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An Expert System Based on Type-1 Fuzzy Logic and Digital Image Processing for Knowledge Based Edge and Contour Detection

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ABSTRACT

In computer vision, contour/edge detection is a crucial phenomenon. Edge detection is an important step in contour detection, which is helpful in the identification of important data. The accuracy of the edge detection process is heavily dependent on edge localization and orientation. In recent years, due to their versatility, soft computing approaches have been considered effective edge detection strategies. Broadly, edge detection accuracy is deeply affected by weak and dull edges. In recent works, edge detection based on fuzzy logic (FL) was proposed, and image edges were improved using guided filtering. However, guided image filtering (GIF) does not take into account the local features of an image. To include local features of an image for edge detection, an improved version, i.e., an offset enable sharpening-guided filter is used in this paper, and FL is used for edge detection. The figure of merit (FoM) and F-score are used to evaluate the method's accuracy. Using visual representations and performance metrics, the results are compared with those from cutting-edge techniques.

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1. INTRODUCTION

Edge detection is quite vital in various processes like object detection, image processing, and computer vision. The information gained from edge detection is crucial for numerous other visual tasks [1-3]. As a result, stable detection of image edge features is necessary to effectively carry out such tasks. An edge can be defined as the black pixels in binary images with white neighbours [1]. A group of pixels with abrupt intensity fluctuations, similar to a step function, constitutes an ideal edge. An edge contour is defined by Torre et al. [4] as a collection of points with sharp brightness fluctuations. Such abrupt variations in brightness could be brought on by variations in the image's texture, grayscale, or colours. According to Shui et al. [5], the edges were discovered to be in between regions and the background. Since traditional approaches like Canny [6], Gao et al. [7], etc. are based on masks; the challenge of efficient mask generation is still an open problem. These masks additionally alter the pixel positions due to the convolution effect. Moreover, all the existing methods, due to the behaviour of masks, are not very accurate in either accepting the correct edges or rejecting the false edges, leading to inaccurate edge identification. Edge detection methods using thresholds either accept incorrect edges or reject legitimate ones. Therefore, to address this problem in Canny Edge detection, two thresholds were used, but even using more than one threshold failed to solve the problem. Threshold-based systems are like binary systems, where if the gradient of a pixel is greater than the threshold, then the chosen pixel is considered an edge pixel; otherwise, it is chosen as a non-edge pixel. It is to be further noted that threshold will depend on the pixel values of an image; therefore, threshold-based methods fail or require other morphological operations as done in Canny method [6]. For an edge detector to be considered reasonably accurate, it must be able to recognise actual edge contours with reasonable precision [8]. This is necessary because edge contours are used in computer vision and image processing activities to link different feature regions [9]. In order to handle a variety of noise sources, it is required that the edge detectors be very resilient

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under a variety of imaging conditions. In addition to being able to extract edge contours in real-time, the optimal edge detection method should also be manageable in terms of memory and storage requirements [8, 9].

The rest of the paper is organized as follows: in section 2, related work is presented. In section 3 of the paper, the proposed method is discussed. In section 4 of the paper, results are discussed, and finally, the major conclusions of the paper are discussed in section 5.

2. RELATED WORKS

This section provides an overview of both traditional and cutting-edge methods.

2. 1. Kernel Based Methods The classical edge detection methods are based on masking and are very easy to implement. Some of the basic algorithms of these methods were developed by Gao an improved Sobel edge detection [7] which was based on the pixel gradient [10]. These methods generate a large number of spurious edges, and the detected edges are thick. In recent work, in place of traditional square masking, a hexagonal masking scheme is proposed where square masks are converted into hexagonal masks using the interpolation method and corresponding new pixel values are obtained [11]. Later on, the hexagonal scheme is considered under Canny edge detection method, and the superiority of hexagonal masking has been proven [12]. As an application, the usefulness of Canny edge detection in content-based image retrieval is discussed by Fadaei [13].

