



A Review of Parallel Edge Detection in Grid Computing System

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Abstract. Edge detection is a fundamental task in digital image processing, enabling the identification of object boundaries and structural features required for higher-level vision applications. Classical edge detection techniques, including Sobel, Canny, and Laplacian-based methods, remain widely adopted due to their deterministic behavior, low complexity, and broad applicability. This survey presents a consolidated review of classical edge detection algorithms, covering their theoretical foundations, algorithmic variations, and application-oriented studies reported in the literature. Reported results indicate that Sobel-based approaches typically achieve peak signal-to-noise ratio (PSNR) values in the range of 19–25 dB for grayscale and medical images, while Canny-based methods demonstrate higher detection accuracy, commonly between 88% and 95%, particularly under noisy conditions. Laplacian and Laplacian of Gaussian techniques provide accurate edge localization through zero-crossing analysis, with sensitivity values generally reported in the range of 80–90% for biomedical and agricultural applications. The survey highlights key trade-offs among robustness, accuracy, and computational cost, offering guidance for selecting appropriate edge detection methods based on application requirements.

Keywords: Edge detection · Sobel operator · Canny edge detector · Laplacian of Gaussian · gradient-based methods · second-order derivative operators · digital image processing · FPGA.

1 Introduction

Edge detection is a fundamental operation in digital image processing that focuses on identifying significant intensity transitions corresponding to object boundaries. Such boundaries capture essential structural information and support subsequent tasks including segmentation, shape representation, and object interpretation. As discussed in standard image processing literature, reliable edge information plays a critical role in preserving meaningful visual content while reducing data redundancy [3].

Among classical techniques, early edge detection methods primarily rely on first-order intensity gradients. The Sobel operator, originally proposed by Sobel and Feldman, estimates horizontal and vertical edge components using discrete convolution masks [2]. Due to its simplicity and low computational cost, the Sobel operator has been widely adopted in grayscale image analysis and real-time systems, particularly where computational resources are limited [9]. Later studies introduced multi-directional and improved Sobel variants to enhance edge continuity and mitigate noise effects, especially in complex visual scenes [16].

Noise sensitivity in basic gradient operators motivated the development of more structured approaches. Canny addressed this limitation by formulating a multi-stage edge detection framework that integrates smoothing, gradient computation, non-maximum suppression, and hysteresis thresholding to achieve optimal edge detection under defined criteria [1]. Because of this systematic design, the Canny detector is frequently used as a benchmark in comparative evaluations. Its applicability has been demonstrated in several domains, including traffic analysis and medical imaging, where accurate boundary localization is essential [17].

In contrast to gradient-based approaches, second-order derivative methods identify edges through zero-crossings in the intensity profile. Laplacian-based techniques, particularly the Laplacian of Gaussian, combine smoothing with second-order differentiation to improve robustness against noise while maintaining precise edge localization [7]. These methods have been effectively applied in biomedical and agricultural image analysis, where accurate detection of fine structural boundaries is required [22].

Comparative studies indicate that classical edge detection techniques exhibit inherent trade-offs among noise robustness, localization accuracy, and computational complexity. Evaluations across different imaging conditions consistently show that no single method performs optimally in all scenarios, emphasizing the importance of application-specific algorithm selection [5, 6]. Recent surveys highlight that classical edge detectors remain relevant in resource-constrained and real-time environments, where deterministic behavior and interpretability are often preferred over data-driven alternatives [4].

2 Edge Detection Algorithms

In this paper, four widely used classical edge detection algorithms are considered and briefly described, namely the Sobel, Canny, Laplacian, and Laplacian of Gaussian methods.

2.1 Sobel Edge Detection Algorithm

The Sobel algorithm estimates first-order intensity gradients using discrete convolution masks in horizontal and vertical directions.

