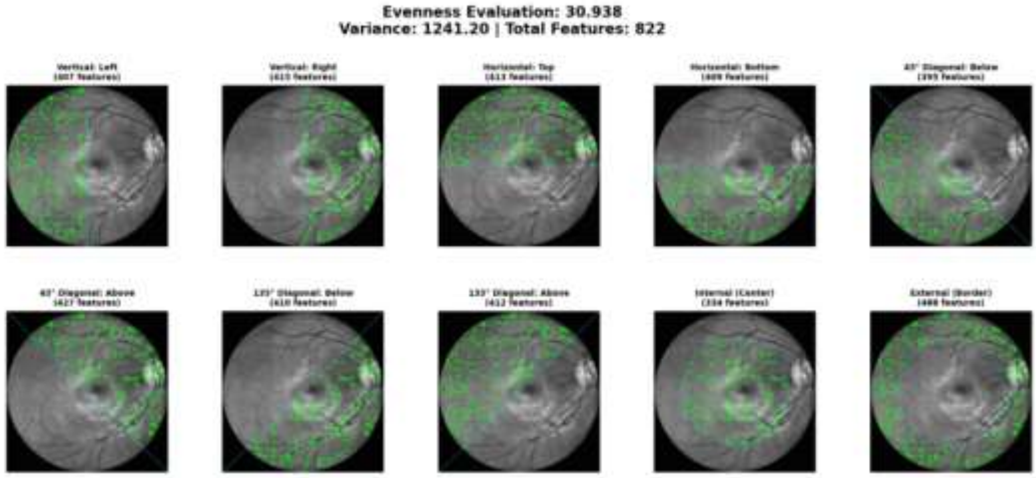


Figure 4.2 Regional keypoint distributions for Enhanced ORB divided into ten directional regions.

Figure 4.1 and Figure 4.2 show the regional keypoint distributions for a representative retinal image, divided into ten directional regions based on Ma et al. (2020). The Standard ORB in figure 4.1 shows uneven keypoint concentrations, with strong clustering along the vertical right (609) and 135°-below (567) regions, and sparse detections on the vertical left (58) and diagonal upper regions. In contrast, the Enhanced ORB (figure 4.2) demonstrates a more balanced distribution, with keypoints ranging between 334 and 488 across all regions. This reflects a substantial reduction in variance (from 38,439.05 to 1,241.20) and improved evenness (from 45.848 to 30.938), indicating more uniform keypoint coverage across retinal regions.

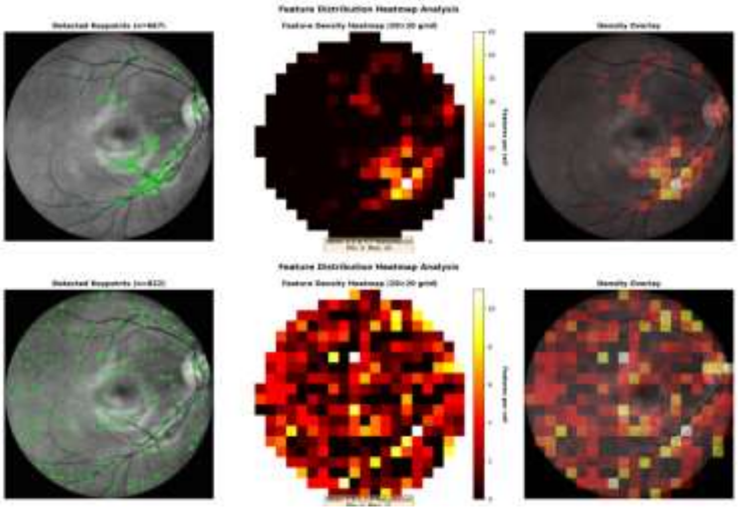


Figure 4.3. Heatmap comparison of uniformity, Standard vs Enhanced ORB

Figure 4.3 shows the heatmap comparison of keypoint distribution uniformity between standard and enhanced ORB. The standard ORB exhibits dense, localized clusters corresponding to over-detection in high-contrast vessel areas, while the enhanced ORB shows smoother, evenly distributed heat intensities across the image. This confirms that the adaptive thresholding mechanism effectively balances feature detection between bright and low-contrast retinal regions, improving overall spatial uniformity.

Table 4.3. Comparison of precision and RMSE between standard ORB and enhanced ORB across 15 retinal images.