2. 2. Machine Learning Based Methods A probabilistic boundary (Pb)-based edge detection method was proposed by Martin et al. [14]. In this method, a texture feature description and an approach using image local cues and logistic regression were developed for recognising edges. An advanced version of the Pb method, i.e., the multi-scale probabilistic boundary (MsPb)-based edge detection technique, was introduced by Ren et al. [15]. Arbelaez et al. [16] expanded the Pb approach [14] and proposed a global probabilistic boundary (g-Pb) approach that makes use of multi-scale and spectral clustering.

2. 3. Deep Learning Based Methods Recently, deep learning algorithms have made incredible progress in the area of image edge identification. As explained in the following two sub-sections, the currently available deep learning-based edge detection techniques can be loosely classified into supervised and unsupervised learning-based techniques.

2. 3. 1. Supervised Learning-based Methods Currently, supervised learning is used to perform the majority of image processing tasks. Payet and Sinisa [17] applied image edges for boundary detection. Dollar et al. [18] introduced an advanced probabilistic boosting tree classification. For edge detection, Rahebi et al. [19] employed an artificial neural network. Etemad and Chelappa [20] proposed a neural network based edge detector. Lim et al. [21] used a random forest classifier for effective edge detection based on a sketch marker. The holistically nested edge detection (HED) was developed. This method considers convolutional neural networks [20] for feature extraction and a deep supervised network [22] for the classification of edges. The HED technique also has the capacity to autonomously learn and may be successfully applied to handle difficult ambiguities in edge detection. Still, edge refinement is needed, as discussed by Elharrouss et al. [23], where a cascaded convolutional neural network (CNN) is used for the refinement of edges. The summary of the discussed methods is presented in Table 1.

TABLE 1. State-of-the-art methods

Authors	Techniques
Canny et al. [6]	Masking
Gao et al. [7]	Masking
Fadaei and Abdolreza [11]	Hexagonal Masking
Firouzi, et al. [12]	Hexagonal Masking
Martin et al. [14]	Probabilistic boundary (pb)
Ren et al. [15]	Multi-scale probabilistic boundary (MsPb)
Arbelaez et al. [16]	Global probabilistic boundary (g-Pb)
Dollar et al. [18]	Probabilistic boosting tree
Rahebi et al. [19]	Artificial neural network
Lim et al. [21]	Random forest classifier
Elharrouss et al. [23]	CNN
Xiaofeng et al. [24]	Sparse code gradients (SCG)
Isola et al. [25]	Crisp boundary detection
Fano [26]	Transmission of information
Yang et al. [27]	Convolutional encoder-decoder
Anandan et al. [28]	Hierarchical model-based motion
Xia and Kulis [29]	Unsupervised image segmentation
Baterina et al. [30]	Ant Colony Optimization (ACO)
Kumar et al. [31]	ACO
Kumar et al. [32]	ACO+ Guided Filtering
Ravivarma et al. [33]	Particle Swarm Optimization (PSO)
Verma et al. [34]	Fuzzy + Guided Filtering

Kumar and Raheja [35]	Fuzzy + L_0 Guided Filtering
Raheja and Kumar [36]	FL
Kaur et al. [37]	Fuzzy Logic
Aborisade [38]	FL
Begol and Maghooli [39]	FL
Zhang et al. [40]	Adaptive Neuro-Fuzzy
Dorrani et al. [41]	Edge detection fuzzy ant colony
Siddharth et al. [42]	Edge detection + ANN
Ranjan et al. [43]	Fuzzy + Weighted Guided Filtering

2. 3. 2. Unsupervised Learning Based Methods In an unsupervised learning based methods, edge contours can be identified from the main understanding of the image without the need for edge features to be manually labelled for training. As per Xiaofeng et al. [24] SCG can be used to remarkably increase the performance of edge detection methods. For extracting edge contours, Isola et al. [25] used a pointwise mutual information architecture [26]. For the purpose of extracting object contours, Yang et al. [27] proposed a completely convolutional encoder-decoder network. The basic concept behind this network was based on a full convolution network [28]. Xia and Kulis [29] proposed unsupervised semantic segmentation for edge detection using encoder-decoder architecture.

