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Analysis of Determinant of Hessian based Multiscale Blob Detection

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ABSTRACT: Blob detection is a crucial technique in computer vision and image processing, enabling the identification of regions in an image that differ in properties such as intensity or texture compared to their surroundings. This paper presents a robust and efficient method for multiscale blob detection using the determinant of the Hessian matrix. The proposed method leverages the second-order partial derivatives of the image intensity function to construct the Hessian matrix, which captures the local curvature of the image surface. The key contributions of this method are as follows: First, it utilizes the determinant of the Hessian matrix to identify blob-like structures, ensuring invariance to rotation and scale changes. Second, the method operates across multiple scales by incorporating a Gaussian scale-space representation of the image, allowing for the detection of blobs of varying sizes. By computing the Hessian determinant at different scales and identifying the scale at which this determinant is maximized, the method accurately localizes blobs in both space and scale dimensions. Extensive experiments on synthetic and real-world images demonstrate the effectiveness of the proposed approach in detecting blobs with high precision and recall rates. The method outperforms traditional blob detection techniques, such as the Laplacian of Gaussian and Difference of Gaussian, particularly in scenarios involving complex and cluttered backgrounds. The computational efficiency of the determinant of Hessian based approach makes it suitable for real-time applications in areas such as object recognition, medical imaging, and remote sensing.

KEYWORDS: Image processing, Blob detection, Determinant of the Hessian matrix

I. INTRODUCTION

In image processing, a "blob" refers to a region in an image that shares certain common properties, such as intensity or color, which make it distinct from its surrounding areas. Blobs are typically characterized by their smooth and coherent structure within the region and by having a well-defined boundary or contour that separates them from the background[1]. A blob often stands out in an image due to its significantly different intensity or color compared to the neighboring pixels or regions. This contrast is essential for distinguishing the blob from its background. Blobs can vary in shape and size, ranging from small, circular regions to larger, irregular shapes. The shape and size of a blob depend on the specific application and the nature of the objects or features being detected. Blobs are typically connected regions of pixels that exhibit similar properties. The connectivity can be binary (foreground vs. background) or based on a range of intensity or color values.

There are various fields where we can use blob detection methodology like: Blobs are often used as features for object recognition tasks. They can represent salient parts of objects that help in distinguishing one object from another. In medical imaging, blobs can represent abnormalities or structures of interest, such as tumors or organs, based on their distinct properties like intensity or texture. Blobs can be used to track objects or analyze motion in video sequences. Tracking blobs across frames helps in understanding object movements and interactions.

Traditional methods for blob detection, such as the Laplacian of Gaussian (LoG) [2] and the Difference of Gaussian (DoG) [2], have been widely used but suffer from limitations in scale-space representation and computational efficiency. These methods often struggle to detect blobs at different scales effectively and may not robustly handle complex image backgrounds or noise. To address these challenges, this paper introduces a novel approach to multiscale blob detection based on the determinant of the Hessian matrix [3]. The Hessian matrix represents the second-order derivatives of the image intensity function and provides a local measure of curvature at each pixel.

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II. RESEARCH BACKGROUND

Numerous blob-like detectors have been designed for various applications; the majority of these are compared in [4]. The methods that have garnered the most attention in the literature is, however, shift invariant feature transform (SIFT) based on the difference of Gaussians (DOG) [5], salient regions depending on entropy[6], scale normalized Laplacian (SNL) depending on the Laplacian of Gaussian (LOG) [7], and speeded-up robust features (SURF) depending on the determinant of Hessian (DOH) [8]. The study [9] presents an algorithm for the quick and accurate detection of tiny, compact picture primitives, or "blobs," at the subpixel level. The approach includes a full scale-space description and is based on differential geometry.

Therefore, by simply changing the scale parameter, blobs of any size can be retrieved. Numerous characteristics are collected from a blob in addition to its perimeter and center point.

They enable a later classification of blobs by providing a more detailed description of the particular blob properties.

