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REVIEW

Notes on edge detection approaches

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Abstract
Edge detection is an important research area that finds widespread applications in various fields, like image segmentation, shape extraction, pattern recognition, medical image processing, and motion analysis, etc. It is a mathematical model that identifies points in a digital image at which the intensities of an image changes significantly are known as edges or region boundaries. However, it is a critical concern that what is the minimum value of significant intensity change or the threshold for a situation. To cope with this concern, different edge detection methods are being developed. But still, this concern is not completely solved—as the problem is ill-posed. This article briefly describes important notes on the requirements and difficulties of various edge detection approaches classifying into five categories to find accurate edges. It critically reviews the setting of thresholds by different techniques through investigating the performances to find the state-of-the-art. In addition, it points out the current challenges and shows possible future research directions.

Keywords Edge detection · Gradient operator · Fuzzy inferencing · Evolutionary algorithms

1 Introduction

Edge is a dominant image feature that is useful in many applications of image processing, computer- and robot-vision, like image segmentation, feature description, image enhancement, pattern recognition, image restoration, image compression, and object tracking (Wei et al. 2008; Pirzada et al. 2013; Bhadauria et al. 2013; Gupta et al. 2016; Rezai-Rad and Aghababaie 2002; Shin et al. 1998; Yang and Sheu 2016; Pal and King 1983; Ma et al. 2018). Edges are the significant changes in image intensity level, which usually occur between the boundaries of two different objects in an image (Marr and Hildreth 1980; Hildreth 1983). The edge detection method refers to the process of finding the boundaries of objects within the image. It is used to detect the discontinuities of brightness or abrupt changes in pixel intensity, which is used to characterize the boundaries of objects in a scene.

Various edge detection methods have been developed which can be divided into three domains: spatial domain, frequency domain, and wavelet domain. In the spatial domain, gradient operations are performed directly on image pixels. Roberts, Prewitt, and Sobel edge detectors are of first-order type methods, and Laplacian, Gaussian-Laplacian, and Canny are of second-order type methods (Rashmi and Saxena 2013; Wang 2007; Haralick 1984; Nalwa and Binford 1986; Mahalle and Shah 2017; Basu 2002; Gonzalez and Woods 2002; Canny 1986; Rong et al. 2014; Bao et al. 2005). The first-order type edge detector searches for points where the gradient value is large, but the second-order type finds for points where zero-crossings occur. In the frequency domain, an image is first converted to a frequency domain, and then various operations were performed (Shanmugam et al. 1979). Phase congruency (Kovesi 2003) is a good frequency-domain method that utilizes the phase coherence property of the principal moment components to determine the edge information. Though this method is somehow robust to illumination and contrast variations but is sensitive to noise and, also computationally expensive. In the wavelet domain, an image is transformed into sub-banded multifrequency levels, which is helpful for noise suppression to find improved edge detection (Kovesi 2003). Fine details are extracted in low frequencies

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and the image contour is extracted in high frequencies. The multiresolution analysis finds importance in contour detection (Han et al. 2019; Papari and Petkov 2011a; Grigorescu et al. 2003, 2004). In the active shape model (ASM), edge or contour detection of an object is done by searching for an optimum location of one point of the ASM based on the principal component analysis (PCA) of gray values located at each point on the boundary of the object through a distance minimization procedure (Papari and Petkov 2011b). A review of different approaches of contour detection is available in Papari and Petkov (2011b).

In addition, some cases require high precision edge detection. To handle these cases, various subpixel methods are developed, such as curve-fitting (Ziou and Tabbone 1998), partial area effect (Guo Sheng Xu 2009), and moment-based methods (Trujillo-Pino et al. 2013; Ghosal and Mehrota 1993). Among these, the curve fitting method is noise sensitive, partial area effect, and moment-based methods are computationally expensive.

The classical edge detector operators, such as Sobel operator, Robert operator, Prewitt operator are easy to implement and simple to detect edges along with their orientations. Zero-crossing operators like Laplacian and other second-order derivative operators have fixed characteristics in all directions concerning the detection of edges. But all these operators are sensitive to noise. On the other hand, a Canny operator (Canny 1986; Rong et al. 2014; Bao et al. 2005) detects better edges in noisy conditions, as it accommodates a method to counter this noise problem before edge detection. Compare to Canny, Smith and Brady (Christian 2017) developed a non-derivative filtering method named SUSAN (Smallest Univalue Segment Assimilating Nucleus), which is also able to suppress noise and detect edges in a faster way. Besides, some other methods (Smith and Brady 1997; Demigny 2002; Shen Mar. 1992; Petrou and Kittler May 1991; Sarkar and Boyer Nov. 1991; Rao and Ben-Arie Dec. 1994; Failed 1990; Zhang et al. 2008, 2014; Simoncelli and Farid 1996; Fan 2005; Jiang 2007; Pascal Fua 1990; Yuan 2013; Seung Woo Lee 2018; Mittal et al. 2019; Di et al. 2017; Morronea and Owens 1987; Wenbo et al. 2012; Xiang et al. 2017; Kisworo et al. 1994; Yu-qian et al. 2005) have already been developed based on the fitting of analytical models, mathematical morphology, linear filtering, local energy, and orientation analysis.

In all edge detection techniques, a clear demarcation or threshold is required between the pixels with significant local intensity variations (i.e. edge pixels) and not significant local intensity variations (i.e. non-edge pixels). However, noise always poses a problem in this demarcation. The threshold selection required a stringent precondition that the error probability of false alarm in recognizing edge pixels is minimum. To handle this, researchers adopted the fuzzy reasoning for the successful detection of edge-strengths without being misled by the noises (Pal and King 1983; Evans and Liu 2006; Russo 1998; Tao et al. 1993; Liang and Looney 2003; Hanmandlu et al. 2004; Wu et al. 2007; Hu et al. 2007; Alshennawy and A. Aly 2009; Zhang et al. 2009, 2010; Melin et al. 2010; Zhao et al. 2001a; Khunteta and Ghosh 2014; Laishram et al. 2014; Khalid et al. 2010; Verma and Parihar 2017; Verma et al. 2013; El-Khamy et al. 2002; Li and Gao 2011; Thakkar and Shah 2011). Later, for finding the exact edges they moved to evolutionary optimization algorithms, such as particle swarm optimization (PSO) (Zhao et al. 2001a; Khunteta and Ghosh 2014; Laishram et al. 2014), bacterial foraging algorithm (BFA) (Khalid et al. 2010; Verma and Parihar 2017; El-Khamy et al. 2000; Kaur and Maini 2013; Verma et al. 2011a), genetic algorithm (GA) (Agarwal and Goel 2016), ant colony optimization (ACO) (Yoshimura and Oe 1997), bee colony optimization (BCO) (Verma et al. 2011b), etc. to fix an optimum threshold.

In all edge detection techniques, the prime concerns are accuracy, edge connectivity, and edge uniformity (Seung Woo Lee 2018). The performances of edge detection techniques are being measured both qualitatively (subjectively) and quantitatively (objectively). In this work, we have reviewed the edge detection methodologies in the threshold selection perspective dividing into five major categories.

The contributions of this work are as follows:

(i) Summarizes the existing edge detection methods in five major categories along with the setting of thresholds.
(ii) Compares and investigates the performance of various edge detection algorithms to find out the state-of-the-art.
(iii) Point out the challenges that must be addressed by future researchers.

The remainder of the paper is organized as follows. Section 2 presents the basic concept of the edge detection method. Section 3 highlights the requirements and challenging issues of edge detectors. Section 4 describes the methodologies of different edge detectors. Section 5 focuses on different evaluation metrics for measuring the quantitative performance of different edge detectors. Section 6 extracts the state-of-the-art edge detection approaches. Section 7 shows the directions for future research for further improvements. Finally, Sect. 8 concludes the paper.

