Konya Mühendislik Bilimleri Dergisi, c. 12, s. 1, 177-191, 2024
Konya Journal of Engineering Sciences, v. 12, n. 1, 177-191, 2024
ISSN: 2667-8055 (Electronic)
DOI: 10.36306/konjes.1116833

COMPARISON OF CLASSICAL AND FUZZY EDGE DETECTION METHODS

Gülcihan ÖZDEMİR

Istanbul Technical University, Informatics Institute, Applied Informatics, Istanbul, TÜRKİYE
ozdemirg@itu.edu.tr

Highlights

- To find the optimum methodology for edge detection in image processing, eight distinct approaches those are four classical edge detection methods—Sobel, Prewitt, Roberts, and Canny and four fuzzy-logic-based inference systems - type-1, type-2, hybrid-1, hybrid-2 are investigated.
- The performance of each approach is evaluated against three error metrics - Mean Square Error (MSE), Peak Signal Noise Ratio (PSNR), and Structural Similarity Index (SSIM) using two distinct data sets one is street images (three different data sets are utilized in this category) the other is blood vessel recognition in retinal images with varied attributes.
- The BIPED data set contains street images. The methods are presented in the order of best to worst; Roberts > Hybrid-1 Fuzzy > Prewitt > Sobel > Type-2 Fuzzy …
- The STARE data set contains medical images of blood vessels in the retina.
  The methodological success order operates as follows:
  Type-2 Fuzzy > Hybrid-1 Fuzzy > Prewitt > Hybrid-2 Fuzzy > Roberts …
- The hybrid-1 fuzzy inference methodology can be applied effectively for edge detection in most types of image-processing tasks.

***Corresponding Author:** Gulcihan Ozdemir, ozdemirg@itu.edu.tr

Konya Mühendislik Bilimleri Dergisi, c. 12, s. 1, 177-191, 2024
Konya Journal of Engineering Sciences, v. 12, n. 1, 177-191, 2024
ISSN: 2667-8055 (Electronic)
DOI: 10.36306/konjes.1116833

COMPARISON OF CLASSICAL AND FUZZY EDGE DETECTION METHODS

* **Gülcihan ÖZDEMİR**

Istanbul Technical University, Informatics Institute, Applied Informatics, Istanbul, TÜRKİYE
ozdemirg@itu.edu.tr

(Received: 15.05.2022; Accepted in Revised Form: 02.02.2024)

ABSTRACT: Edge detection is one of the challenging problems in image processing. Four different classical edge detection methods—Sobel, Prewitt, Roberts, and Canny—and type-1 and type-2 fuzzy logic-based edge detection methods are applied to analyze two separate datasets with various properties. The datasets are STARE which contains medical images of the retina and BIPED which contains images of the street. Furthermore, two separate hybrid fuzzy logic methods are implemented. The type-1 and type-2 fuzzy inference techniques are combined to produce the hybrid-1 and hybrid-2 approaches, using the "AND" and "OR" logic operators. We compare the simulation results for each technique using three different image quality metrics. These are Mean Square Error (MSE), Peak Signal Noise Ratio (PSNR), and Structural Similarity Index (SSIM). The type-2 fuzzy technique outperformed the hybrid-1 fuzzy method in visual quality metrics comparison, demonstrating superior blood vessel recognition on the STARE retinal image dataset—a dataset that more closely resembles the human visual system. Using the BIPED street image dataset, the hybrid-1 fuzzy approach outperformed the Roberts method. The hybrid-1 fuzzy technique showed good results in the second order for both kinds of datasets. Any data and general applications can take advantage of it.

Keywords: *Edge detection, Fuzzy inference system, Hybrid fuzzy inference system, Image processing, Type-1 fuzzy inference system, Type-2 fuzzy inference system*

1. INTRODUCTION

Edge detection is among the most significant topics in computer vision. The study of medical images [1] and object recognition [2] are two common uses of edge detection. The focus of edge detection techniques in the past has been on grayscale images. Today, RGB (Red, Green, and Blue) images are frequently used for edge detection instead of grayscale images because they can provide more information. Despite taking more time, processing RGB images is more efficient than processing grayscale images [3]. Techniques for recognizing edges are improved using type-1 fuzzy logic [4].