Watershed detection: Blobs typically have a border line encircling them and a very homogeneous interior. Watershed techniques are capable of extracting these types of structures. These algorithms mimic the procedure of rain falling onto terrain, flowing down mountain ranges, and collecting in valleys and basins. They operate under the assumption that the image contains "grayvalue mountains." Until all basins are filled and just the watersheds connecting various basins are left, this procedure is continued. In [10], a corresponding approach is provided that focuses on the subpixel-precision direct extraction of watersheds. Watersheds are usually recovered from the gradient amplitude image in order to retrieve both bright and dark blobs. It is possible to execute the rainfall and accumulating process quite effectively, enabling these algorithms to handle needs in close to real-time. In actual use, nevertheless, these algorithms' intrinsic noise sensitivity—which frequently produces over segmented results—is their bottleneck.

Structure tensor analysis: By identifying different points and evaluating the concept of circularity this technique separates blobs [11]. First, by examining and thresholding the structure tensor's eigenvalues in a manner akin to the traditional Harris-Operator, possible interest points are found. The next step is to estimate the common intersection point of all gradients, assuming circularity, and compute the gradient directions in the local vicinity of a candidate location. Ultimately, the acceptance or denial of the candidate point is determined by a hypothesis test on the precision of the intersection, that is, the deviation of the gradient directions from the intersection point. This approach has a number of benefits: It requires simply a few initialization parameters, yields subpixel exact results for blob center points, and may be effectively applied with recursive filters that have noise suppression integrated. However, this method's drawback is that it can only extract circular structures.

Blob detection using scale-space: It is possible to think of the blob detection methodology presented in [7] as a variation of the previous technique applied to various (Gaussian) scales. The entire scale space representation is examined for local maxima, or the ideal scale, as opposed to looking for features at a single scale. The similar gradient intersection approach as previously is used to determine the subpixel-precise location of a blob once its center has been detected. Nonetheless, the ideal scale for localization is once more presented as an arbitrary parameter to be estimated. The ideal scale for localizing the blob is thought to be that one, which minimizes the gradients' departure from their projected junction point. This scheme is considered to be the most sophisticated theoretically. The computing effort required to analyze at multiple scales and the limitation to circular forms are the key drawbacks. As a result, the application in practice is quite restricted.

III. PROPOSED METHODOLOGY

Following are the multiples phases of the proposed method, Determinant of Hessian based Multiscale Blob Detection (DOHMBD).

Step 1: Edge Detection Using Harris:

The Harris edge detector, often known for its application in corner detection, can be adapted for edge detection in image processing. The Harris detector primarily identifies points of interest where the signal changes significantly in multiple directions. Below is a detailed explanation of the Harris edge detection technique, its theoretical foundation, and its implementation.

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Theoretical Foundation

The Harris detector is based on the second-order derivatives of the image, capturing the local structure in terms of intensity changes. It uses the autocorrelation matrix (also known as the second-moment matrix) to analyze the variations in image intensities. The autocorrelation matrix M at a point P (x, y) in the image is defined as:

$$M = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (1)$$

Where, I_x and I_y are the image gradients in the x and y directions respectively.

To detect edges, the following steps are involved:

1. Gradient Computation: Compute the image gradients using a derivative mask, such as Sobel operators.

2. Structure Tensor Calculation: Construct the structure tensor (second-moment matrix) M for each pixel using a Gaussian window function to weigh the gradients.

3. Corner Response Function: Calculate the corner response function R for each pixel, typically given by:

$$R = \det(M) - k.(\mathrm{trace}(M))^2 \quad (2)$$

Where k is the sensitivity aspect (0.04-0.06), det(M) is the determinant of M and trace(M) is the trace of M.

4. Edge Detection: Modify the corner response function to emphasize edge-like structures. One way to achieve this is to apply non-maximum suppression to the gradient magnitudes to detect edges.

Step 2: Harris Laplacian method for corner detection

It is a combination of Herris and Laplacian Method.

The Harris corner detection algorithm is based on the idea that corners can be detected by looking at the changes in intensity in different directions. The steps involved in Harris corner detection are:

1. Compute Image Gradients: Calculate the gradients I_x and I_y of the image in the x and y directions using Sobel filters.

2. Compute Products of Gradients: Compute the products of the gradients at each pixel:

I_x, I_y, I_x^2, I_y^2

3. Compute the Harris Matrix: Construct the Harris matrix M at each pixel using Equation 1. The summation is performed over a small window around each pixel.