2. 4. Soft Computing Based Image Edge Detection In soft computing techniques, the ACO technique was also employed for edge identification, but accuracy was limited because there was only one optimal solution and many of the genuine edges were ignored [30]. By employing guided image filtering to strengthen weak edges, the drawbacks of the ACO edge detection approach were reduced [31, 32]. In other recent work, the performance of a Sobel operator-based edge detection mechanism is further improved by 8-directional mask developments, and the inverse of entropy is used for threshold detection [33]. This method produces better results as compared to the traditional Sobel operator, but is still unable to detect some of the genuine edges. Verma et al. [34] considered image sharpening along with PSO for edge detection; however, the main limitation is noise in edge detection.

2. 5. FL Based Image Edge Detection Fuzzy set-based edge detection is based on fuzzy theory. Here, the intensity of the pixels is represented in terms of membership functions. The membership functions are derived for both inputs and outputs. For pixels, neighbourhood fuzzy rules are developed, and a fuzzy inference engine is used for the output prediction. Recently, for accurate edge detection, guided image filtering was combined with FL [35, 36]. In a method based on fuzzy rules that Kaur et al. [37] explored, edge detection was performed using sixteen fuzzy rules. To address more noteworthy vulnerabilities in edge detection, more studies have been conducted with higher types of FL, particularly fuzzy type 2 [38, 39]. Zhang et al. [40] developed an adaptive neuro-fuzzy system for edge detection. An edge detection mechanism based on ACO and fuzzy logic was proposed by Dorrani et al. [41] to minimize false edges. An edge detection approach, based on Kalman filtering and ANN was proposed by Siddharth et al. [42].

2. 6. Edge Detection Based on GIF and Fuzzy Logic Recently, edge identification based on FL and image sharpening using GIF was proposed by Ranjan et al. [43]. In the next sub-section GIF is discussed.

2. 6. 1. Guided Image Filtering (GIF) Guided image filtering is a filtration process where edges are preserved, and the filtered image pixels are scaled and shifted version of the original unfiltered image. The scaling and shifting co-efficient are dependent on the mean and variance of input and guided image. Considering an image *Y*, which could be either the input image *X* or another image, serves as the initial filtering guide for GIF. Further assuming that 'X_p' and 'Y_p' represent the intensities values at pixel 'p' of the input and guided images, respectively. Let Ω_h represent the kernel window centred at pixel 'h'. Now, GIF is defined as:

$$GIF(X)_p = \frac{1}{\sum_{q\in\Omega_h} W_{GIF_{pq}}(Y)} \sum_{q\in\Omega_h} W_{GIF_{pq}}(Y) X_q \tag{1}$$

Here, the kernel weights functions $W_{GIF_{pq}}(Y)$ can be defined as:

$$W_{GIF_{pq}}(Y) = \frac{1}{|w|^2} \sum_{h:(p,q)\in\Omega_h} \left(1 + \frac{(Y_p - m_h)(Y_q - m_h)}{\sigma_h^2 + \varepsilon}\right) \tag{2}$$

where $|w|$=9, m_h and σ_h^2 are the mean and variance of the guided image Y in the local window. The term $\frac{(Y_p - m_h)(Y_q - m_h)}{\sigma_h^2 + \varepsilon}$ plays an important role in deciding filter weights. The above term can be positive and negative depending on the position of Y_p and Y_q and if they are on the same side of an edge or on the opposite side. The parameter ε is utilized to modify the level of smoothing. The smoothness of the image will grow as is raised.