In [5] a 3x3 kernel is employed to determine the derivative for four different directions. This technique yields four distinct inputs. Zero-order Sugeno Inference System is utilized for the fuzzy inference system. Triangle membership functions are available for inputs. There are 20 rules altogether set for the system, with 5 rules being applied to each input. The system produces 4 outputs, which are collected and added together to provide the edge image as the end result. According to [5], the proposed method produces results that are comparable to those of conventional methods.

The study in [6] uses fuzzy if-then rules to implement the suggested strategy for detecting the edges. The maximum entropy principle is used in the proposed algorithm to define the initial membership function. The suggested approach figures out gray-level differences. There are two defined trapezoidal membership functions for this. Fuzzy rules are then used to obtain the edges. In the suggested method, 16 fuzzy rules are defined. The output is then retrieved after applying defuzzification. The pixel is known as an edge pixel if its value is greater than a certain threshold and a non-edge pixel in all other cases. The proposed method, according to the publication, performs effectively even when there is image noise [6].

A new neuro-fuzzy (NF) operator for edge recognition in digital images which is distorted by impact noise is presented in [7]. Edge detection provides details about objects in the image. For instance, procedures like object recognition and classification in the image. Edge identification was carried out on

***Corresponding Author:** Gülcihan ÖZDEMİR, ozdemirg@itu.edu.tr

noisy digital images using the Neuro-fuzzy method without the use of pre-filtering, and it was found that the results were superior to those of traditional edge detection methods [7].

A new edge detection approach is introduced in [8]. Grayscale and RGB images can be used with this technique. The study makes use of a 3x3 mask. To determine the edge density and orientation of the pixels in the mask, the values of the target function are used as a guide. Thus, the direction map and the edge map are obtained. Edge points are found using the Non-Maximum Suppression approach on these maps. The results of the method were compared with those of traditional edge detection techniques like Sobel and Canny [8].

The grayscale image in [9] has been modified using 3x3 Sobel masks. Then, a fuzzy inference system (FIS) was created by applying the Gaussian membership function to both the inputs and the output in the low, medium, and high linguistic variables. There are seven fuzzy inference rules used. The suggested method performed better than conventional edge detection techniques [9].

Various camera systems, including rotating and fisheye camera systems utilized for Omnidirection, are mentioned along with the challenges these systems face [10]. Omnidirectional vision is frequently used in the imaging industry nowadays. However, there are significant radial distortions in these images. Because traditional edge detection techniques are inadequate for these images, fuzzy edge detection techniques are used in this study. The Prewitt method, one of the traditional edge detection techniques, was utilized to examine the effectiveness of the fuzzy edge detection technique [10].

The proposed approach in the study [4] uses fuzzy logic and morphological gradient. Four inputs representing various orientations for the fuzzy system are obtained using morphological gradients. There are three linguistic variables in these inputs: low, medium, and high. Fuzzy systems of type-1 and interval type-2 are employed for detection. Images are used as input membership function parameters in the method. Images with different gray scales can be processed using this method. The input membership function for the type-1 system is the Gaussian membership function. Calculating the minimum, middle, and maximum values of each input gives the center of the Gaussian membership functions for that input. The system produces a single output with three linguistic variables—black, gray, and white. The output range is set to be between 0 and 255. The main modification in the architecture of the interval type-2 fuzzy system is the addition of a footprint of uncertainty (FOU) for the membership functions. Several sizes are used to calculate the FOU's value. As a consequence, interval type-2 systems outperformed type-1 systems by retaining greater visual details [4].

Image processing steps like edge detection, object recognition, and classification are carried out [11]. This study made edge detection in MRI (magnetic resonance imaging) images easier using the Mamdani fuzzy inference method. The cancerous area in MR images can be found utilizing the edge detection technique. The Mamdani fuzzy inference system was utilized to achieve this judgment, and the K-means clustering technique was used as the input. The Sobel edge detector then receives these threshold values. In comparison to the traditional Sobel edge detector, it was shown that the results were better [11].