4. Compute the Corner Response: The corner response R is computed using equation 2.

5. Threshold and Non-Maximum Suppression: Apply a threshold to R to find potential corners and then apply non-maximum suppression to refine the corner locations.

Scale Selection with Laplacian

To make the Harris corner detection scale-invariant, the Laplacian-based scale selection is integrated into the process:

1. Multi-Scale Representation: Create a multi-scale representation of the image by constructing Gaussian pyramids. Each level of the pyramid corresponds to a different scale of the image.

2. Laplacian of Gaussian (LoG): For each scale level, compute the Laplacian of Gaussian:

$$LoG = \sigma^2(I_{xx} + I_{yy}) \quad (3)$$

Where, σ is the scale parameter, and I_{xx} , I_{yy} are the second derivatives of the image.

3. Scale Normalized Harris Response: For each scale level, compute the Harris response and multiply it by the LoG response. This helps in selecting the appropriate scale for each detected corner.

4.Detect Local Extrema: Identify local maxima in the scale-space to detect corners. This involves finding points that are maxima in both the spatial domain and the scale domain.

Step 3: Multi scale Blob detection using Herris of determinant

1. **Preprocessing**: Convert the image to grayscale if it's not already. This simplifies the calculations.
2. **Scale-space Representation**: Create a scale-space representation by convolving the image with Gaussian filters at different scales.
3. **Hessian Matrix Computation**: For each scale, compute the Hessian matrix for each pixel in the image. The Hessian Matrix H for a pixel at position (x ,y) in an image is defined as:

$$H = \begin{bmatrix} L_{xx} & L_{xy} \\ L_{xy} & L_{yy} \end{bmatrix} \quad (3)$$

Here, L_{xx} , L_{xy} , L_{yy} are the second-order partial derivatives of the image intensity with respect to x and y.

4. **Determinant of the Hessian Matrix**: Compute the determinant of the Hessian matrix at each scale. The determinant is given by:

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$$\mathrm{Det(H)} = L_{xx}L_{yy-}(L_{xy})^2 \quad (4)$$

5. **Blob Detection**: Identify blobs by finding local maxima in the scale-space of the determinant of the Hessian matrix.
6. **Non-maximum Suppression**: Apply non-maximum suppression to remove redundant blob detections.
7. **Thresholding**: Apply a threshold to the determinant values to keep only significant blobs

Step 4: Enhancement of blob detection using Point of Interest (POI) and Integral Images

Using Points of Interest (POI) and integral images can enhance blob detection following the determinant of the Hessian matrix. Integral images, also known as summed-area tables, allow for rapid computation of the sum of values in a rectangular subset of a grid, which can be particularly useful in speeding up operations like convolution with box filters.

Incorporation of Points of Interest and integral images into blob detection after computing the determinant of the Hessian matrix:

a) **Compute the Hessian Matrix Determinant**: As before, compute the determinant of the Hessian matrix at multiple scales.
b) **Generate Integral Images**: Create integral images for the original image, which will allow for fast computation of rectangular regions.
c) **Compute Points of Interest**: Use the integral images to quickly identify areas of interest in the image. These areas will typically have high values in the determinant of the Hessian matrix.
d) **Refine Blob Detection**: Use the identified points of interest to refine blob detection, ensuring that only significant regions are considered.

IV. SIMULATION AND RESULTS

We have implemented our method in MATLAB 2023. Initially we have tested an image for edge detection. We mixed the image with Noise and then filter it with Gaussian Filter.