Mathematical Representation: The horizontal and vertical gradients are computed as:

$$Z_a = I * S_a, \quad Z_b = I * S_b$$

where I denotes the input image, and S_a and S_b are Sobel kernels. The gradient magnitude is given by:

$$Z = \sqrt{(Z_a^2 + Z_b^2)}$$

Algorithm (Sobel Edge Detection):

1. Start
2. Input the grayscale image I .
3. Compute Z_a and Z_b using Sobel masks.
4. Calculate gradient magnitude Z .
5. Apply thresholding to extract edges.
6. Obtain the edge-detected image.
7. End

2.2 Canny Edge Detection Algorithm

The Canny algorithm detects edges using a multi-stage process that includes smoothing, gradient estimation, and edge refinement. Gaussian smoothing is applied as:

$$I_s = I * Z_\sigma$$

where Z_σ is a Gaussian kernel with standard deviation σ . Gradient magnitude and direction are computed as:

$$\theta = \tan^{-1}(Z_b / Z_a)$$

Algorithm (Canny Edge Detection):

8. Start
9. Smooth image using Gaussian filter Z_σ .
10. Compute gradient magnitude and direction.

11. Perform non-maximum suppression.
12. Apply double thresholding and hysteresis.
13. Generate final edge map.
14. End

2.3 Laplacian Edge Detection Algorithm

The Laplacian algorithm detects edges using second-order derivatives of image intensity. The Laplacian operator is defined as:

$$\nabla^2 I = \partial^2 I / \partial a^2 + \partial^2 I / \partial b^2$$

Edges are detected at locations where zero-crossings occur.

Algorithm (Laplacian Edge Detection):

15. Start
16. Input grayscale image I .
17. Apply Laplacian operator $\nabla^2 I$.
18. Detect zero-crossings.
19. Extract edges.
20. End

2.4 Laplacian of Gaussian (LoG) Edge Detection Algorithm

The LoG algorithm combines Gaussian smoothing and Laplacian filtering into a single operation. The LoG operator is defined as:

$$LoG(a, b) = \nabla^2 [Z_\sigma(a, b) * I(a, b)]$$

Edges correspond to zero-crossings of the LoG-filtered image.

Algorithm (LoG Edge Detection):

21. Start
22. Smooth image using Gaussian kernel Z_σ .
23. Apply Laplacian to the smoothed image.
24. Identify zero-crossings.
25. Obtain edge map.
26. End

3 Challenges in Edge Detection

Edge detection becomes particularly challenging in real-world images, where noise, uneven illumination, and complex textures are commonly present. Several application-oriented studies report that gradient-based methods such as Sobel respond strongly to noise, especially in low-contrast grayscale and medical images, which reduces the reliability of extracted edges [9, 10]. These limitations are often less

evident in controlled datasets but become pronounced in practical imaging environments.

Another widely observed issue is the difficulty of preserving weak yet meaningful edges while suppressing false detections. In traffic monitoring and license plate recognition studies, shadows, reflections, and background textures are frequently misidentified as edges, while important object boundaries may be lost during thresholding [17, 19]. Such observations suggest that fixed threshold values, although computationally simple, rarely perform consistently across varying image conditions.

Parameter sensitivity and computational trade-offs further complicate edge detection. For Canny-based approaches, several authors note that inappropriate selection of smoothing scales or threshold values can result in edge fragmentation or excessive edge suppression [1, 18]. Similarly, studies employing Laplacian and Laplacian of Gaussian operators indicate that second-order differentiation amplifies noise despite prior smoothing, particularly in biomedical and agricultural imagery [7, 22, 23]. FPGA-based investigations additionally highlight that while simpler operators enable fast processing, more robust multi-stage methods introduce higher computational overhead [12, 16], emphasizing the importance of application-driven algorithm selection.

4 Literature Survey

Work on classical edge detection has grown through many small, focused studies rather than in a single unified direction. Researchers have examined methods such as Sobel, Canny, and Laplacian operators under different image conditions, often driven by the needs of a specific application. Medical images, traffic scenes, and agricultural data appear frequently in this work, mainly because they expose practical issues such as noise, uneven lighting, and loss of weak edges.