A method for edge detection that makes use of general type-2 fuzzy logic has been presented by [3]. The technique is applied to colored images. For the suggested algorithm, two methods are combined. These methods use picture gradients and general type-2 fuzzy logic. This method is considered helpful when there is image noise. The system receives 12 inputs from the 4 different gradients that are utilized for gradient images, each of which is applied to a separate channel of a color image. The system employs 12 inputs and produces 3 outputs for each of the image's channels. For inputs and outputs, Gaussian membership functions are employed. Every input uses low, middle, and high linguistic variables. As linguistic variables for the outputs, background, and edge are employed. The nine fuzzy rules are set up to process inputs. To demonstrate how well the approach performs in comparison to grayscale images, color images are used for evaluation.

The edges of blood vessels are derived from retinal images using the proposed method [12]. The method employs only the green channels from RGB images. Four separate image gradients are produced using filters and supplied to the type-2 Mamdani fuzzy inference system after the contrast enhancement and background extraction are implemented. Each input has two Gaussian membership variables and the output has two triangle membership functions. The parameters needed to define these membership variables are obtained using the Otsu threshold method. Two fuzzy rules are defined for the proposed approach. After fuzzy edge detection has been performed, the final output is produced using postprocessing. Multiple datasets are used to evaluate the method and obtain positive findings [12].

Our contribution to this research is the application of two fuzzy logic-based edge detection methods as well as various classical edge detection methods from the literature to two different datasets, and the comparison of the results using various metrics like PSNR, SSIM, and MSE. In addition, we have suggested two hybrid fuzzy approaches (hybrid 1 and hybrid 2) that combine type-1 fuzzy and type-2 fuzzy methods using the "AND" and "OR" operators, respectively. As classical techniques Sobel, Prewitt, Roberts, and Canny are utilized. As fuzzy logic-based techniques type-1, type-2, hybrid-1, and hybrid-2 fuzzy inference systems are utilized. The BIPED data set contains street images. The STARE data set contains medical images. We concluded that Roberts's methodology performs best for street images while type-2 fuzzy methodology works best for medical images detecting blood vessel edges in the retina. Hybrid-1 fuzzy methodology ranks the second best follows Robert's methodology for the street images and type-2 fuzzy for the medical images. Lastly, the Hyrid-1 fuzzy approach can be applied to image recognition problems for general-purpose edge detection.

2. IMAGE QUALITY METRICS

2.1. Peak signal-to-noise ratio, Mean-square error

Image compression quality is compared using the mean-square error (MSE) and peak signal-to-noise ratio (PSNR). The PSNR represents a measure of the peak error, whereas the MSE represents the total squared error between the original and compressed image. The error decreases as the MSE value decreases. The higher the PSNR, the better the quality of the compressed, or reconstructed image [13], [14]. First, use the following equation to determine the mean-squared error before computing the PSNR:

Given a noise-free m×n monochrome image I and corresponding noise image K. MSE is defined as in Equation 1:

$$MSE = \frac{1}{m*n}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j)-K(i,j)]^2 \qquad (1)$$

Here, m and n denote the size, which is the number of rows and columns in the input images.

The PSNR measurement is typically converted from MSE [13]. Even with noise and corruption present, PSNR is utilized to evaluate the quality of an image. The degree of representation fidelity depends on the ratio between the maximal power of a signal and the power of corrupting noise. The PSNR, represented in decibel (dB) scale, is defined as Equation 2:

$$PSNR = 10*\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad (2)$$

Here, MAXI is the maximum possible pixel intensity value of the image.

2.2. Structural Similarity Index

When comparing images, MSE may not be a very reliable measure of how similar two images are, despite being easy to compute [13].

The Structural Similarity Index (SSIM) seeks to fix this weakness by considering texture and assigning a higher score to images that may appear similar.

Since SSIM collects important data including brightness (l), contrast (c), and structure (s), it is more analogous to the human visual system. It can be utilized to assess noise reduction and structure preservation. Based on the computation of these three components, the SSIM Index quality assessment index is created. These three elements are multiplicatively combined to form the overall index (Wang et al., 2004) is given in Equations 3 and 4:

$$SSIM(x,y) = [l(x,y)]^{\alpha} . [c(x,y)]^{\beta} . [s(x,y)]^{\gamma} \qquad (3)$$

where

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu^2{}_x + \mu^2{}_y + C_1}$$
$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma^2{}_x + \sigma^2{}_y + C_2} \qquad (4)$$
$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

where μx, μy, σx,σy, and σxy are the local means, standard deviations, and cross-covariance for images x, y.