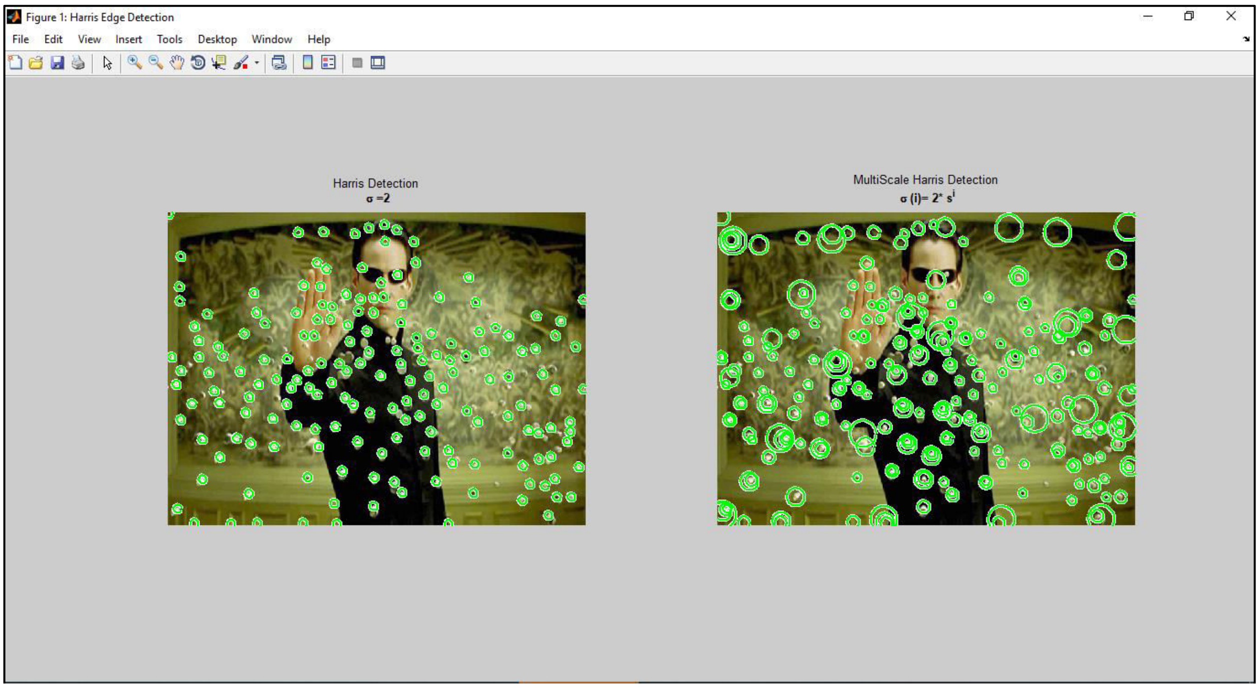

Figure 1: Edge and Corner Detection

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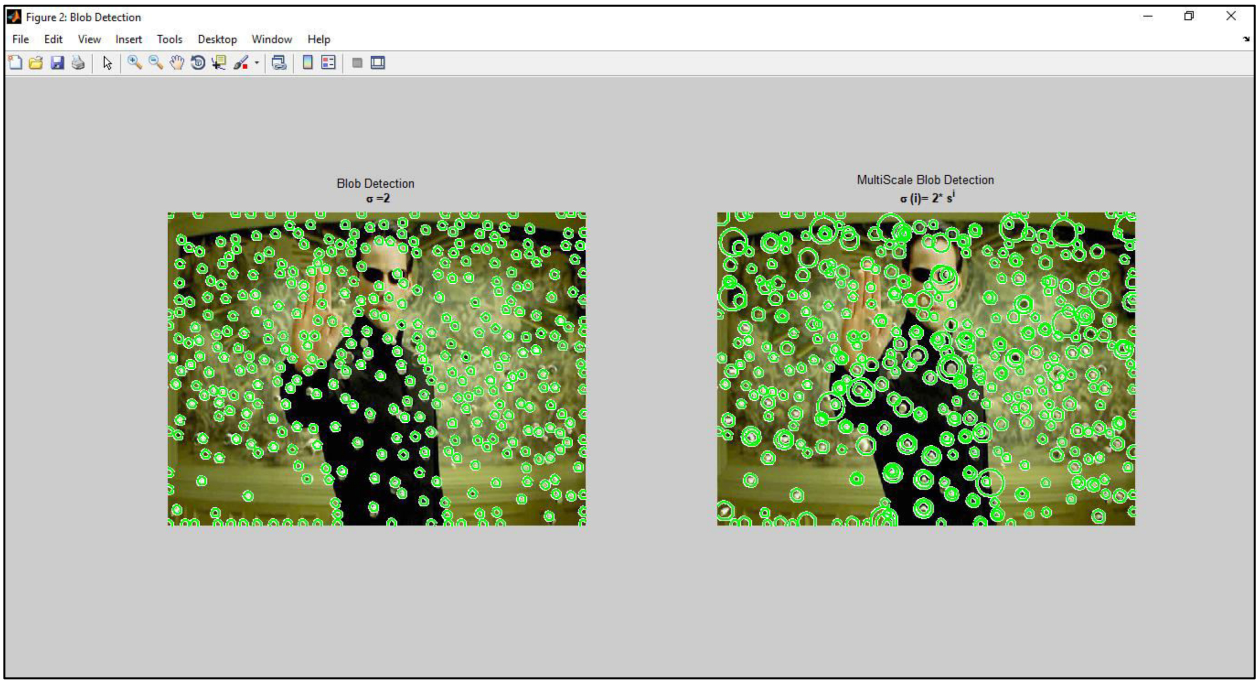