2. 6. 2. Limitations of the Previous Works The previous works do not consider the local patches intensity variations thus problem of broken edges occur which leads to in-accurate edge detection. In the local patches where edges occur, variance is comparatively larger than in patches without edges. The GIF is based on the variance of local patches; if the variance exceeds a threshold, only the selected patches are kept; if the variance is below a threshold, the local patch is smoothed. Thus, in the resultant image, edges are highlighted, which leads to better edge detection. Still, this method has a shortcoming as it heavily depends on thresholds. Moreover, in Ranjan et al. [43] work, triangular membership functions are considered, which are well suited to ramp-like intensity variations that are not always evident in different images.

2. 7. Aim of Proposed Works In this work, the broken edge problem is minimized by considering offset-based guided filtering, which considers the local intensity variations with the help of intensity offsets. The main objectives of the proposed work are:

1. To capture local intensity variation using offset enable GIF (OEGIF)
2. To use the Gaussian membership function to capture variations in intensity.

3. PROPOSED METHOD

The proposed method is an advanced version of the previous work [43]. The main problem in edge detection is the detection of weak edges; in doing so, some spurious edges are detected. The fundamental issue with guided filtering is that it smoothes the pixels without edges but does not enhance the quality of the edges. In this work, an enhanced version of guided image filtering is used, which improves the edges before FL is used for edge identification. The main steps for the proposed edge detection method are described in Algorithm 1.

Algorithm 1: Proposed Edge Detection Mechanism
Step 1: Choose input and guided image
Step 2: Apply guided filtering, choose smoothing parameter using equation 6
Step 3: Evaluate offset (η_p) based on LoG filter
Step 4: Evaluate final offset ($\eta_p^{'}$) based on LoG filter using equations 5,7
Step 5: define input and output membership function for edge and non edge pixels
Step 6: set fuzzy rules
Step 7: Get edge enhanced image from steps 4, apply FL and classify pixels as edge and non edge
Step 8: Apply performance measure to evaluate accuracy

3. 1. Offset Enabled Guided Image Filtering (OEGIF) Adaptive Guided Image Filtering is based on the shifting technique of pixel value and an offset is added to the pixel under investigation. The following equations provide the AGF's filter kernel and weighting function:

$$OEGIF(X)_p = \frac{1}{\sum_{q\in\Omega_h} W_{OEGIF_{pq}}(Y)} \sum_{q\in\Omega_h} W_{OEGIF_{pq}}(Y) X_q \tag{3}$$

$$W_{OEGIF_{pq}}(Y) = \frac{1}{|w|^2} \sum_{h:(p,q)\in\Omega_h} \left(1+\frac{\left(\left(Y_p+\eta_p^{'}\right)-m_h\right)\left(Y_q-m_h\right)}{\sigma_h^2+\varepsilon}\right) \tag{4}$$

where ε is the smoothing parameter, and $\eta_p^{'}$ is the extra offset. The offset is chosen as

$$\eta_p^{'} = \begin{cases} Y_{\max}-Y_p & if\ Y_p > m_h \\ Y_{\min}-Y_p & if\ Y_p < m_h \\ 0 & if\ Y_p = m_h \end{cases} \tag{5}$$

where Y_{max} and Y_{min} is maximum and minimum values of the pixels in given window. It is further important to note that the smoothing parameter also satisfies:

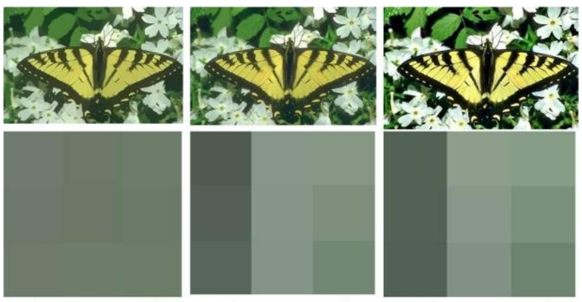
$$\varepsilon = \sigma_r^2 / 255 \tag{6}$$

It is further to note that the pixel offset is also constraint by the minimum and maximum values of the pixel intensity in the chosen window using:

$$\eta_p^{'} = \begin{cases} Y_{\max}-Y_p & if\ \left(Y_p+\eta_p\right) > Y_{\max} \\ Y_{\min}-Y_p & if\ \left(Y_p+\eta_p\right) > Y_{\min} \\ \eta_p & Otherwise \end{cases} \tag{7}$$

where η_p is the optimal offset which depends on the strength of the edge and obtained from LoG filter [44].