A block diagram of the SSIM measurement process is shown in Figure 1.

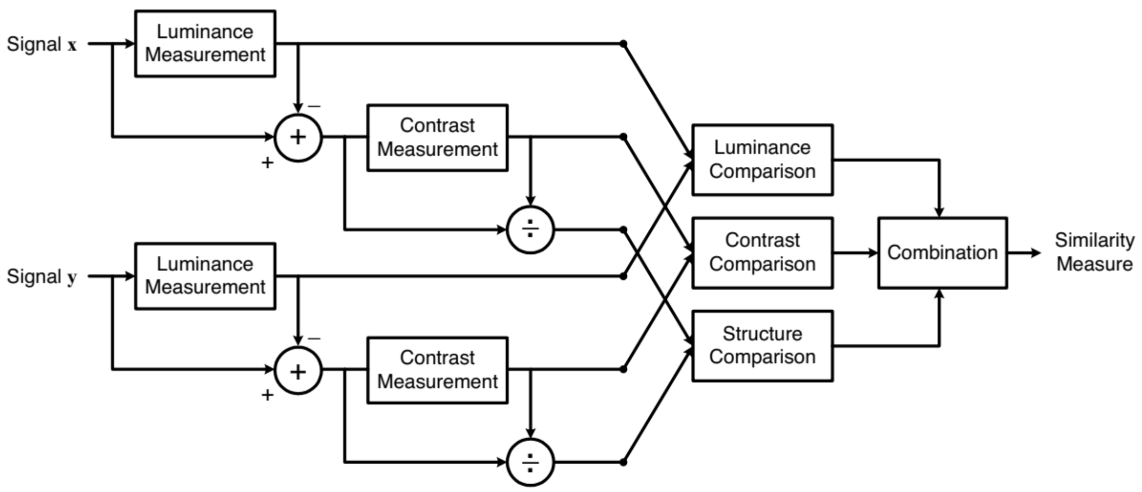

Figure 1. Structural similarity (SSIM) measurement diagram [15].

The images to be used for quality measurement are supplied as a numeric array and could be a 2-D grayscale image or 3-D grayscale volume, such as an RGB image or stack of grayscale images.

Input Arguments:
- Signal x— Image for quality measurement, numeric array
- Signal y— Reference image, numeric array

Output Arguments:
- Similarity measure — SSIM index, numeric scalar

As expected from identical images, an SSIM score of 1.00 indicates perfect structural similarity.

3. A BRIEF SUMMARY OF CLASSICAL EDGE DETECTION METHODS

Image edge detection has drawn a lot of interest from researchers since it was first introduced. Edge detection operators can be categorized under two groups [16]:

- Gradient-based operators which compute first-order derivatives such as;
  - Robert operator
  - Prewitt operator
  - Sobel operator

- Gaussian-based operators which compute second-order derivatives such as;
  - Canny edge detector
  - Laplacian of Gaussian

The Robert operator [17], also known as the cross-differential algorithm as the simplest operator, was the first edge detection operator and was proposed by Lawrence Roberts in 1963. Its basic idea is to locate the image contour with the aid of a local difference operator.

The Prewitt operator, followed it in 1970, which is frequently used on high-noise, pixel-value fading images [18].

Then, in the 1980s, the Sobel operator introduced the concept of weights [19], and the Laplacian operator used second-order differentiation [20].

Later, the best operator for detection in the area of edge detection at the time was the optimal Canny operator [21], which constantly optimized the image contour information through filtering, enhancing, and detecting processes.