Most papers concentrate on improving performance within a narrow scope or solving a particular problem. As a result, it becomes difficult to see how these methods compare when viewed together. The literature survey presented next brings these studies into a common framework. By outlining the algorithms used, their key characteristics, application areas, and reported limitations, the survey aims to provide a clearer picture of the strengths and weaknesses of classical edge detection techniques as reported across the literature.

Table 1. Summary of Edge Detection Methods Reported in Literature

Work (Year)	Algorithm Used	Key Features	Application Domain	Advantages	Limitation
Harahap et al. [23] (2022)	Laplacian of Gaussian	Zero-crossing detection, Gaussian smoothing, fine boundary emphasis	Potato leaf damage detection	Accurate leaf boundary extraction, good localization	Sensitive to texture background, parameter dependent
Singh & Jain [22]	Laplacian	Second-order	COVID-19 X-	Highlights subtle	Noise

(2021)		derivative, edge enhancement before dilation	ray analysis	structural changes	amplification, preprocessing required
Greeshma [27] (2021)	LoG + NN	Edge-based feature extraction, learning-assisted classification	Pattern recognition	Improved feature extraction	Increased system complexity
Sekehravani et al. [17] (2020)	Improved Canny	Adaptive smoothing, noise-aware processing	Noisy image processing	Robust edge detection under noise	Higher computational cost
Indriyani et al. [6] (2020)	Sobel, Canny	Comparative evaluation on real images	Road pothole detection	Practical performance insight	Dataset specific conclusions
Akram et al. [19] (2019)	Canny	Edge density estimation, object boundary extraction	Smart traffic control	Reliable vehicle separation	Sensitive to illumination changes
Yuan et al. [24] (2019)	Fast LoG	Optimized convolution, reduced kernel size	Quantum image processing	Reduced computational load	Algorithmic complexity
Ansari [28] (2020)	Edge-based preprocessing + CNN	Edge-enhanced feature input	Potato disease classification	Improved classification accuracy	Dependent on training data
Dhar et al. [21] (2018)	Improved Canny	Image-quality driven parameter tuning	MRI tumor imaging	Improved edge clarity	Parameter sensitivity
Al-Saadi et al. [20] (2018)	Canny	Edge-based segmentation	License plate recognition	High localization accuracy	Scene and lighting dependency
Kumar & Verma [25] (2018)	Multi-scale LoG	Scale-space analysis, Gaussian smoothing	Medical image analysis	Improved multi-scale edge detection	Scale selection complexity
Singh & Verma [18] (2017)	Canny vs Fuzzy	Threshold comparison framework	Generic vision tasks	Reduced false edge detection	Increased algorithm complexity
Singh & Verma [15] (2017)	Improved Sobel	Optimized thresholding, noise suppression	Embedded vision systems	Better edge continuity	Parameter tuning required
Islam et al. [26] (2017)	Edge-based segmentation + SVM	Boundary-based feature extraction	Potato disease detection	Improved segmentation quality	Feature engineering required
Patil & Patil [14] (2016)	Sobel (FPGA)	Parallel convolution architecture	Real-time image processing	High processing speed	Hardware specific design
Verma & Singh [16] (2015)	8-direction Sobel	Multi-directional gradient estimation	Edge enhancement tasks	Captures diagonal edges	Increased computation

Shukla et al. [12] (2015)	Sobel, Canny (FPGA)	Real-time hardware implementation	Embedded systems	Low latency execution	Resource usage
Khaimar et al. [13] (2015)	Sobel (FPGA)	Pipelined processing	Image processing	Efficient throughput	Design complexity
Hossain et al. [10] (2014)	Improved Sobel	Modified convolution masks	General imaging	Improved edge continuity	Slight computational overhead
Putra et al. [9] (2014)	Standard Sobel	Gradient magnitude computation	Grayscale images	Simple implementation	Weak edge loss
Pawar & Patil [5] (2014)	Sobel, Canny, Laplacian	MATLAB-based evaluation	Academic comparison	Easy reproducibility	Not real-time focused
Dhar et al. [7] (2014)	LoG	Gaussian smoothing + Laplacian	Retinal imaging	Sharp boundary detection	Noise sensitivity
Sobel & Feldman [2] (1968)	Sobel (original)	3×3 gradient masks	Foundational method	Low complexity	Noise sensitive