	Precision (%) - Higher is Better			**RMSE (px) - Lower is Better**		
File Name	Standard ORB	Enhanced ORB	Improvement	Standard ORB	Enhanced ORB	Improvement
2508_right.jpg	82.361	96.250	+16.9%	0.775	0.581	+25.1%
2394_left.jpg	61.667	95.302	+54.5%	0.838	0.504	+39.8%
10116_right.jpeg	92.047	97.780	+6.2%	1.046	0.591	+43.5%
2349_right.jpg	84.660	98.644	+16.5%	0.688	0.509	+25.9%
1123_left.jpeg	89.411	97.331	+8.9%	0.867	0.383	+55.8%
1146_right.jpeg	90.009	97.722	+8.6%	0.948	0.437	+53.8%
1096_left.jpeg	84.862	98.385	+15.9%	1.063	0.317	+70.2%
10078_left.jpeg	90.057	97.471	+8.2%	0.874	0.498	+43.1%
10109_left.jpeg	93.652	98.366	+5.0%	0.879	0.434	+50.6%
2403_right.jpg	87.369	98.449	+12.7%	0.960	0.395	+58.8%
2463_right.jpg	92.857	98.763	+6.4%	0.747	0.419	+43.9%
2438_right.jpg	87.731	96.249	+9.7%	0.678	0.510	+24.7%
2427_left.jpg	91.480	98.553	+7.7%	1.000	0.469	+53.1%
2486_right.jpg	84.486	94.891	+12.3%	0.670	0.518	+22.7%
2444_right.jpg	73.864	97.829	+32.4%	0.803	0.539	+32.8%
Mean Result	**85.768**	**97.612**	**+14.79%**	**0.856**	**0.474**	**+42.9%**

Objective 2: To enhance ORB's feature descriptor by incorporating intensity-difference information, improving its ability to distinguish subtle variations in retinal structures for more robust feature matching. This objective focuses on enhancing the ORB feature descriptor by incorporating intensity-difference information. The goal is to improve ORB’s ability to distinguish subtle variations in retinal structures, resulting in more robust and accurate feature matching compared to the standard ORB algorithm. In order

to evaluate the effectiveness of the enhancement, two quantitative metrics were computed across 15 retinal images: Precision (%) and Root Mean Square Error (RMSE, px).

The performance of the standard ORB and the enhanced ORB descriptors across all 15 images is summarized in Table 4.3.

As shown in Table 4.3, the enhanced ORB consistently improves precision across all images, with an average increase of 14.79%. RMSE is reduced on average by 42.9%, demonstrating that the enhanced descriptor not only increases the number of correct matches but also improves their spatial accuracy.

The largest precision improvement was observed in '2394_left.jpg' (+54.5%), while the smallest improvement occurred in '10109_left.jpeg' (+5.0%). For RMSE, '1096_left.jpeg' showed the greatest reduction (+70.2%), indicating particularly strong localization improvements in that image. In general, images with lower initial precision or higher RMSE benefited the most, suggesting that intensity-difference information is especially effective in challenging or low-contrast regions.

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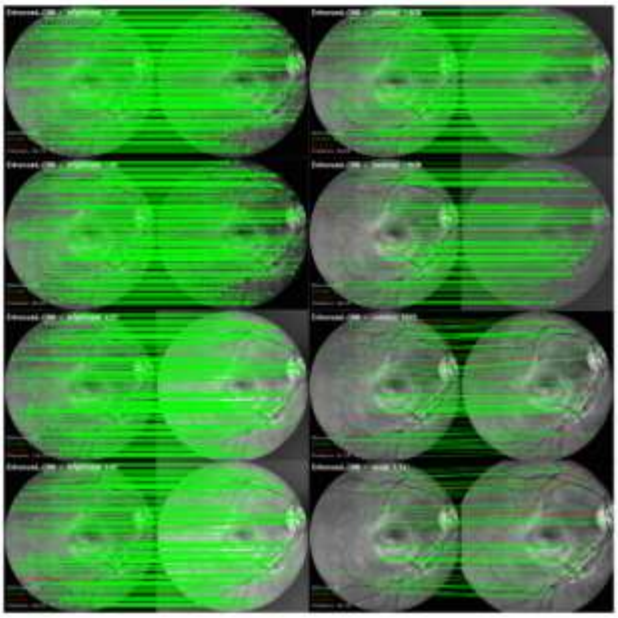

Figure 4.4. Feature matching using Enhanced ORB under multiple transformations.