4. MODELLING

First, the method that is proposed by [12] is implemented. In this method, a fuzzy edge detection method is presented to obtain blood vessels from retinal images. In the method, the RGB image is taken as input. Operations for edge detection are continued on the green channel of the image. Then, contrast enhancement is applied to the extracted green channel. After contrast enhancement, to remove the background of the image, the contrast-enhanced version of the image is subtracted from the median filtered image. The median-filtered image is obtained by applying a median filter to contrast the enhanced image. After the background is removed from the image, the fuzzy edge detection part of the method is applied. In this part, first, a Gaussian kernel is applied for blurring. Then, 8 gradients given in Figure 2 are applied and 4 gradients with the highest value are chosen by comparing mirror kernels [12].

These four gradients are used as input to the fuzzy inference system. For each input, two Gaussian membership functions named *BP* (Black Pixel) and *WP* (White Pixel) are defined. Some of the parameters of these functions are obtained from the Otsu thresholding technique. For the output of the system, two triangle functions named *EO* (Edge Output) and *NEO* (Not Edge Output) are defined. Two fuzzy rules are defined for the proposed system as given below:

1. IF I_x is *BP* AND I_y is *BP* AND I_z is *BP* AND I_k is *BP* THEN *EO*

2. IF I_x is *WP* AND I_y is *WP* AND I_z is *WP* AND I_k is *WP* THEN *NEO*

Pixel values of the fuzzy inference system's output are checked and if the pixel value is higher than some threshold, that pixel is assigned as 0 otherwise it is assigned as 255.

Even though edges are detected using the method explained, there is noise in the output. In the article a morphological operation called erosion is applied but, in our implementation, we have applied a 4x4 median filter because when erosion is used, some of the edge parts of the output are affected. Flowcharts of the type-2 fuzzy edge detection method and the fuzzy edge detection part of the flowchart are given in Figures 3 and 4, respectively [12].

$$G(0) = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad G(180) = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$G(45) = \begin{bmatrix} -2 & -2 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix} \qquad G(225) = \begin{bmatrix} 2 & 2 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix}$$

$$G(90) = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad G(270) = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

$$G(135) = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix} \qquad G(315) = \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix}$$

Figure 2. Mirrored kernels [12].

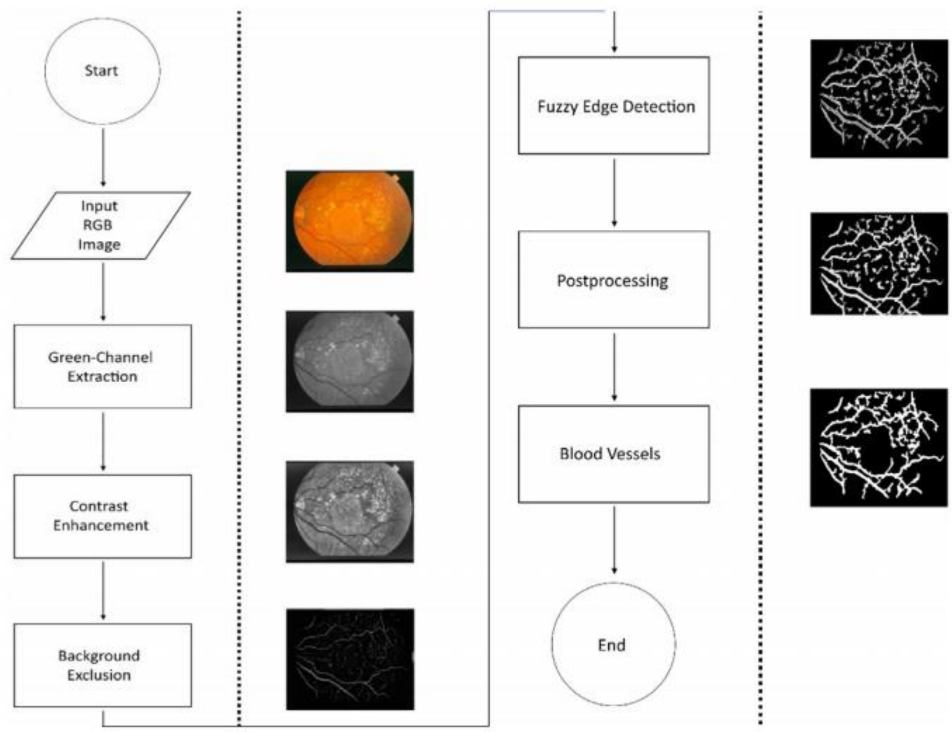

Figure 3. Flowchart of the type-2 fuzzy edge detection method [12].