2 Basic edge detection principle

As discussed in the previous section that edge is extracted by estimating the local variation in intensity through thresholding. The variation in intensity is usually

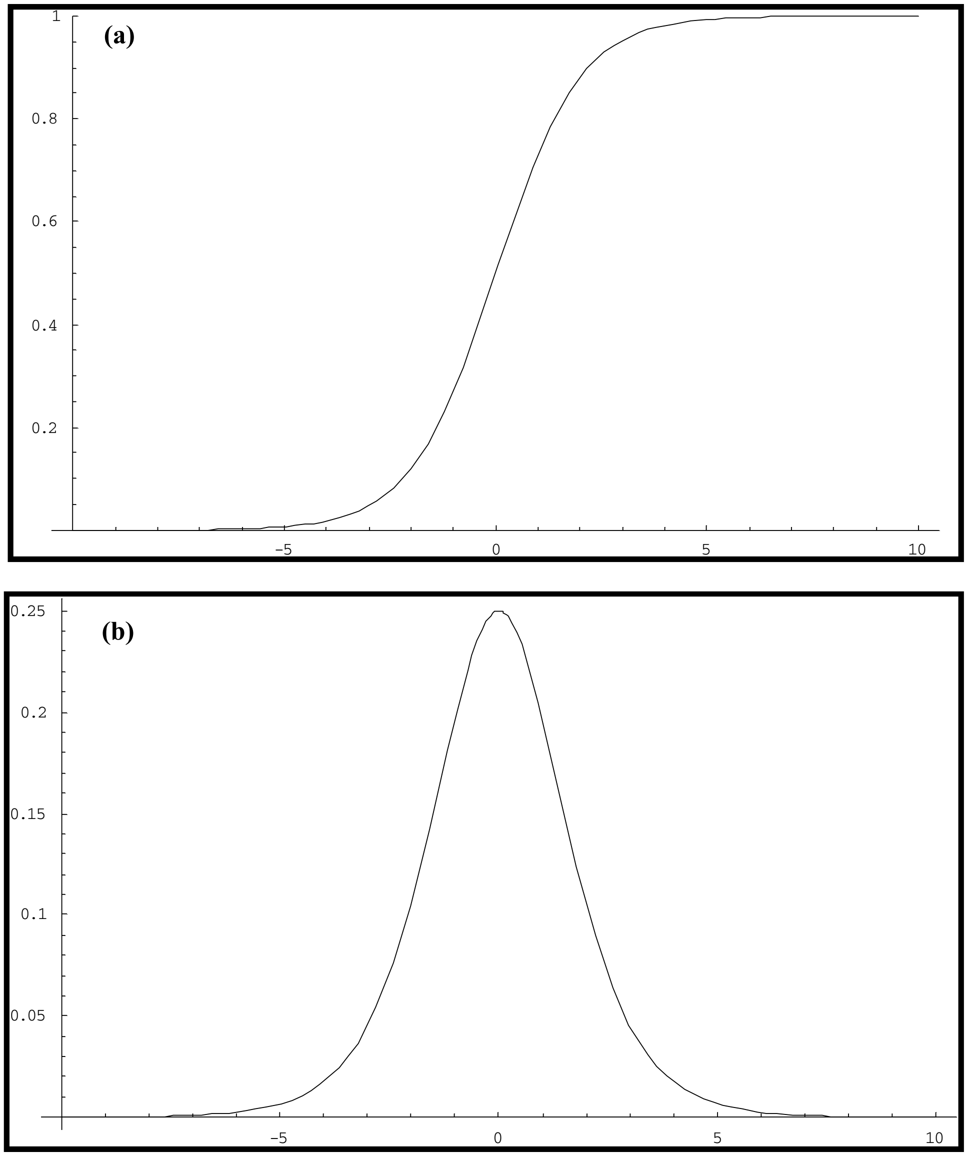


Fig. 1 **a** 1D function of intensity distribution, **b** its derivative shows a (spike) high-intensity change at the edge boundary and low-intensity change at the homogenous region

determined by the first-order differentiation of the image function. Figure 1 shows the detection of intensity variation for a one-dimensional (1D) continuous function.

For a two-dimensional (2D) image function $f(x, y)$, edge strength can be represented by a gradient vector as,

$$\nabla \boldsymbol{f} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\nabla f}{\nabla y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{f}_x \\ \boldsymbol{f}_y \end{bmatrix} \tag{1}$$

where f_x and f_x are the partial derivatives of intensity along with the x-axis and y-axis directions, respectively. The gradient vector magnitude (which is the candidate edge) at a pixel location (x, y) can be determined vectorially (by L_2 norm) as

$$|\nabla \boldsymbol{f}| = \sqrt{\boldsymbol{f}_x^2 + \boldsymbol{f}_y^2} \tag{2}$$

To reduce the computational burden, it can also be represented (by L_1 norm) as.

$$|\nabla \boldsymbol{f}| = |\boldsymbol{f}_x| + |\boldsymbol{f}_y| \tag{3}$$

After that, a thresholding operation is applied on this candidate edge (edge strength) to determine the exact edge.

3 Requirements and difficulties in edge detection

An image can be divided into two regions: foreground (object region) and background (non-object region). The region separation in an image is a helpful clue for the image as well as for object understanding and recognition. As mentioned earlier that edge detection is a mechanism to extract the object boundaries through locating intensity changes. However, due to diverse additive or multiplicative noise, imaging defects, and uneven lighting situations, modification of true image intensity are frequent phenomena. Therefore, an edge detection algorithm should possess three fundamental operations, such as smoothing (for noise reduction), differentiation (for candidate edge image creation through image derivatives), and labeling (for localizing true edges through discarding false edges) (Papari and Petkov 2011b).

From a computer vision perspective, according to Zhu (Verma et al. 2016) edge detection has to fulfill four requirement criteria, such as edges are to be (i) correctly identified, (ii) at right positions, (iii) forming continual lines (edge connectivity), and (iv) with uniform width. These can be reduced to three basic requirements as accuracy, connectivity/continuity, and uniformity.

The basic problem in edge detection is that there is an uncertainty in finding edge positions, which means there is a possibility of false negatives (failed to detect true edges) and false positives (non-edge detected as edge points).

Point-wise summarization of the problems in edge detection which are responsible for performance deterioration is as follows:

(i) Uncertainty in finding true edges at the right locations due to noise and imaging defects.

(ii) Introduction of smoothing/blurring effect by noise suppressor linear filter at the point of sharp intensity transitions.

(iii) Edge detectors usually produce crowded or sparse edges containing many isolated edge points or broken segments without continuity and uniformity due to the wrong threshold selection. This causes a big problem for the application of computer vision tasks which require a concise and accurate representation of the object boundaries.

4 Edge detection methods

Based on the above discussions, a framework of edge detection methodology is shown in Fig. 2. Figure 3 presents the various approaches to edge detection techniques.

4.1 Gradient-based edge detection

The Gradient-based edge detection method works basically on the first derivative of the image intensity to find the intensity changes. This differentiation is done with different types of horizontal- or/and vertical-mask of the image as discussed in Sect. 2. Commonly used masks (edge operators) are Roberts, Prewitt, Sobel, and isotropic as first-order and Laplacian and Laplacian of Gaussian as second-order. The second-order operators are more sophisticated than those of the first order, as the first-order edge detector searches for the point where the gradient value is high and the second-order edge detector finds the edge point at zero-crossing.

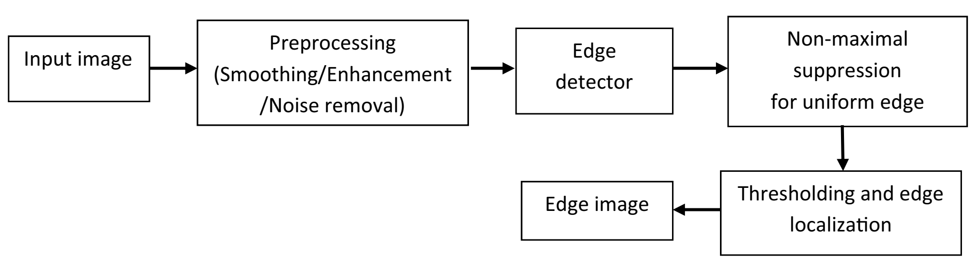


Fig. 2 A framework of the edge detection technique

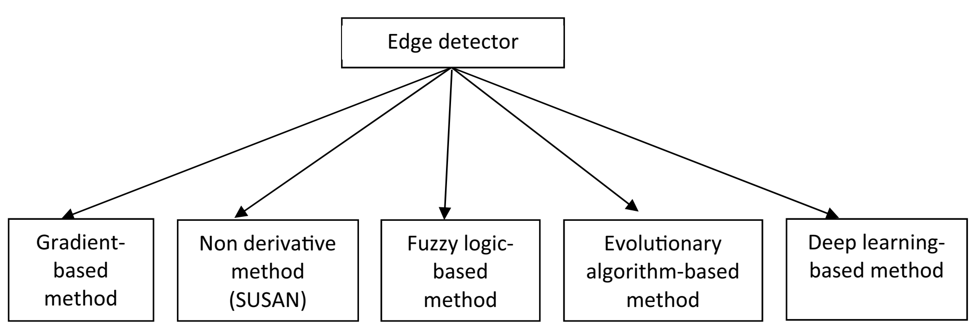


Fig. 3 Different approaches to edge detection

Among the first-order operators, the Sobel operator is putting more stress on the diagonal edge than the horizontal and vertical edges. Figures 4 and 5 show some common types of first-order and second-order derivative edge detectors, respectively. However, these are highly sensitive to noise and exhibit poor performance in noisy or real-life environments. All gradient-based methods need localization through the non-maximal suppression and hysteresis thresholding.