Figure 4.4 illustrates feature matching for Image 1 (original) versus its transformed versions using the enhanced ORB descriptor. The transformations applied include changes in brightness (+20, +40, -20, -40), contrast (-30%, -50%), as well as rotation (10°) and scaling (1.1×). Green lines indicate correct matches, while red lines indicate incorrect matches.

Overall, the enhanced descriptor achieves very high precision across all transformations, with values exceeding 99% for brightness and contrast changes. Precision is slightly lower for geometric transformations, reaching 97.32% for rotation and 95.29% for scaling, indicating that the descriptor is slightly more sensitive to rotational and scale variations. This visualization demonstrates that the enhanced descriptor can robustly identify keypoints under both intensity and geometric transformations, while maintaining high spatial accuracy for subtle retinal structures.

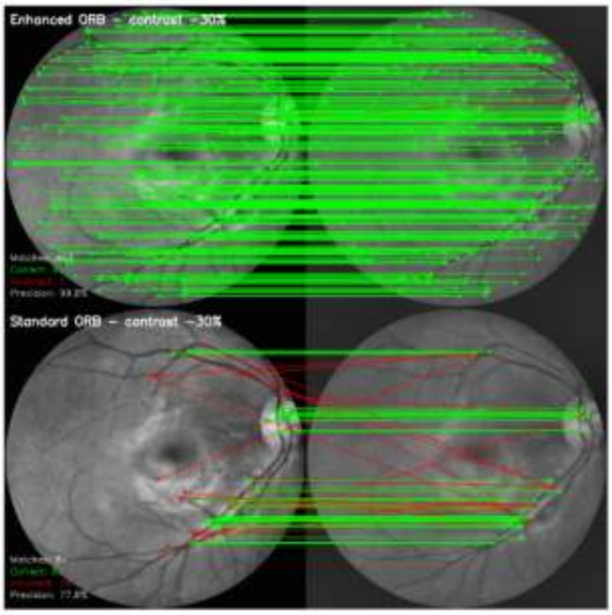

Figure 4.5. Feature matching comparison under -30% contrast, Standard ORB vs Enhanced ORB.

Figure 4.5 shows a comparison of feature matching between enhanced ORB and standard ORB for the same image after reducing retinal image contrast by 30%. The standard ORB achieves a precision of 77.8%, while the enhanced ORB reaches 99.8%. Compared to the standard ORB, the enhanced descriptor exhibits a higher number of correct matches (green lines) and fewer mismatches (red lines).

5. Conclusions and Recommendations

5.1. Conclusion

The goal of this study was to enhance the performance of the Oriented FAST and Rotated BRIEF (ORB) algorithm for feature extraction by addressing its fixed threshold limitation and improving the feature descriptor to better detect subtle intensity variations. Based on the results, the proposed Enhanced ORB algorithm successfully overcame these limitations, demonstrating improved efficiency and reliability in feature extraction of retinal disease images.

The proposed algorithm achieved a lower evenness score of 28.716 compared to the standard ORB algorithm's average of 44.876, as evidenced by the data presented in Table 4.2. This indicates that the Enhanced ORB algorithm significantly improved the balance of keypoint distribution by 33.89% across the retinal regions, reducing bias toward high-contrast regions and enabling the capture of subtle retinal features that might otherwise be overlooked.

Based on the data presented in Table 4.3, the Enhanced ORB improved its overall precision by 14.79% and enhanced the feature descriptor by 42.9% which increased the correct number of correct matches and at the same time improved the spatial accuracy. This improvement can be attributed to the incorporation of intensity-difference information into the feature descriptor, allowing the algorithm to better capture fine-grained variations in retinal structures. As a result, the Enhanced ORB can more effectively distinguish between subtle retinal features. These enhancements contribute to more reliable correspondence matching, which is essential for accurate retinal image registration and automated disease analysis.

5.2. Recommendations

Based on the findings of the study, it is recommended that future researchers who wish to continue this work explore the following directions:

Future studies may consider applying the Enhanced ORB algorithm to other medical imaging domains to determine its adaptability beyond retinal images. Researchers can also integrate the feature extraction process with lightweight classification models, leveraging ORB's efficiency to enable faster and more resource-friendly disease detection systems. In addition, future work can aim to further improve the algorithm's computational performance, particularly in reducing processing time without compromising accuracy.

Future researchers may explore the Enhanced ORB on larger and more diverse retinal image datasets, including images with varying illumination, contrast, and disease severity. This would help verify the algorithm's consistency and reliability in real-world conditions.

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