To numerically illustrate the advantage of the proposed method, a butterfly image initial patch is considered (Figure 1(a)). In Figure 1(b), a sharpened image of Ranjan et al. [43] work along with a local patch is shown. Finally, in Figure 1(c) enhanced image with a local patch is shown. The difference in the pixel values of Figure 1(b) and Figure 1(c) is due to the offset. It is clear that the quality of the enhanced image is much



$$\begin{pmatrix}109 & 104 & 106\\107 & 103 & 104\\106 & 106 & 103\end{pmatrix} \quad \begin{pmatrix}79 & 135 & 130\\86 & 133 & 123\\92 & 135 & 115\end{pmatrix} \quad \begin{pmatrix}83 & 140 & 134\\85 & 136 & 123\\86 & 132 & 112\end{pmatrix}$$

m=105.33 m=114.33 m=114.55

(a) Original Patch (b) Ranjan et. al [43] (c) proposed

Figure 1. Comparison of image sharpening

better in comparison to Ranjan et al. [43] work, but the mean value of the image is almost the same. Thus, the offset changes the intensity in such a way that the overall mean intensity remains the same, but edge distinction improves.

3. 2. FL Based Edge Detection Figure 2 illustrates the design of a fuzzy-based edge detection system. In the initial step of FLED, input and output membership functions are selected, and the image's pixel values are fuzzified. The Mamdani fuzzy inference engine is then used to apply IF-ELSE rules, and lastly, defuzzification is performed to produce crisp values and the desired results.

Membership Functions:
Gaussian membership function is considered at the input, while at the output triangular membership function is considered. The Gaussian membership is of the form [29]:

$$\mu_A(x;c,u,m) = \exp\left(-\frac{1}{2}\left|\frac{x-u}{s}\right|^m\right) \tag{8}$$

While the triangular membership function is specified as [29]:

$$\mu_B\left(x;a,b,c,d\right) = \max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-d}\right),0\right) \tag{9}$$

Next fuzzy rules are devised.

Fuzzy Rules
Figure 3 depicts the rules' formation on a 3x3 mask. In the illustration, "W" stands for white pixels, "**B**" for black pixels, and "**E**" as an edge pixel. A total of 28 rules are devised for edge pixels. If a pixel is surrounded by eight white or black pixels, then the pixel under investigation is considered to be noise; similarly, a single pixel change is also considered a non edge. It is important to note that at least two white pixels surrounded by black pixels or at least two black pixels surrounded by white pixels will qualify for a possible edge.

4. RESULTS

The performance evaluation of the proposed edge detector is done on a large image dataset, and for illustration, four images, i.e., ‘butterfly’, ‘crow’, ‘church, and ‘Lena, are considered (Figure 4). The performance metrics FoM and F-Score are evaluated as detailed in Table 2. The FoM, measures how far the pixels have been shifted from their initial places. The optimal F-score, which is based on the confusion matrix, is 1, which indicates that the edge detection was accurate.

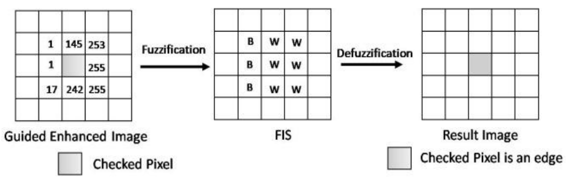


Figure 2. Diagram of FL-based edge detection [43]