To overcome the above problems Canny (1986) derives an optimal edge detection strategy using the Gaussian edge detector based on the Marr-Hildreth edge detection principle (Marr and Hildreth 1980). Canny edge detection performs three operations: smoothing to reduce noise by Gaussian filtering, differentiation by Laplacian zero crossings, and then labeling by hysteresis thresholding that uses two thresholds T_{high} and T_{low}. A sample hysteresis algorithm (Rashmi and Saxena 2013) is given below.

1. **if** gradient > T_{high} **then** keep the edge
2. **if** T_{low} < gradient < T_{high} **then** check any of its neighbors in the gradient mask region has gradient > T_{low} **then** keep the edge
3. **if** gradient < T_{low} **then** discard the edge

4.2 Fuzzy logic-based edge detection

As mentioned earlier that researchers adopted the fuzzy decision-theory for the correct detection of edges without being misguided by the noises. Fuzzy logic, developed by Lotfi Zadeh (Zhu 1996), is a powerful tool to handle the situation of ambiguity due to noise. Fuzzy logic was initially used by Pal and King (Pal and King 1983) in edge detection of the X-ray image. This initiative is intensified by many works, for example, please see (Evans and Liu 2006; Russo 1998; Tao et al. 1993; Liang and Looney 2003; Hanmandlu et al. 2004; Wu et al. 2007; Hu et al. 2007; Alshennawy and A. Aly 2009; Zhang et al. 2009,2010; Melin et al. 2010; Zhao et al. 2001a; Khunteta and Ghosh 2014; Laishram et al. 2014; Khalid et al. 2010; Verma and Parihar 2017; Verma et al. 2013; El-Khamy et al. 2002; Li and Gao 2011; Thakkar and Shah 2011). A basic work-flow mechanism of the fuzzy system in edge detection is shown in Fig. 6. Mostly, it uses membership function and some set of fuzzy IF–THEN rules to find potential edge pixels in ambiguous situations. This can be performed usually by two types of fuzzy sets: Type-1 and Type-2. Type-1 fuzzy sets are simple and can handle uncertainties by using certain membership functions that the user believes capture the uncertainties. It is characterized by 2D membership functions in which each element of the type-1 fuzzy set has a membership value that is a crisp number in [0, 1]. On the other hand, Type-2 fuzzy sets are an extension of Type-1 sets where these are characterized by 3D fuzzy membership functions in a sense that the additional dimension provides extra degrees of freedom to model the Type-1 fuzzy sets to capture the more uncertainties of the element. Therefore, Type-2 fuzzy sets are useful in circumstances where it is difficult to determine the exact membership function for a fuzzy set to incorporate the uncertainties. As an instance, Melin et al. (2009) determined intensity gradients at each image point as the probability of occurrence of an edge. They then used the type-2 fuzzy rule for the detection of edges in the presence of noise.

Many researchers worked on edge detection based on the fuzzy technique. Mansua Zhao et al. proposed (2010) a fuzzy logic used for edge detection of an image based

(a)

-1	-1	-1
-1	8	-1
-1	-1	-1

(b)

0	-1	0
-1	4	-1
0	-1	0

Fig. 5 Second-order derivative (zero crossings) 3 × 3 masks: **a** Laplacian and **b** Laplacian of Gaussian

(a) X-mask

-1	0	+1
-1	0	+1
-1	0	+1

(a) Y-mask

-1	-1	-1
0	0	0
+1	+1	+1

(b) X-mask

-1	0	+1
-2	0	+2
-1	0	+1

(b) Y-mask

-1	-2	-1
0	0	0
+1	+2	+1

(c) X-mask

-1	0	+1
$-1/\sqrt{2}$	0	$1/\sqrt{2}$
-1	0	+1

(c) Y-mask

-1	$-1/\sqrt{2}$	-1
0	0	0
+1	$+1/\sqrt{2}$	+1

Fig. 4 First-order derivative 3 × 3 masks: **a** Prewitt, **b** Sobel, and **c** Isotropic

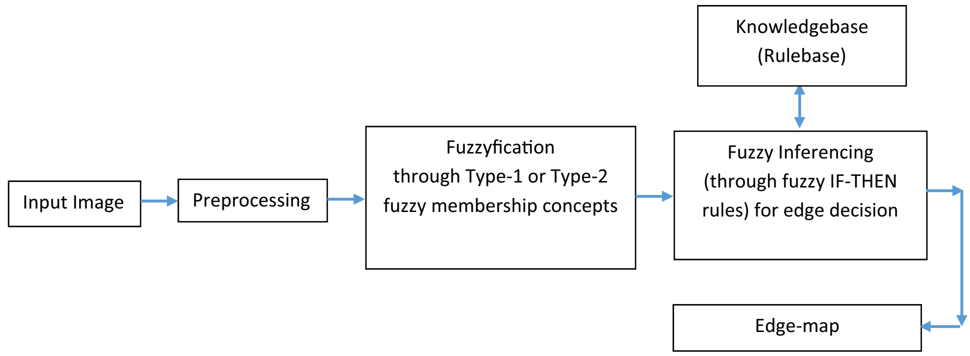


Fig. 6 Basic framework of the fuzzy-based edge detection technique

on the concept of dividing the gray level image ranges into three values. The researcher uses three values as entropy maxima to describe the image and uses different membership functions to represent the transformation from and to the crisp value. In a fuzzy-based system, fuzzification is the first stage where different membership functions (based on Type-1 or Type-2) can be used as an input, in the second stage, IF–THEN rules (as fuzzy inference rules) are used for decision making and in the third stage (as the output stage), the fuzzy values are mapped to new crisp values for producing the edge-map. The fuzzy rule-based edge detection method offers more advantages, such as setting the new rules or changing the parameters to produce uniform width edges. Hence it is a flexible technique with less complexity, and, also gives better accuracy in finding the true edges. Some extensive results and detail analyses can be found in references (Evans and Liu 2006; Russo 1998; Tao et al. 1993; Liang and Looney 2003; Hanmandlu et al. 2004; Wu et al. 2007; Hu et al. 2007; Alshennawy and Aly 2009; Zhang et al. 2009, 2010; Melin et al. 2010; Khalid et al. 2010; Verma and Parihar 2017; Verma et al. 2013; Zhao et al. 2001b; El-Khamy et al. 2002; Li and Gao 2011).

4.3 Non-derivative edge detector

Smith and Brady (Christian 2017) introduced a non-derivative edge detector named SUSAN (Smallest Univalue Segment Assimilating Nucleus) whose basic idea is to associate each pixel of the image to a small area of the neighborhood pixels with similar brightness known as USAN (Univalue Segment Assimilating Nucleus). They used a circular mask consists of 37 pixels whose usual radius is 3.4 pixels in finding USAN area for SUSAN edge detection.

The algorithm of SUSAN edge detection can be briefly described as follows:

Step 1: Compute the USAN area strength of an image point by comparing the luminance of each pixel within the mask with that of the nucleus by using the following equation.

$$n(r_0) = \sum_r \text{compare}(r, r_0) \tag{4}$$

where r_0 is the mask center or nucleus, r is the pixel within the mask, and

$$\text{compare}(r, r_0) = \begin{cases} 1 & \text{if} \left| I(r) - I(r_0) \right| \le th \\ 0 & \text{if} \left| I(r) - I(r_0) \right| \ge th \end{cases} \tag{5}$$

where I is the luminance of a pixel and th is the luminance difference threshold.

Smith and Brady (Christian 2017) simplified this equation using a smooth as well as a stable function as

$$\text{compare}(r, r_0) = e^{-\left(\frac{I(r)-I(r_0)}{th}\right)^6} \tag{6}$$

Step 2: Determine the edge response based on USAN strength by using the following equation.

$$\text{edge\_response}(r_0) = \begin{cases} g - n(r_0) & \text{if}\, n(r_0) < g \\ 0 & \text{if}\, n(r_0) \ge g \end{cases} \tag{7}$$

where g is set as $\frac{3}{4} n_{nmax}$.

Step 3: If required, then apply non-maximum suppression, thinning, and sub-pixel estimation.

Figure 7 shows four circular masks at different places on a simple image to find local areas of USAN describing the algorithmic concept of SUSAN edge detection. As it is a non-derivative-based operator, so no noise is added during edge extraction operation.

The SUSAN algorithm is considered as a robust, noise-resistant, and reliable edge detection compare to the gradient-based methods.