Figure 2: Blob Detection

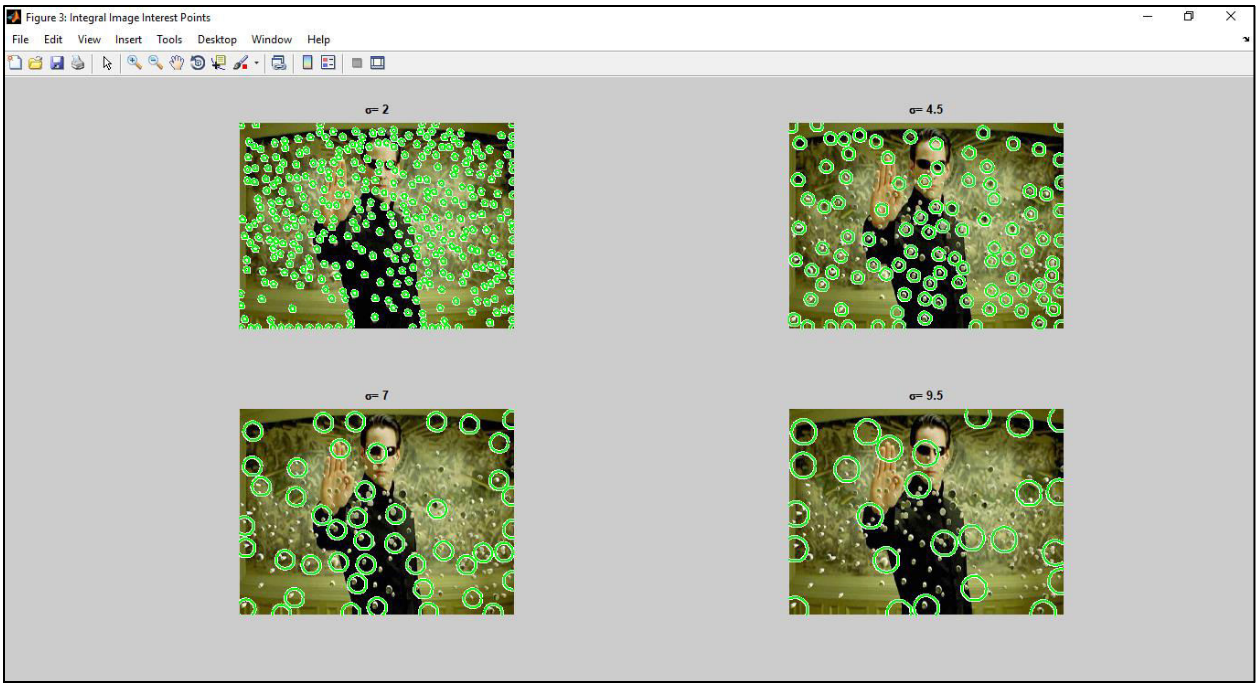

Figure 3: Point of Interest (POI)