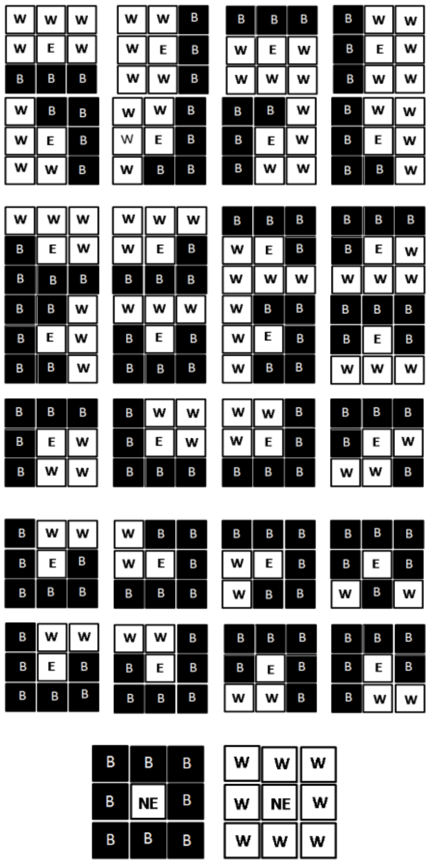


Figure 3. Fuzzy rules pattern for edge pixels [43]

Figure 4. Image datasets

TABLE 2. Performance Measures

Metrics	Formula
FoM	$FoM = \frac{1}{\max(n_A,n_B)}\sum_{i=1}^{n_B}\left(\frac{9}{9+d^2}\right)$ n_A = Ideal edges n_B = detected edges d = displacement between (n_A, n_B)
F Score	F-score= $2TP/(2TP+FP+FN)$ TP: True Positive

In Figure 5, in the first column, three images are shown. The detected edges from the Ranjan et al. [43] work are shown in Figure 1(b), and finally, in Figure 1(c), the results for the proposed method are shown. In the case of the butterfly image, Ranjan et al. [43] fail to detect the edge in the north-west region of the image, which is successfully detected in the proposed method. In the case of the crow image, the difference is clearly visible.

Finally, in the case of the church image in Ranjan et al. [43] work, at the dome area, double edges, i.e., false edges, can be seen. However, the proposed method is free of double edges.

In the recent past, the "Lena" image was used for illustration of results; thus, for a fair comparison, the "Lena" image is used in the subsequent results. Figure 6(a) shows the original image, and Figure 6(b) shows the important marked points. In Figure 6(c), the results of guided image filtering are shown, while for adaptive guided filtering, the results are shown in Figure 6(d).

The edges in Figures 6(c) and 6(d) appear very similar, but differences can be seen in the hair edges and the face and forehead. Figure 7(a) depicts the input membership function, which has a mean (u) of 0 and a variance (s) of 0.1 and 'm'=2 (Equation (8)), and Figure 7(b) depicts the output membership function for black and white pixels. Referring to Equation (9), for black pixels a=0 and b=0.7 and for white pixels c=1 and d=0.

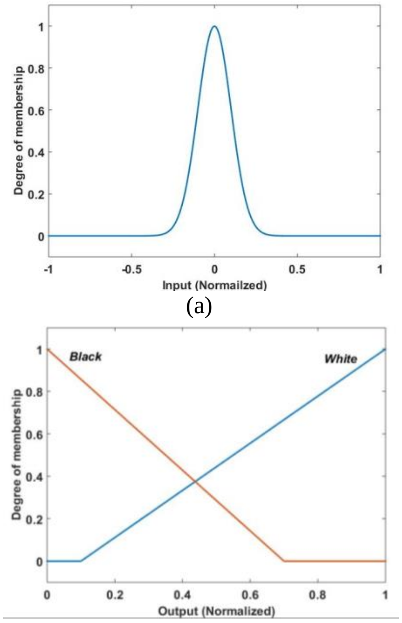
In Figure 8(a), demonstrate the result of canny edge detection and It is evident that while the majority of edges are correctly recognised, a disproportionate number of them are incorrectly accepted. For example, in comparison to the marked edges in regions 2, 4, and 5, there are numerous edges that are falsely detected. As a result, cranny edge detection is quite noisy. Sobel edge detection is displayed in Figure 8(b), and it can be seen that while some actual edges are correctly recognised, others are mistakenly rejected and can be seen in the highlighted regions 1, 2, 3, and 6.