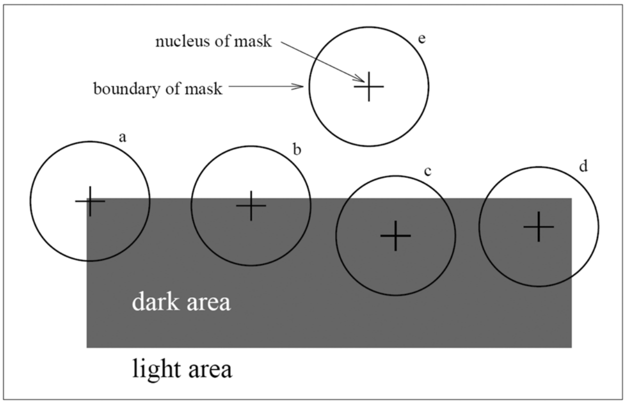


Fig. 7 Four circular masks at different places on a simple image (Papari and Petkov 2011b). The USAN area of each mask is marked in dark color. For a position that gives the highest USAN area indicates a flat region, half or near half USAN area indicates a straight edge and near smallest USAN area indicates a corner

4.4 Evolutionary edge detection algorithms

As mentioned earlier, fuzzy logic along with nature-inspired evolutionary algorithms, such as particle swarm optimization (PSO) (Zhao et al. 2001a; Khunteta and Ghosh 2014; Laishram et al. 2014), bacterial foraging algorithm (BFA) (Khalid et al. 2010; Verma and Parihar 2017; El-Khamy et al. 2000; Kaur and Maini 2013; Verma et al. 2011a), ant and bee colony optimization (ACO-BCO) (Yoshimura and Oe 1997; Verma et al. 2011b) genetic algorithm (GA) (Agarwal and Goel 2016), gravitational search (Zadeh 1965), etc. have recently been applied to edge detection. All these methods use optimization techniques to solve the uncertainty of true edges in the initial edge image through an optimum threshold selection. A GA-based edge detection technique was proposed as early as 1997 (Agarwal and Goel 2016). Sun et al. (1965) developed a true edge detection technique using the theory of universal gravity. Kahlid et al. (2014), developed an edge detection technique through a combination of fuzzy heuristic and PSO. Verma et al. (1997) developed an ant colony optimization to find the well-connected edges based on the local variation of ant movements. Verma et al. (2017) also developed another novel technique to find the possible edge by BFA in the direction of bacteria movement from the probability matrix. To work in noisy scenes, they modified this method by replacing the probabilistic derivative with a fuzzy derivative. In Zhao et al. (2001a), Khunteta and Ghosh developed a method known as the Fuzzy-PSO algorithm where they at first estimated the edge strength by fuzzy decision theory, and then they used the PSO algorithm for fixing an optimal threshold to determine the true edges. They estimated the edge strength (E) into three fuzzy linguistic variables (low, medium, and, high) based on horizontal gradient (f_x) and vertical gradient (f_y) using the following algorithm.

1. **if** f_x is low **AND** f_y is low **then** E is low
2. **if** (f_x is low AND f_y is high) **OR if** (f_x is high **AND** f_y is low) **then** E is medium
3. **if** f_x is high AND f_y is high **then** E is high

The edge strength of a pixel is then converted to edge pixel and non-edge pixel by selecting a threshold based on conditional probabilities P(non_edge|E) and P(edge | E) using Mamdani's max–min inference rule. They selected the optimal threshold by minimizing the overall error (edge pixels as non-edge pixels, i.e., misdetection error and non-edge pixels as edge pixels, i.e., false alarm error) of selecting pixels as edge pixels and non-edge pixels. They used PSO (Particle Swarm Optimization)—a meta-heuristic optimization approach to find an optimal threshold by minimizing the sum of the above two conditional probability errors (misdetection and false alarm). Details are available in reference (Zhao et al. 2001a).

4.5 Deep learning-based edge detection

In the above, we have discussed the conventional gradient-based edge detection method along with some other evolutionary as well as fuzzy techniques. All the techniques possess theoretical fairness but require appropriate thresholding. As deep learning-based approaches are giving extraordinary better and lively results in diverse domains than the traditional approaches, researchers are motivated in applying the deep learning-based methods to detect edges and object boundaries (Contour image database 2020; Xie and Tu 2017; Zhiding et al. 2017; Liu et al. 2017; Liu et al. 2020; Liu and Lew 2016). In usual deep learning, the convolutional neural network extracts feature gradually from layer-to-layer through image-to-image edge prediction into a holistic framework. Currently, among deep learning-based edge detection methods, the remarkable results are presented by Xie and Tu (Contour image database 2020) through their holistically-nested edge detection (HED) approach. The deep CNN HED consisting of 5 convolutional layers and all the layers are nested with VGGNet. It addresses the limitations of the Canny edge detector and solves the ambiguity in edge and detect object boundary. It automatically learns rich hierarchical (guided by deep supervision on layer-wise responses) edge maps to determine the edge or boundary of objects in images. It takes an image as input and in each layer, it performs non-linear operations called image-to-image edge prediction and generates an edge map that is approaching the ground truth image. Moreover, the whole network is fine-tuned from initialization with the pre-trained VGG-16 Net model. The details are available in the reference (Wang et al. 2015).

5 Performance evaluation and experiment

5.1 Evaluation metric

The performance of edge detection algorithms is evaluated both subjectively and objectively. Subjective measurement is done through human visual inspection, as the human is the ultimate evaluator. However, objective evaluation is done through various metrics. The frequent quantitative metrics, such as Entropy, MSE (Mean Square Error), PSNR (Peak Signal to Noise Ratio), SSIM (Structural Similarity Index Metric) (Seung Woo Lee 2018; Sun et al. 2007), and Similarity to the Ground Truth Figure (Sara et al. 2019). These metrics are described below.

(i) Entropy: This function can be defined for an image according to C. E. Shannon (Abdel et al. 2011) as

$$H = -\sum_{i=0}^{i=255} p_i \log(p_i) \tag{8}$$

Where H is the entropy of the 8-bit grayscale image, p_i is the probability of pixel with intensity i. A low value of H indicates less content of information and a high value indicates a high presence of noise. Therefore, the value of H should be of medium value for the best results.

(ii) MSE (Mean Squares Error): MSE between two images such as $g\ (x, y)$ and $g\hat{}\ (x, y)$ is defined as

Where M ×N is the image size. It indicates the mismatch (error) between the estimated edge image and the corresponding ground truth. Hence, a low value of MSE indicates better results.

$$MSE = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\|g(x,y) - \hat{g}(x,y)\|^2 \tag{9}$$

(iii) PSNR(Peak Signal to Noise Ratio): PSNR of an image is calculated as a ratio of the maximum possible signal power and the power of the distorting noise which affects the quality. This represents the approximate human perception of quality. For an 8-bit grayscale image, PSNR can be defined in decibel form as

$$PSNR = 20\log_{10}\frac{255}{\sqrt{MSE}} \tag{10}$$

(iv) SSIM (Structural Similarity Index Metric): SSIM a quality measurement metric is calculated based on the computation of three major aspects termed as luminance, contrast, and structural or correlation term. This index between two images is defined as

$$SSIM = [l(x,y)]^{\alpha} \times [c(x,y)]^{\beta} \times [s(x,y)]^{\gamma} \tag{11}$$

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

$$c(x,y) = \frac{2\sigma_x\mu\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

l, c, and s are used to compare the luminance, contrast, and structural similarities, respectively, of two image regions x and y. μ and σ are the mean and variance of the corresponding image region, respectively, C_1, C_2, C_3 are constants, α, β and γ are usually taken as unity.

(v) The similarity to the Ground Truth Figure: For binary edges, the following metric is used for performance evaluation as a similarity to the ground truth figure.

The **similaritytotheGroundTruthFigure**

$$= \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|} \tag{12}$$

where A is the estimated edge image and B is its ground truth image. This is a normalized score and the higher is the figure the better is the edge detection. This metric can also be represented through P values using the cardinality measure by Grigorescu et al. (Papari and Petkov 2011a).

$$P = \frac{card(E_T)}{card(E_T) + card(E_{FN}) + card(E_{Fp})} \tag{13}$$

where $card(E_T)$ is the number (cardinality) of true edge pixels that are detected by the edge detector, $card(E_{FN})$ is the number of true edge pixels that are missed by the edge detector (false negative) $card(E_{FP})$ number non-edge pixels that are detected as edges by the edge detector (false positive).