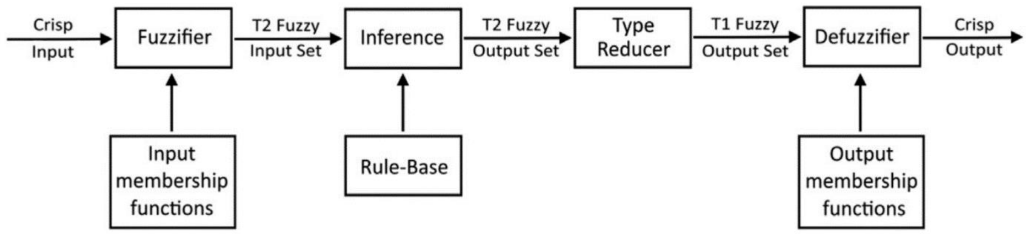

Figure 4. Fuzzy system of the type-2 fuzzy edge detection method [12].

The method in [9] is the second method that we have implemented. In this method, RGB images are first converted to grayscale images. To obtain the inputs for the fuzzy inference system four different kernels are used. These kernels are Sobel in the x direction, Sobel in the y direction, and high-pass and low-pass filters. They are given in Equations 5 through 8:

$$Sobel_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (5)$$

$$Sobel_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad (6)$$

$$hHP = \begin{bmatrix} \frac{-1}{16} & \frac{-1}{8} & \frac{-1}{16} \\ \frac{-1}{8} & \frac{3}{4} & \frac{-1}{8} \\ \frac{-1}{16} & \frac{-1}{8} & \frac{-1}{16} \end{bmatrix} \quad (7)$$

$$hMF = \frac{1}{25} * \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (8)$$

Inputs S_x, S_y, H and L are obtained by applying $Sobel_x$, $Sobel_y$, hHP and hMF filters, respectively. After obtaining inputs by applying filters, mamdani fuzzy inference system is defined. For each input, three gaussian membership functions called low, medium and high are defined. An example is given in the Figure 5.

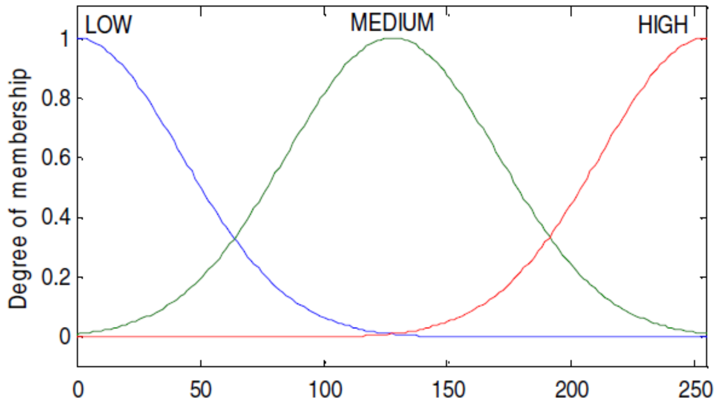

Figure 5. One of the four input membership functions [9].

In the same way, one output named E (Edge) with three gaussian membership functions is defined. Then seven fuzzy rules are defined as follows:

1. (E is LOW) If (S_x is LOW) and (S_y is LOW)
2. (E is HIGH) If (S_x is MEDIUM) and (S_y is MEDIUM)
3. (E is HIGH) If (S_x is HIGH) and (S_y is HIGH)
4. (E is HIGH) If (S_x is MEDIUM) and (H is LOW)
5. (E is HIGH) If (S_y is MEDIUM) and (H is LOW)
6. (E is LOW) If (L is LOW) and (S_y is MEDIUM)
7. (E is LOW) If (L is LOW) and (S_x is MEDIUM)

By applying these rules output of the system is obtained and to get the final result, a threshold is applied. The threshold is calculated as mean + 2*standard deviation in both methods.