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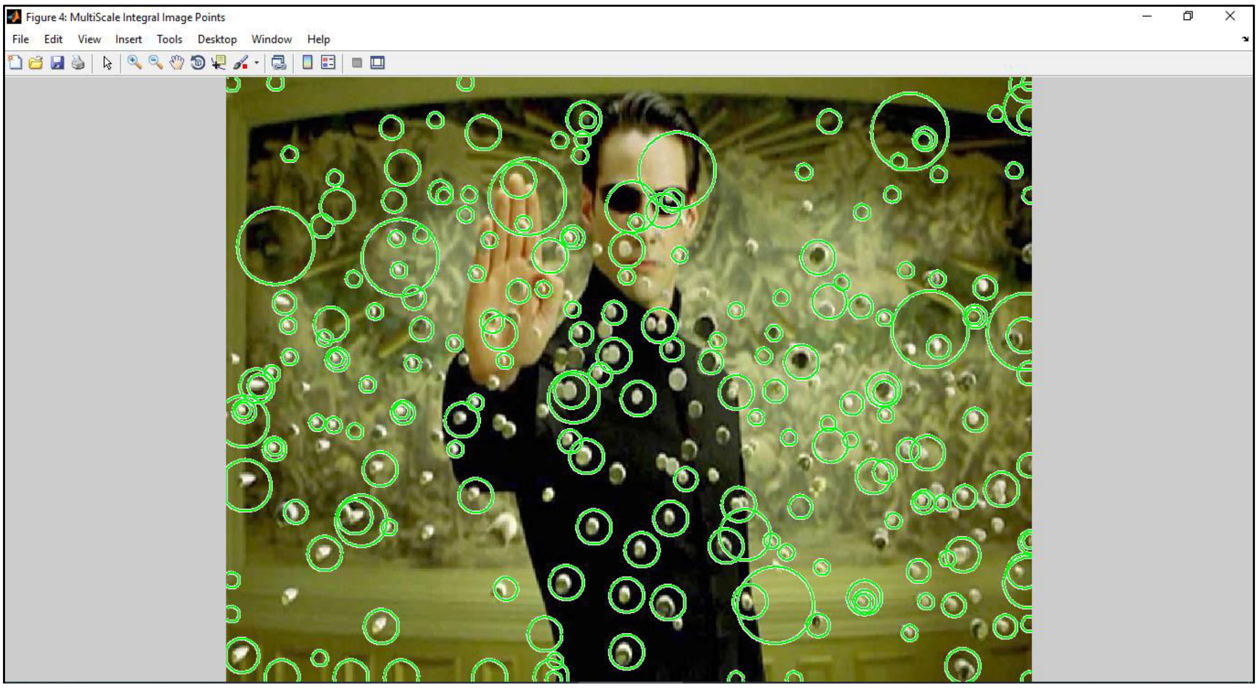

Figure 4: Integral Image of Blobs

V. CONCLUSION

Blob detection is a fundamental task in image processing and computer vision, playing a crucial role in various applications from object recognition to medical imaging. The choice of blob detection method depends on factors such as the nature of the image data, the desired level of accuracy, and computational efficiency requirements. The proposed method integrates various advanced techniques to enhance the process of edge and blob detection, culminating in a robust system for image analysis. Each method has its strengths and limitations, making it important to select the most suitable approach based on the specific application and image characteristics. **Edge Detection Using Harris**: Identifies prominent edges in the image. Utilizes the Harris corner detection method, which detects corners by looking for significant changes in gradient magnitude and direction. Provides a reliable edge map that highlights areas with high intensity changes, forming the basis for further image analysis. **Harris-Laplacian Method for Corner Detection:** Enhances the corner detection by combining Harris and Laplacian of Gaussian (LoG) methods. Harris method identifies potential corners, while the Laplacian refines this by focusing on scale-space representation. Results in more accurate and scale-invariant corner detection, crucial for identifying key points in varying image scales. **Multi-scale Blob Detection Using Determinant of the Hessian**: Detects blobs at multiple scales, which are regions that differ significantly in properties like brightness or color from their surroundings. Calculates the determinant of the Hessian matrix for various scales to identify local maxima, indicating potential blobs. Facilitates the detection of blobs of varying sizes and intensities, enhancing the robustness of feature detection in images. **Integral Images**: Allow rapid computation of sum of values within a rectangular region, significantly speeding up convolution operations. **Points of Interest (POI)**: Identified from integral images to highlight regions with high determinant values, reducing computational load. The integration of these techniques forms a comprehensive image analysis pipeline capable of efficiently and accurately detecting edges, corners, and blobs. The combination of multi-scale analysis with POI and integral images optimizes both the accuracy and performance of the detection process.

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