5.2 Experiment

In this work, we have compared the performance of five frequently used edge detectors (Canny, SUSAN, Fuzzy-BFA, Fuzzy-PSO, deep-learning) from the five categories for both subjective and objective evaluations using three bench-marked images of elephant, hyena, and rhino from

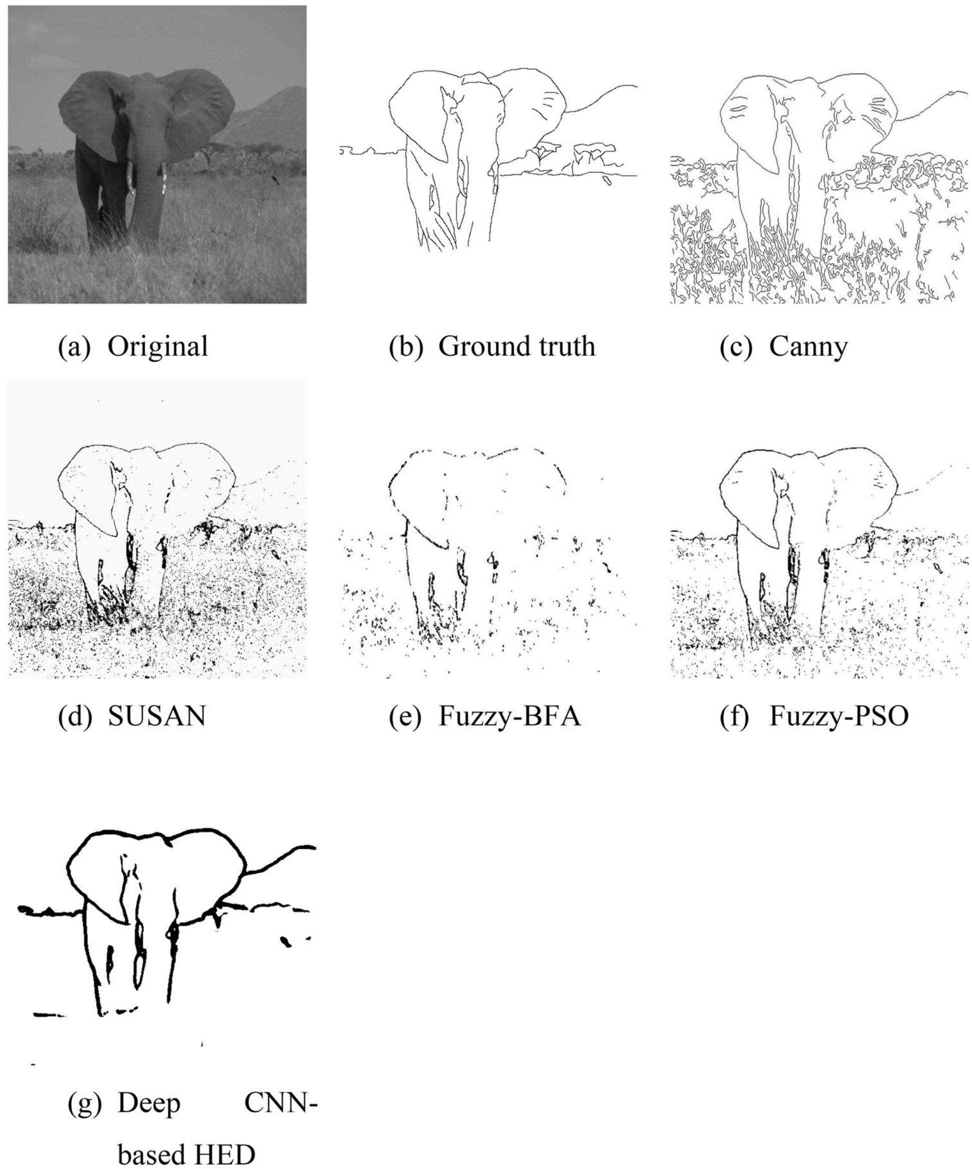
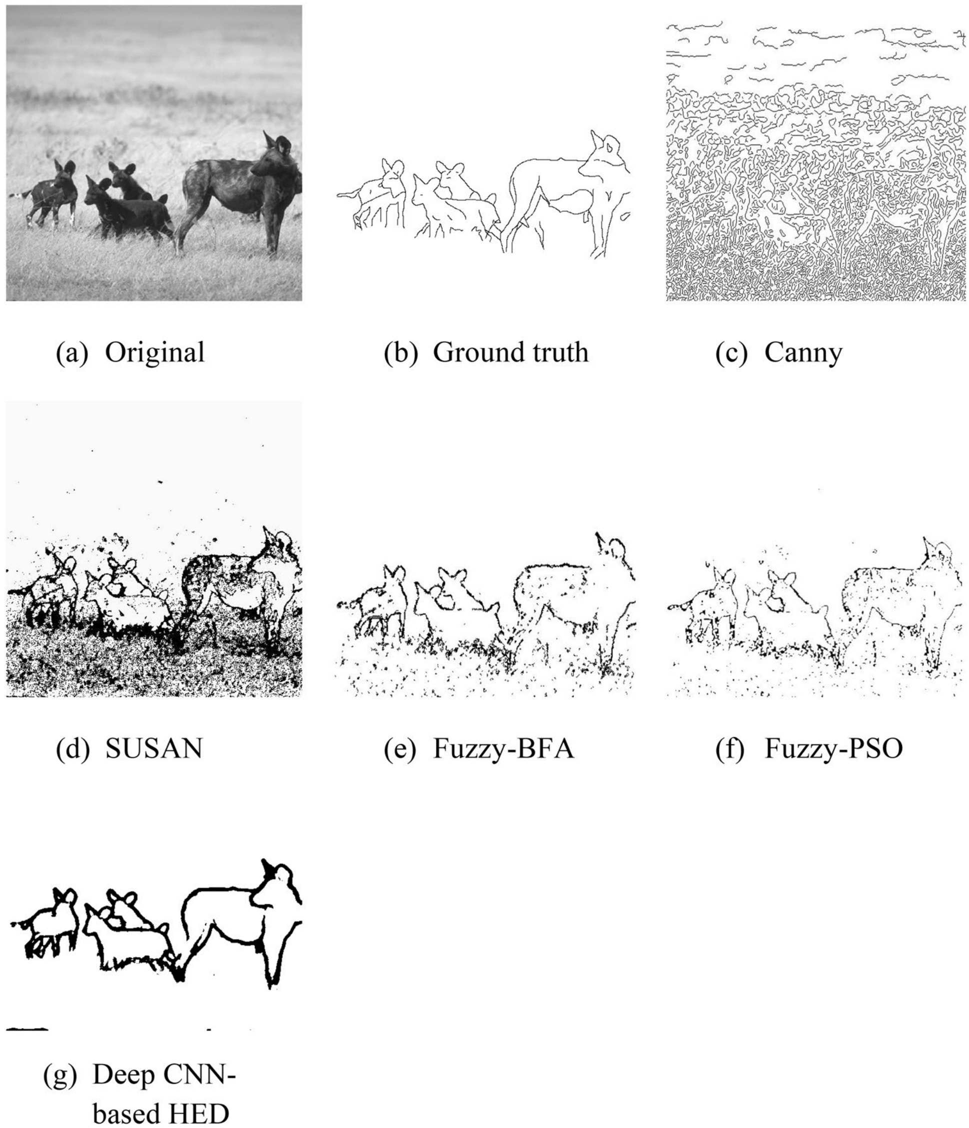


Fig. 8 Visual results of "elephant" image: by **a** Original image **b** Hand-drawn ground truth **c** Canny ($th = 0.05$), **d** SUSAN, **e** Fuzzy-BFA, **f** Fuzzy-PSO method (optimal $th = 0.22$), **g** Deep learning-based HED

the publicly available Contour Image Database (Shannon 1948). Figure 8 shows the subjective (visual) evaluation results for the elephant image and Figs. 9 and 10 show the same results for the hyena and rhino images. Table 1 shows the objective (quantitative) evaluation scores using P values. In calculating P-values we considered an edge pixel is correctly detected if it is present in the ground truth image in a 5×5 neighborhood of the concerned pixel, as suggested in (Papari and Petkov 2011a). This is a rational suggestion as the ground truth image of this database is manually drawn by a human, so a ground truth edge pixel is not always perfectly coincided with a local maximum of the estimated gradient magnitude. Canny, Fuzzy-BFA, and Fuzzy-PSO results are taken from (Zhao et al. 2001a) and the SUSAN results are estimated by us using the usual circular mask consists of 37 pixels given in the original paper of the SUSAN's pioneers Smith and Brady (Christian 2017) with the default threshold parameter. The threshold parameters of the Canny and the optimal parameter of the Fuzzy PSO are shown in the captions of Figs. 8, 9, 10. Results of the deep CNN-based HED method are produced using the algorithm given in the reference (Contour image database 2020) The figures and the table indicate that the deep-CNN-based method is the best approach, as it works on automatically learning-rich hierarchical (guided by deep supervision on layer-wise responses) edge maps to determine the edge or boundary of the object which is approaching to the ground truth image. On the other hand, fuzzy PSO works on minimizing the sum of the total misdetection and false alarm errors. However, still, there is a big difference between the ground truth and the obtained edge map by fuzzy PSO as well as other techniques.