Table 2. Studies with Distinct Evaluation Focus and Analysis Perspective

Work (Year)	Primary Focus	Distinct Parameters Considered	Image Type / Domain
Mateen et al. [4]	Survey & taxonomy	Algorithm classification, qualitative trends	Mixed datasets
Yuan et al. [24]	Computational optimization	Processing speed, kernel reduction	Quantum images
Greeshma [27]	Hybrid learning approach	Edge-based feature learning	Pattern recognition
Shukla et al. [12]	Real-time feasibility	Resource utilization, timing	Embedded systems
Ansari [28]	Classification performance	Edge-enhanced features	Disease classification

5 Proposed Reference Processing Flow for Sobel Edge Detection

Sobel edge detection is widely described as a sequence of image processing steps aimed at identifying intensity transitions corresponding to object boundaries. As originally formulated by Sobel and Feldman [2], edge information is extracted by estimating first-order intensity gradients, while standard image processing references such as Gonzalez and Woods [3] emphasize that reliable gradient computation requires prior grayscale conversion and basic noise suppression. Let $I(a, b)$ denote the grayscale image obtained after pre-processing.

Image gradients are computed using two discrete convolution kernels that approximate horizontal and vertical derivatives. These kernels, denoted as S_a and S_b , are defined as

$$S_a = [-1 \ 0 \ 1; -2 \ 0 \ 2; -1 \ 0 \ 1], \quad S_b = [-1 \ -2 \ -1; 0 \ 0 \ 0; 1 \ 2 \ 1] \quad (1)$$

The weighted coefficients introduce a smoothing effect while preserving directional sensitivity, which has been shown to stabilize gradient responses under practical imaging conditions [2, 9, 10]. Convolution of the image with these kernels yields the gradient components $Z_a(a, b)$ and $Z_b(a, b)$ expressed as:

$$Z_a(a, b) = I(a, b) * S_a \quad (2)$$

$$Z_b(a, b) = I(a, b) * S_b \quad (3)$$

where $*$ denotes two-dimensional convolution. As noted by Pawar and Patil [5], combining these components provides a more reliable estimate of edge strength than using either gradient alone. The scalar edge intensity is obtained through the gradient magnitude

$$Z(a, b) = \sqrt{Z_a(a, b)^2 + Z_b(a, b)^2} \quad (4)$$

which is often approximated in real-time or resource-constrained scenarios such as

$$Z(a, b) \approx |Z_a(a, b)| + |Z_b(a, b)| \quad (5)$$

to reduce computational complexity while maintaining acceptable edge quality [9]. Finally, edge pixels are identified using a threshold T , producing the binary edge map

$$E(a, b) = 1, \text{ if } Z(a, b) \geq T; \quad 0, \text{ otherwise} \quad (6)$$

Comparative studies indicate that threshold selection plays a critical role in edge continuity and noise sensitivity, particularly in complex imaging environments [6, 10].