(a) (b) (c)

Figure 5. (a) Original image (b) Ranjan et. al. [43] (c) Proposed

(a) (b) (c) (d)

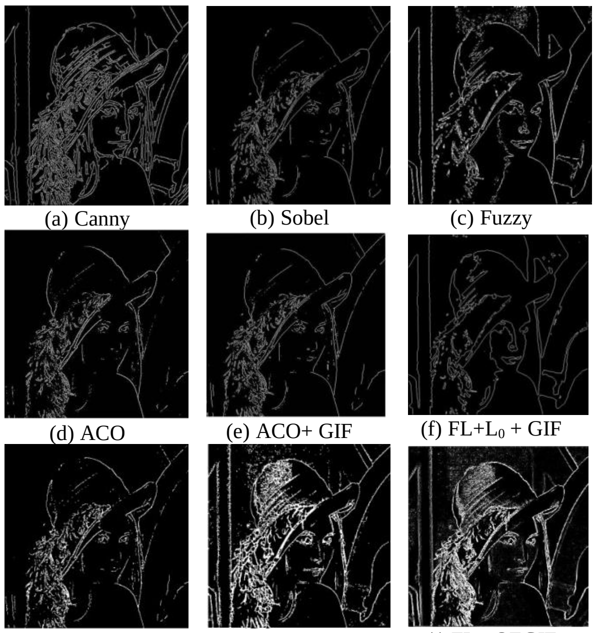
Figure 6. (a) Original Lena image (b) Marked Lena image (c) Guided filtering [40] (d) adaptive guided filtering (Proposed)



(a)

(b)

Figure 7. (a) Input membership function (Gaussian) (b) Output membership function (Triangular)



(a) Canny (b) Sobel (c) Fuzzy

(d) ACO (e) ACO+ GIF (f) FL+L_0 + GIF

(g) PSO (h) PSO+ GIF (i) FL+ OEGIF

Figure 8. Comparison of edge detection methods

Although fuzzy edge identification performs better than Canny and Sobel approaches, as can be seen in marked regions 2, 3, and 4, some true edges are still mistakenly rejected (Figure 8(c)). Additionally, the face boundary is incorrectly detected, and noise can be observed across the hat area. ACO edge detection is displayed in Figure 8(d), and it can be seen that while some actual edges are correctly recognised, many of them are mistakenly rejected. These locations are indicated as 1, 2, 3, and 6. The results of Kumar et al.'s [32] edge detection method, which is based on ACO and guided filtering, are shown in Figure 8(e). As can be observed, the number of falsely rejected real edges falls as compared to the ACO method, although they are still numerous and can be seen in highlighted regions 1 and 6. Figure 8(f) shows the outcome of fuzzy + guided filtering edge detection. In this method, the problem of broken edges has been cured, but the area around the neck and face is not well identified. Results for PSO edge detection are displayed in Figure 8(g), and it can be seen that, with a little more noise, it performs remarkably similarly to Sobel approach. However, marked regions 1 and 6 still reveal missing edges. Results for Verma et al. [34] whose method is based on PSO and sharpening, are displayed in Figure 8(h), and it is evident that its performance is good. Although the majority of edges have been located, designated regions 3 still have some missing edges. The result for fuzzy and adaptive sharpening is presented in Figure 8(i), and it can be seen that performance is excellent for the most part and noise is significantly reduced as compared to the PSO+ sharpening method.