Fig. 9 Visual results of "hyena" image: by **a** Original image **b** Hand-drawn ground truth **c** Canny ($th = 0.05$), **d** SUSAN, **e** Fuzzy-BFA, **f** Fuzzy-PSO method (optimal $th = 0.24$), **g** Deep learning-based HED



6 Current state-of-the-art approaches

Edge detection finds diverse real-life applications in both natural and medical image processing, computer and robot vision for segmentation, shape analysis, and enhancement, object recognition and tracking, restoration, compression, etc. People widely use Canny's approach (Canny 1986; Rong et al. 2014) and SUSAN (Christian 2017) technique for edge detection, as these are somehow simple and have noise handling capability. Canny utilized a Gaussian filter with a gradient operator and this helps it to handle noise. Smith and Brady (Christian 2017) did rigorous experiments with different concentrations of noise and found better results using the SUSAN operator. Later, people moved to fuzzy reasoning and evolutionary algorithms for better accuracy, edge continuity, and edge uniformity. As a consequence, Khunteta and Ghosh (Zhao et al. 2001a) developed a method known as the Fuzzy-PSO algorithm where they estimated the edge strength by fuzzy decision theory and selected the optimal threshold by PSO. They did sufficient experimentations and found better results in comparison to the conventional Sobel, Canny and fuzzy-BFA methods. A comparison between BFA and the Canny method is done by Agarwal and Goel (Verma et al. 2011a) and found that BFA gives better performance than Canny, as BFA utilizes swarm intelligence-based optimal threshold but Canny utilizes hysteresis thresholding (without optimization) and Gaussian filter as noise suppressor. As deep-learning-based approaches proved quite satisfactory performance in diverse domains, hence, researchers are now applying these techniques in the edge or boundary detection. It is found that the deep learning-based HED approach (Contour image database 2020) gives the best performance among all the existing methods.

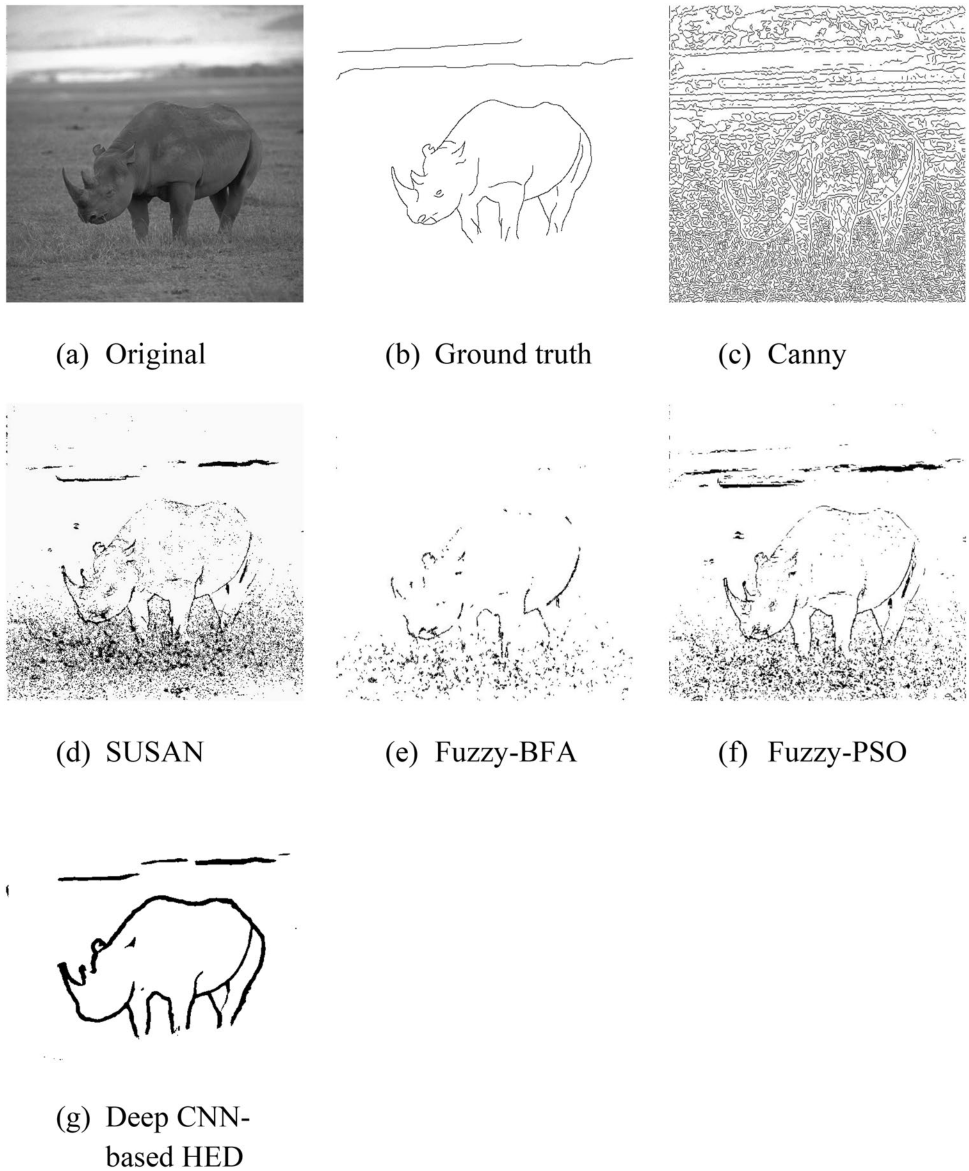


Fig. 10 Visual results of "rhino" image: by **a** Original image **b** Hand-drawn ground truth **c** Canny ($th = 0.05$), **d** SUSAN, **e** Fuzzy-BFA, **f** Fuzzy-PSO method (optimal th = 0.23), **g** Deep learning-based HED

7 Recommendations for future research

In the above section, we mentioned five state-of-the-art methods for edge detection applicable to real-life applications. In addition to this, some works also started on the real-time implementation of edge detection algorithms (Sarkar et al. 2017; Failed 2018, 2019). The real-time implementation is very important, as the whole world is seriously heading to developing autonomous systems where real-time edge detection will find direct applications in autonomous driving, security, and surveillance systems. This study suggests that researchers should focus on the following: (i) Going through the results of the state-of-the-art methods, we have found that still there is a difference between the obtained edge map and the corresponding ground truth, so this issue needs to be handled; (ii) There are not enough edge image databases (we found two databases which are given in Shannon 1948 and Wang et al. 2015) where the developed edge detection algorithms can be tested, so still, scopes are available to generate more challenging edge databases.

Table 1 Quantitative evaluation results by *P* values obtained for the test images

Edge detection approaches	*P* values obtained for the test images		
	Elephant	Hyena	Rhino
Canny	0.13	0.10	0.09
SUSAN	0.22	0.21	0.25
Fuzzy-BFA	0.32	0.35	0.33
Fuzzy-PSO	0.34	0.37	0.29
Deep CNN-based HED	0.59	0.65	0.52

8 Conclusion

In this paper, we have studied and analyzed various edge detection techniques for digital image processing. Gradient-based operators such as Sobel, Prewitt have significant drawbacks. They are very sensitive to noise, and not suitable for weak edges. On the other hand, the Canny edge detector also has drawbacks in selecting correct thresholds. Non-derivative SUSAN edge detector is somehow suitable for low contrast and noisy images. As, the threshold selection between the edge and non-edge pixels in an image is very important for effective edge detection in maintaining accuracy, edge continuity, and width uniformity, hence researchers moved to optimal thresholding through fuzzy reasoning as well as evolutionary algorithms. As a result, some good methods have been developed, such as Fuzzy-BFA and Fuzzy-PSO. Finally, due to better accuracy, deep-learning-based methods came into practice. We have comprehensively studied the various edge detection approaches, highlighted the requirements and difficulties in edge detection, state-of-the-art methods, and showed future research directions. This paper will help the researchers to find as well as to work for the optimal algorithm focused on real-time edge detection.