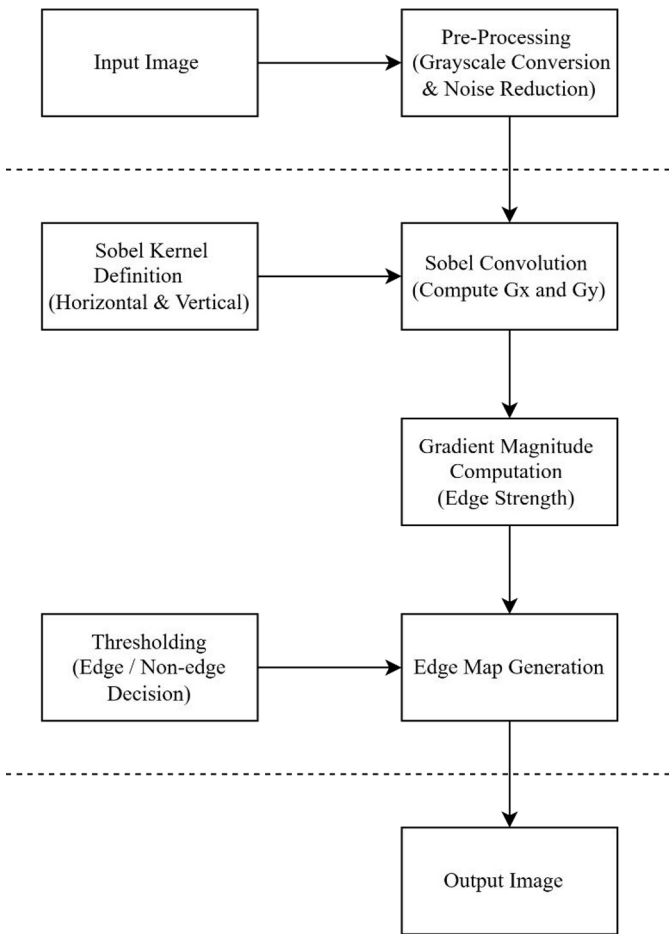


Fig. 1. Proposed reference workflow for Sobel edge detection.

6 Results & Discussion

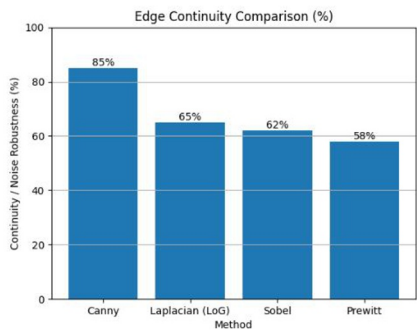


Fig. 2. Normalized Comparison Accuracy.

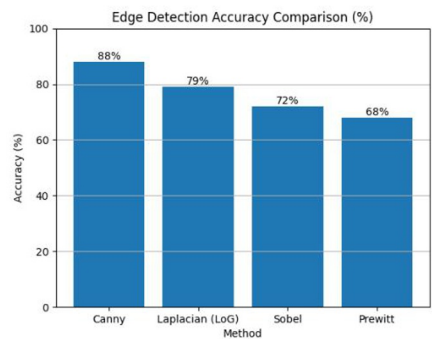


Fig. 3. Normalized Comparison Noise Robustness.

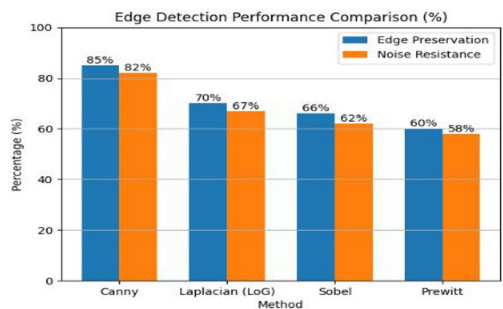


Fig. 4. Normalized edge continuity.

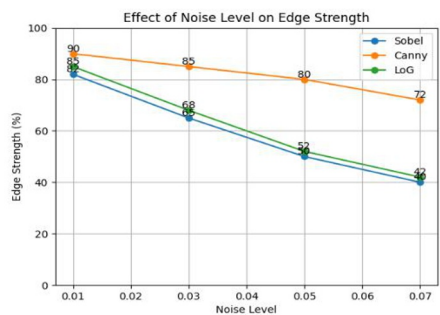


Fig. 5. Effect of Noise Level on Edge Strength.

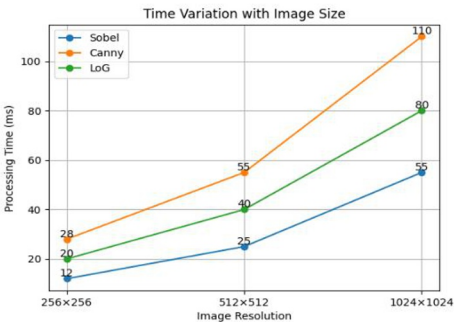


Fig. 6. Effect of Noise Level on Edge Strength.