5. RESULTS AND DISCUSSIONS

Methods in [9] and [12] are implemented and they are evaluated using two datasets. These datasets are STARE (Structured Analysis of the Retina) [22] and BIPED (Barcelona Images for Perceptual Edge Detection) [23] datasets. STARE (available at https://cecas.clemson.edu/~ahoover/stare/probing/index.html) is a dataset for blood vessel segmentation in retinal images. Twenty images were selected and labeled by hand. Labels provided by Valentina Kouznetsova were chosen as ground truth for this work. Each image is an RGB retinal image with a dimension of 605 x 700. BIPED (available at https://github.com/xavysp/MBIPED) is another dataset that includes street and car images for edge detection. The dataset contains 250 RGB outdoor images with a dimension of 1280 x 720. Ground truths for these images were obtained by experts. Fifty images from this dataset are used for validation and the rest is used for training. In this work, we only use validation images for testing since we do not use deep-learning approaches.

These images have been thoroughly examined by computer vision experts, hence no redundancy has been considered. These datasets are available for free and serve as a benchmark for evaluating edge detection techniques.

Three image quality metrics were used to evaluate and compare the results for the fuzzy and classical edge detection methods, Sobel, Prewitt, Roberts, and Canny. These are PSNR, SSIM, and MSE; their details are given in section 2. Results of evaluations and example visual outputs are given below. Images were converted to grayscale before using classical methods. Edge results obtained using type-1 and type-2 fuzzy methods were connected with “AND” and “OR” operators. These results are given as hybrid 1 fuzzy method and hybrid 2 fuzzy methods, respectively.

Table 1. PSNR, SSIM, and MSE results of the fuzzy and classical methods for the STARE dataset.

Method/Metric	PSNR	SSIM	MSE
Sobel	9.2358	0.5818	7980.3
Prewitt	9.6734	0.5951	7269.5
Roberts	9.5697	0.5910	7462.8
Canny	8.3984	0.4399	9542.5
Type-1 Fuzzy Method	9.3015	0.5752	7816.8
Type-2 Fuzzy Method	**10.475**	**0.6557**	**6005.3**
Hybrid 1 Fuzzy Method	10.040	**0.6558**	6700.5
Hybrid 2 Fuzzy Method	9.5334	0.5713	7343.4

Table 1 shows that the type-2 fuzzy method has the highest PSNR and SSIM values and the lowest MSE value, indicating that it gives the best solution among these methods for detecting the blood vessel edges from retinal images according to the image quality metrics given in Equation 1, 2 and 3. The hybrid 1 fuzzy method has the second highest PSNR value, the best SSIM value, and the second lowest MSE value for STARE dataset. From the classical methods Prewitt is the best and Canny is the worst numerically. For an image from STARE dataset, original image, ground truth and visual results of the methods are given in Figure 6. From visual results, it can be seen that Canny, type-2 fuzzy method and hybrid 2 fuzzy method perform well. Rest of the methods perform poorly. We can put the methods in an order from the best to worst value quantitatively in terms of quality metrics used above as follows:

Type-2 Fuzzy > Hybrid 1 Fuzzy > Prewitt > Hybrid 2 Fuzzy > Roberts>...

From Table 2, it seems that Roberts from classical methods gave the best result regarding all three metrics PSNR, SSIM, and MSE. The hybrid 1 fuzzy method has the second best of all the methods and the best result with higher PSNR and SSIM values and the lowest MSE value among all fuzzy methods. In Figure 7, a visual comparison of the methods is provided for an image from the BIPED dataset. Between type-1 and type-2 fuzzy methods, in terms of PSNR and SSIM, the type-2 fuzzy method has a higher value and in terms of MSE error, it has a lower value. Results of fuzzy methods for STARE and BIPED datasets are different which is understandable since the type-2 fuzzy method has pre-process and post-process designed for retinal images. Also, the number of fuzzy rules used in these methods is different. Even though the type-2 fuzzy method is designed for retinal images, it also works well on other images but the same thing cannot be said for type-1 fuzzy method since it performed poorly on retinal images. The methods in an order from the best to worst value quantitatively in terms of quality metrics used are as follows:

Roberts > Hybrid 1 Fuzzy > Prewitt > Sobel > Type-2 Fuzzy > ...