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Data availability The works used publicly available datasets mentioned in reference (Shannon 1948).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Agarwal A, Goel K (2016) Comparative analysis of digital image for edge detection by using bacterial foraging and canny edge detector. In: Proc. 2nd Int. Conf. Comput. Intell. Commun. Technol., Feb. 2016, pp. 125–129

Alshennawy A, Aly A (2009) Edge detection in digital images using fuzzy logic technique. World Acad Sci Eng Technol 27:178–186

Baareh AKM, Smadi AM, Freihat K, Al-Jarrah A (2011) Evaluating the performance of edge detection techniques through gradient method. Adv Comput Sci Eng 6(2):115–127

Bao P, Zhang L, Wu X (2005) Canny edge detection enhancement by scale multiplication. IEEE Trans Pattern Anal Mach Intell 27(9):1

Basu M (2002) Gaussian-based edge-detection methods—a survey. IEEE Trans Syst Man Cybern Part C Appl Rev 32(3):252–260

Bhadauria HS, Singh A, Kumar A (2013) Comparison between various edge detection methods on satellite image. Int J Emerg Technol Adv Eng 3(6):324–328

Canny J (1986) A computational approach to edge detection. IEEE Trans Pattern Anal Mach Intell 8(6):679–698

Christian J (2017) Accurate planetary limb localization for image-based spacecraft navigation. J Spacecr Rockets 54(3):708–730

Contour image database, Available Online: http://www.cs.rug.nl/~imaging/databases/contour_database/contour_database.html

Demigny D (2002) On optimal linear filtering for edge detection. IEEE Trans Image Process 11(7):728–737

Di Y, Li M-Y, Qiao T, Na Lu (2017) Edge detection and mathematic fitting for corneal surface with matlab software. Int J Ophthalmol 10(3):336–342

El-Khamy SE, Lotfy M, El-Yamany N (2000) A modifed fuzzy Sobel edge detector. In: Proc. IEEE 17th Nat. Radio Sci. Conf., Feb. 2000, pp. 1–9

El-Khamy SE, Ghaleb I, El-Yamany NA (2002) Fuzzy edge detection with minimum fuzzy entropy criterion. In: Proceedings of the 11th IEEE mediterranean electronical conference. pp. 498–503, Cairo, Egypt, May 2002

Evans AN, Liu XU (2006) A morphological gradient approach to color edge detection. IEEE Trans Image Process 15(6):1454–1463

Fan J (2005) A local orientation coherency weighted color gradient for edge detection. IEEE international conference on image processing, 14–14 Sept. 2005, Genova, Italy

Ghosal S, Mehrota R (1993) Orthogonal moment operators for subpixel edge detection. Pattern Recogn 26(2):295–306

Gonzalez RC, Woods RE (2002) Digital image processing, 2nd edn. Prentice Hall, Upper Saddle River

Grigorescu C, Petkov N, Westenberg MA (2003) Contour detection based on nonclassical receptive field inhibition. IEEE Trans Image Process 12(7):729–739

Grigorescu C, Petkov N, Westenberg MA (2004) Contour and boundary detection improved by surround suppression of texture edges. Image Vis Comput 22(8):609–622

Guo SX (2009) Sub-pixel Edge Detection Based on Curve Fitting. Proc. international conference on information and computing science, Manchester, UK, 21–22 May 2009

Gupta V, Kumar Singh D, Sharma P (2016) Image segmentation using various edge detection operators: a comparative study. Int J Innov Res Comput Commun Eng 4(8):14819–14824

Han F, Liu B, Zhu J, Zhang B (2019) Algorithm design for edge detection of high-speed moving target image under noisy environment. Sensors MDPI 19:343

Hanmandlu M, See J, Vasikarla S (2004) Fuzzy edge detector using entropy optimization. In: Proceedings of the international conference on information technology: coding computing (ITCC '04), pp. 665–670, Las Vegas, Nev, USA, April 2004

Haralick RM (1984) Digital step edges from zero-crossings of second directional derivatives. IEEE Trans Pattern Anal Mach Intell 6(1):58–68

Hildreth EC (1983) The detection of intensity changes by computer and biological vision systems. Comput Vis Graph Image Proc 22(1):1–27

Hu L, Cheng HD, Zhang M (2007) A high performance edge detector based on fuzzy inference rules. Inf Sci 177(21):4768–4784

Jiang X (2007) Extracting image orientation feature by using integration operator. Pattern Recogn 40:705–717

Kaur P, Maini R (2013) BFO based multi-thresholding edge detection technique. Int J Eng Res Appl 3(4):1872–1880

Khalid N, Manaf M, Aziz M (2010) Fusion of fuzzy heuristic and particle swarm optimization as an edge detector. In: Proceedings

of the international conference on information retrieval knowledge management, pp. 250–254, Shah Alam, Malaysia, 2010
Khunteta A, Ghosh D (2014) Edge detection via edge-strength estimation using fuzzy reasoning and optimal threshold selection using particle swarm optimization. Adv Fuzzy Syst Hindawi
Kisworo M, Venkatesh S, West G (1994) Modeling edges at subpixel accuracy using the local energy approach. IEEE Trans Pattern Anal Mach Intell 16(4):405–410
Kovesi P (2003) Phase congruency detects corners and edges. Proceedings of the seventh international conference on digital image computing: techniques and applications, DICTA 2003, 10–12 December 2003, Sydney, Australia. Available Online at http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.83.975&rep=rep1&type=pdf
Laishram R, Kumar WK, Gupta A, Prakash KV (2014)` A novel MRI brain edge detection using PSOFCM segmentation and canny algorithm. In: Proc. Int. Conf. Electron. Syst., Signal Process. Comput. Tech-nol. (ICESC 2014), January 2014, pp. 398–401
Lee C, Kim Y, Lee Y (2018) Design of real-time hardware for edge detection. International conference on computational science and computational intelligence (CSCI), Las Vegas, NV, USA, 2018, pp. 348–353, doi: https://doi.org/10.1109/CSCI46756.2018.00073
Li Y, Gao Z (2011) Edge detection based on fuzzy 2-partition entropy approach. In: Proceedings of the 3rd IEEE international conference on advanced computer control (ICACC 2011), pp. 616–619, Harbin, China, January 2011
Liang LR, Looney CG (2003) Competitive fuzzy edge detection. Appl Soft Comput J 3(2):123–137
Liu Y, Lew MS (2016) Learning relaxed deep supervision for better edge detection. Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR). pp. 231–240
Liu Y, Cheng M-M, Hu X, Wang K, Bai X (2017) Richer convolutional features for edge detection. Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), 2017, pp. 3000–3009
Liu Y, Cheng M-M, Fan D-P, Zhang L, Bian J-W, Tao D (2020) Semantic edge detection with diverse deep supervision. Available online: https://arxiv.org/pdf/1804.02864.pdf
Ma X, Liu S, Hu S, Geng P, Liu M, Zhao J (2018) SAR image edge detection via sparse representation. Soft Comput 22(8):2507–2515
Mahalle AG, Shah AM (2017) FPGA implementation of gradient based edge detection algorithms. Int J Innov Res Comput Commun Eng 5(5):10610–10616
Marr D, Hildreth E (1980) Theory of edge detection. Proc R Soc Lond B 207(1167):187–217
Melin P, Mendoza O, Castillo O (2010) An improved method for edge detection based on interval type-2 fuzzy logic. Expert Syst Appl 37(12):8527–8535
Mittal M, Verma A, Kaur I, Kaur B, Sharma M, Mohan Goyal L, Roy S, Kim T-H (2019) An efficient edge detection approach to provide better edge connectivity for image analysis. IEEE Access 7:33240–33255
Morronea MC, Owens RA (1987) Feature detection from local energy. Pattern Recogn Lett 6(5):303–313
Nalwa VS, Binford TO (1986) Ondetecting edges. IEEE Trans Pattern Anal Mach Intell 8(6):699–714
Pal SK, King RA (1983) On edge detection of x-ray images using fuzzy sets. IEEE Trans Pattern Anal Mach Intell 5(1):69–77
Papari G, Petkov N (2011a) An improved model for surround suppression by steerable filters and multilevel inhibition with application to contour detection. Pattern Recogn 44(9):1999–2007
Papari G, Petkov N (2011b) Edge and line-oriented contour detection: state of the art. Image Vis Comput 29(2–3):79–103
Pascal Fua YG (1990) Leclerc, "Model driven edge detection." Mach Vis Apps 3:45–56
Petrou M, Kittler J (1991) Optimal edge detectors for ramp edges. IEEE Trans Pattern Anal Machine Intell 13:483–491
Pirzada SJH, Siddiqui A (2013) Analysis of edge detection algorithms for feature extraction in satellite images. 2013 IEEE international conference on space science and communication, 1–3 July 2013, Melaka, Malaysia
Rao K, Ben-Arie J (1994) Optimal edge detection using expansion matching and restoration. IEEE Trans Pattern Anal Machine Intell 16:1169–1182
Rashmi A, Kumar M, Saxena R (2013) Algorithm and technique on various edge detection: a survey. Signal Image Process Int J (SIPIJ) 4(3):65–75
Rezai-Rad G, Aghababaie M (2002) Comparison of SUSAN and sobel edge detection in MRI images for feature extraction. international conference on information and communication technologies, Damascus, Syria, 24–28 April 2002
Rong W, Li Z, Zhang W, Sun L (2014) An improved Canny edge detection algorithm. Proc IEEE Int Conf Mechatron Automat 2(2):577582
Russo F (1998) Edge detection in noisy images using fuzzy reasoning. IEEE Trans Instrum Meas 47(5):1102–1105
Sara U, Akter M, Shorif Uddin M (2019) Image quality assessment through FSIM, SSIM, MSE and PSNR—a comparative study. J Comput Commun 7:8–18
Sarkar S, Boyer K (1991) On optimal infinite impulse response edge detection filters. IEEE Trans Pattern Anal Machine Intell 13:1154–1171
Sarkar S, Venugopalan V, Reddy K, Ryde J, Jaitly N, Giering M (2017) Deep learning for automated occlusion edge detection in RGB-D frames. J Signal Process Syst. 88:205–217. https://doi.org/10.1007/s11265-016-1209-3
Seung WL, Sin YL, Heui JP (2018) Precise edge detection method using sigmoid function in blurry and noisy image for TFT-LCD 2D critical dimension measurement. Cur Opt Photon. 2(1):69–78
Shanmugam KS, Dickey FM, Green JA (1979) An optimal frequency domain filter for edge detection in digital pictures. IEEE Trans Pattern Anal Mach Intell 1(1):37–49
Shannon CE (1948) A mathematical theory of communication. Bell Syst Tech J 27(3):379–423
Shen SCJ (1992) An optimal linear operator for step edge detection. CVGIP: Graph Models Image Process 54:112–133
Shen SCJ, Zhao J (1990) New edge detection methods based on exponential filter. Proc ICPR 10:1
Shin MC, Goldgof D, Bowyer KW (1998) An objective comparison methodology of edge detection algorithms using a structure from motion task. Proc. 1998 IEEE CVPR, Santa Barbara, CA, pp. 190–195
Simoncelli EP, Farid H (1996) Steerable wedge filters for local orientation analysis. IEEE Trans Image Process 5(9):1377–1382
Smith SM, Brady JM (1997) SUSAN—a new approach to low level image processing. Int J Comput Vis 23(1):45–78
Sun G, Liu Q, Ji C, Li X (2007) A novel approach for edge detection based on the theory of universal gravity. Pattern Recogn 40(10):2766–2775
Tao CW, Thompson WE, Taur JS (1993) A fuzzy if-then approach to edge detection. In: Proceedings of the 2nd IEEE international conference on fuzzy systems. 2:1356–1360. San Francisco, Calif, USA
Thakkar M, Shah H (2011) Edge detection techniques using fuzzy thresholding. In: Proceedings of the world congress on information and communication technologies (WICT 2011), pp. 307–312, Mumbai, India, December 2011