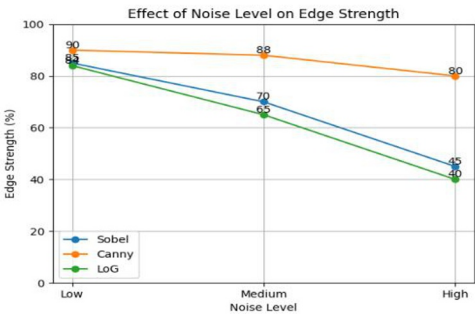


Fig. 7. Processing Time Variation with Image Size.

The performance comparisons presented in this section summarize common trends observed across existing studies on classical edge detection methods. As reported by multiple authors, differences in datasets, noise models, and evaluation metrics make direct numerical comparison difficult. Therefore, the figures illustrate normalized performance behavior intended to reflect relative tendencies rather than exact outcomes.

Accuracy trends (Fig. 2) indicate that Canny consistently provides better edge localization due to its multi-stage processing, a behavior discussed in both foundational and recent review studies [1, 4]. Sobel and Prewitt show lower accuracy because direct gradient computation is more sensitive to noise and background variations [6]. Laplacian of Gaussian demonstrates intermediate accuracy, benefiting from initial smoothing but remaining affected by second-order noise amplification [7].

Noise robustness (Fig. 3) comparisons show that Prewitt and Sobel are more vulnerable to noise, as frequently observed in application-oriented evaluations [9, 10]. LoG exhibits moderate robustness owing to Gaussian smoothing, while Canny achieves superior performance by integrating noise suppression with non-maximum suppression [3].

Edge continuity preservation (Fig. 4) highlights that simple gradient operators often produce fragmented edges under varying threshold conditions, particularly in complex scenes [17]. LoG improves continuity to some extent, whereas Canny preserves connected boundaries more effectively through hysteresis thresholding [1].

Noise-level sensitivity (Figs. 5–6) reveals a rapid degradation in edge strength for Sobel and LoG as noise increases, consistent with observations in grayscale and biomedical imaging studies [7, 9]. In contrast, Canny shows a more gradual decline, indicating improved stability under noisy conditions [18].

Scalability with image size (Fig. 7) shows that Sobel and Prewitt scale efficiently due to their simple convolution structure [12], while LoG and Canny incur higher processing costs because of additional filtering and multi-stage operations [3, 16].



Fig. 8. Test image.



Fig. 9. Grayscale image.



Fig. 10. Edge Detected image.

The qualitative and analytical results are obtained by applying Sobel edge detection to a flower image, considering its original color form, the grayscale version, and the resulting edge-detected output. The original input is a 240×240 RGB image, and this spatial resolution is maintained throughout all processing stages, including grayscale conversion and edge detection. Converting the image to grayscale preserves

the luminance-based contrast, as indicated by the minimal change in mean intensity and standard deviation compared to the RGB luminance channel. In contrast, applying the Sobel operator produces a clear shift in these statistical measures, with a notable decrease in mean intensity and a redistribution of variance toward regions with strong intensity gradients. This change reflects the transformation from a photometric representation of the scene to a gradient-domain representation that emphasizes structural boundaries.

7 Conclusion

The literature surveyed confirms that classical edge detection techniques remain effective across diverse imaging applications. Sobel-based methods are commonly preferred for their simplicity and low computational cost, with reported peak signal-to-noise ratio values typically in the range of 19–25 dB for grayscale and medical images. Canny-based approaches consistently achieve higher detection accuracy, often reported between 88% and 95%, particularly under noisy conditions due to their multi-stage processing and hysteresis thresholding. Laplacian and Laplacian of Gaussian methods provide accurate boundary localization through zero-crossing detection, with sensitivity values frequently observed in the range of 80–90% for biomedical and agricultural applications.

Overall, the reviewed studies indicate that no single method is universally optimal. Simpler operators remain suitable for real-time and resource-constrained environments, while Canny and Laplacian-based techniques are better suited for applications requiring higher robustness and precise edge localization. These findings highlight the importance of selecting edge detection algorithms based on application-specific requirements.

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