Table 3 compares the effectiveness of various edge detection techniques using FoM and F-Score. The F-score for Canny is 0.49 and FoM is 0.3, while for the Sobel method, the F-score is 0.4 and FoM is 0.42. The F-score for the learning-based sketch method token is 0.73. In the case of fuzzy and ACO-based methods, the F-score is 0.64 and 0.72, respectively, with the FoM around 0.4. Thus, various methods without edge enhancement do not perform well. Kumar et. al. [32] proposed the ACO+ Guided Filtering method, and the F-score improved to 0.81 with a FoM of 0.46. Raheja and Kumar [36] proposed Fuzzy + L_0 guided filtering method, and the F-score improved to 0.84 with a FoM of 0.5. Verma et al. [34] proposed PSO+ sharpening, and the F-Score improved to 0.851. Ranjan et al. [43] proposed Fuzzy+ Weighted Guided Filtering with an impressive FoM of 0.58. The performance of the proposed work is very impressive, with a FoM of 0.63 and an F-Score of 0.87. The result is improved due to the reduction in incorrect edges and noise.

TABLE 3. Classical and State-of-the –art methods comparison (FoM and F-Score)

Reference	Methods	FoM	F-Score
Canny [6]	Masking	0.3	0.49
Gao et al. [7]	Masking	0.42	0.40
Lim et al. [21]	Sketch Token	-	0.73
Kumar and Raheja [35]	Fuzzy	0.4	0.64
Kumar et al. [31]	ACO	0.44	0.72
Kumar et al. [32]	ACO+ GIF	0.46	0.81
Raheja and Kumar [36]	Fuzzy+ L_0 +GIF	0.5	0.84
Setayesh et al. [45]	PSO	0.51	0.84
Verma et al. [34]	PSO+ GIF	0.51	0.851
Ranjan et al. [43]	Fuzzy+ W-GIF	0.58	0.859
Ranjan et al.	Proposed	0.63	0.87

(-) *Data Not Available

5. CONCLUSIONS

Edge detection is a significant phenomenon that has applications in both engineering and medicine. Since edges are complex in nature, there are many different kinds of edge detection methods that have been investigated, ranging from classical masking-based methods to soft computing and deep learning-based methods. This work proposes an edge detection technique based on FL and AGIF. The adaptive guided images filtering method is useful for improving weak edges and smoothing low variance zones. The suppression of inaccurate edges is the key characteristic of the proposed edge detection method. The FoM and F-score are used to compare the performance of various edge detection methods. The FoM for the proposed method is 0.63, and the F-score is 0.87. In the future, fuzzy logic structure can be combined with deep neural network for more accurate contour/edge classification.

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Persian Abstract

چکیده

در بینایی کامپیوتر، تشخیص کانتور/لبه یک پدیده حیاتی است. تشخیص لبه یک مرحله مهم در تشخیص کانتور است که در شناسایی داده های مهم مفید است. دقت فرآیند تشخیص لبه به شدت به محلی سازی و جهت گیری لبه بستگی دارد. در سال های اخیر، به دلیل تطبیق پذیری، رویکردهای محاسباتی نرم به عنوان استراتژی های موثر تشخیص لبه در نظر گرفته شده اند. به طور کلی، دقت تشخیص لبه عمیقاً تحت تأثیر لبه های ضعیف و کسل کننده است. در کارهای اخیر، تشخیص لبه بر اساس منطق فازی (FL) پیشنهاد شد و لبه های تصویر با استفاده از فیلتر هدایت شونده بهبود یافتند. با این حال، فیلتر تصویر هدایت‌شده (GIF)ویژگی‌های محلی یک تصویر را در نظر نمی‌گیرد. برای گنجاندن ویژگی‌های محلی یک تصویر برای تشخیص لبه، یک نسخه بهبودیافته، به عنوان مثال، یک فیلتر هدایت‌شونده شفاف‌سازی افست در این مقاله استفاده شده است، و FL برای تشخیص لبه استفاده می‌شود. برای ارزیابی دقت روش از رقم شایستگی (FoM) و امتیاز F استفاده می شود. با استفاده از نمایش‌های بصری و معیارهای عملکرد، نتایج با نتایج حاصل از تکنیک‌های پیشرفته مقایسه می‌شوند.