The Berkeley Segmentation Dataset and Benchmark, available online, https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/
Trujillo-Pino A, Krissian K, Alemán-Flores M, Santana-Cedrés D (2013) Accurate subpixel edge location based on partial area effect. Image Vis Comput 31(1):72–90
Verma OP, Parihar AS (2017) An optimal fuzzy system for edge detection in color images using bacterial foraging algorithm. IEEE Trans Fuzzy Syst 25(1):114–127
Verma OP, Hanmandlu M, Kumar P, Chhabra S, Jindal A (2011a) A novel bacterial foraging technique for edge detection. Pattern Recogn Lett 32(8):1187–1196
Verma OP, Singhal P, Garg S, Chauhan DS (2011b) Edge detection using adaptive thresholding and ant colony optimization. In: Proceedings of the world congress on information and communication technologies (WICT 2011), pp. 313–318, December 2011
Verma OP, Hanmandlu M, Sultania A, Parihar AS (2013) A novel fuzzy system for edge detection in noisy image using bacterial foraging. Multidimens Syst Signal Process 24(1):181–198
Verma OP, Agrawal N, Sharma S (2016) An optimal edge detection using modified artificial bee colony algorithm.' Proc. Nat. Acad. Sci., India Sect. A, Phys. Sci., vol. 86, no. 2, pp. 157–168, 2016
Wang X (2007) Laplacian operator-based edge detectors. IEEE Trans Pattern Anal Mach Intell 29(5):886–890
Wang J, Wang H, Wu S, Lin X, Yang Q (2015) Design and Implementation of real-time sobel edge detection on FPGA for mobile device applications. In: Proceedings of the ACM international workshop on mobility and middleware management in HetNets (MobiMWareHN), New York, USA, pp. 9–14, 2015, doi:https://doi.org/10.1145/2757757.2757759
Wei C, Guoliang W, Rongjin H, Hao Y (2008) The research of edge detection algorithm for Fingerprint images. 2008 World automation congress, 28 Sept.-2 Oct. 2008, Hawaii, USA (IEEE, Xplore)
Wenbo S, Zelin S, Lin Q (2012) Surface target edge detection based on local energy model in sea clutter background. Proceedings of SPIE. vol. 8419
Wu J, Yin Z, Xiong Y (2007) The fast multilevel fuzzy edge detection of blurry images. IEEE Signal Process Lett 14(5):344–347
Xiang Y, Wang F, Wan L, You H (2017) SAR-PC: edge detection in sar images via an advanced phase congruency model. Remote Sensing MDPI 1:13–15
Xie S, Tu Z (2017) Holistically-nested edge detection. Int J Comput Vis 125:3–18. https://doi.org/10.1007/s11263-017-1004-z
Yaman S, Karakaya B, Erol Y (2019) Real time edge detection via IP-core based sobel filter on FPGA. 2019 International conference on applied automation and industrial diagnostics (ICAAID), Elazig, Turkey, 2019, pp. 1–4, doi: https://doi.org/10.1109/ICAAID.2019.8934964
Yang KX, Sheu MH (2016) Edge-based moving object tracking algorithm for an embedded system. 2016 IEEE Asia Pacific conference on circuits and systems (APCCAS), Jeju, South Korea, 25–28 October 2016, pp. 153–155
Yoshimura M, Oe S (1997) Edge detection of texture image using genetic algorithms. In: Proceedings of the 36th SICE annual conference, international session papers (SICE '97), pp. 1261–1266, Tokushima, Japan, July 1997
Yuan XR (2013) 2-Dimension polynomial fitting for the edge detection. Appl Mech Mater, vol. 389. Trans Tech Publications, Ltd. pp. 969–973.
Yu-qian Z, Wei-hua G, Zhen-cheng C, Jing-tian T, Ling-yun L (2005) Medical images edge detection based on mathematical morphology. IEEE engineering in medicine and biology 27th annual conference, Shanghai, China, September 1–4
Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353
Zhang F, Huang X, Cheng X, Li D (2008) Edge extraction algorithm based on linear perception enhancement. Int Arch Photogramm Remote Sens Spat Inf Sci XXXVII(Part B3b):497–502
Zhang L, Xiao M, Ma J, Song H (2009) Edge detection by adaptive neuro-fuzzy inference system. In: Proceedings of the 2nd international congress on image and signal processing (CISP'09), Tianjin, China, October 2009
Zhang J, Lian Y,Dong L, Zhao X, Liu J (2010) A new method of fuzzy edge detection based on Gauss function. In: Proceedings of the 2nd international conference on computer and automation engineering (ICCAE 2010), pp. 559–562, Singapore, February 2010
Zhang H, Zhang SY, Wang LJ, Wang GZ (2014) Edge detection using the multi-oriented local energy. Appl Mech Mater 568–570:638–642
Zhao M, Fu A, Yan H (2001) A technique of three-level thresholding based on probability partition and fuzzy 3-partition. IEEE Trans Fuzzy Syst 9(3):469–479
Zhiding Y, Chen F, Ming-Yu L, Srikumar R (2017) CASENet: deep category-aware semantic edge detection. Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), 2017, pp. 5964–5973
Zhu Q (1996) Effcient evaluations of edge connectivity and width uniformity. Image Vis Comput 14(1):21–34
Ziou D, Tabbone S (1998) Edge detection techniques—an overview. Int J Pattern Recogn Image Anal 8(4):537–559