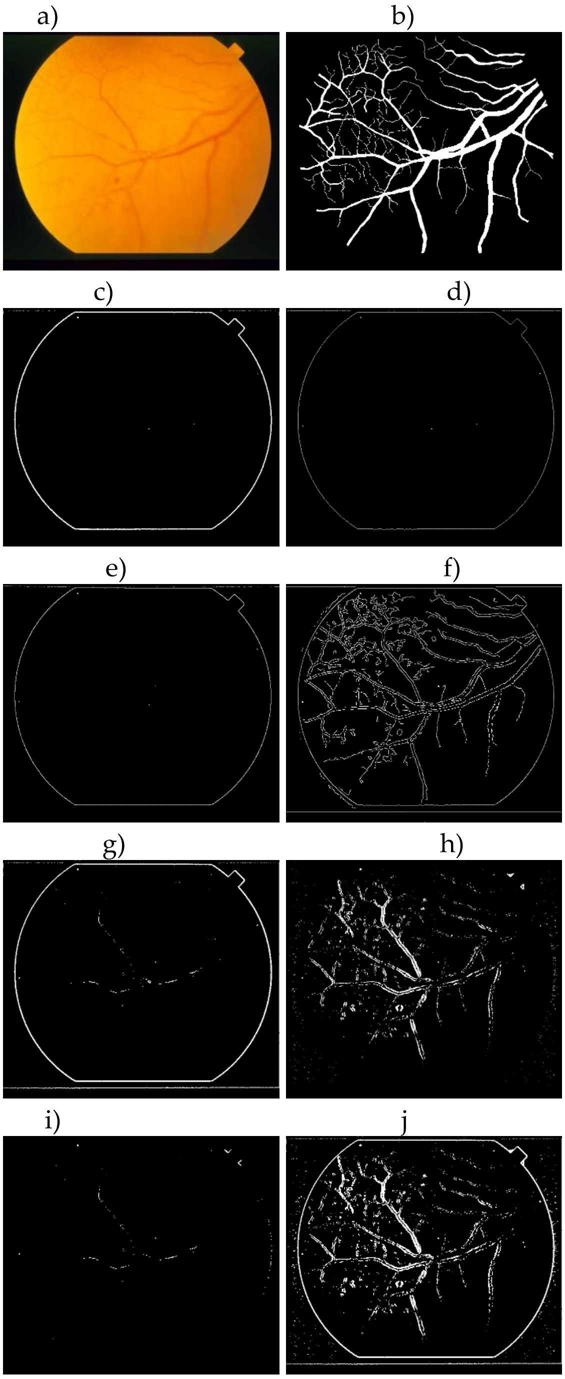

Figure 6. A visual comparison of different methods is given for an image from the STARE dataset. The original image and the ground truth for the image are given in a and b, respectively. Outputs of both classical and fuzzy methods are given as follows: c) Sobel filter, d) Prewitt filter, e) Roberts filter, f) Canny filter, g) Type-1 fuzzy method, h) Type-2 fuzzy method i) Hybrid 1 fuzzy method j) Hybrid 2 fuzzy method.

We concluded that Type-2 fuzzy method is the best for the STARE dataset with the retinal images, Roberts is the best for the BIPED dataset with the street and car images. Hybrid 1 fuzzy method is in the second best for the two distinct dataset used. It can be utilized for general purpose-all kinds of images.

Two different images from the BIPED dataset are simulated again to verify the results of the various methods used in Figure 7. As seen from both Figure 8 and Figure 9 the results confirm the argument made.

Table 2. PSNR, SSIM and MSE results of the fuzzy and classical methods for the BIPED dataset.

Method/Metric	PSNR	SSIM	MSE
Sobel	12.876	0.6649	3470.9
Prewitt	13.230	0.6499	3171.7
Roberts	**13.487**	**0.6621**	**2997.6**
Canny	9.1863	0.3731	7898.9
Type-1 Fuzzy Method	10.442	0.5267	5947.7
Type-2 Fuzzy Method	12.601	0.5899	3620.1
Hybrid 1 Fuzzy Method	**13.154**	**0.6310**	**3222.7**
Hybrid 2 Fuzzy Method	9.2007	0.4870	7897.6

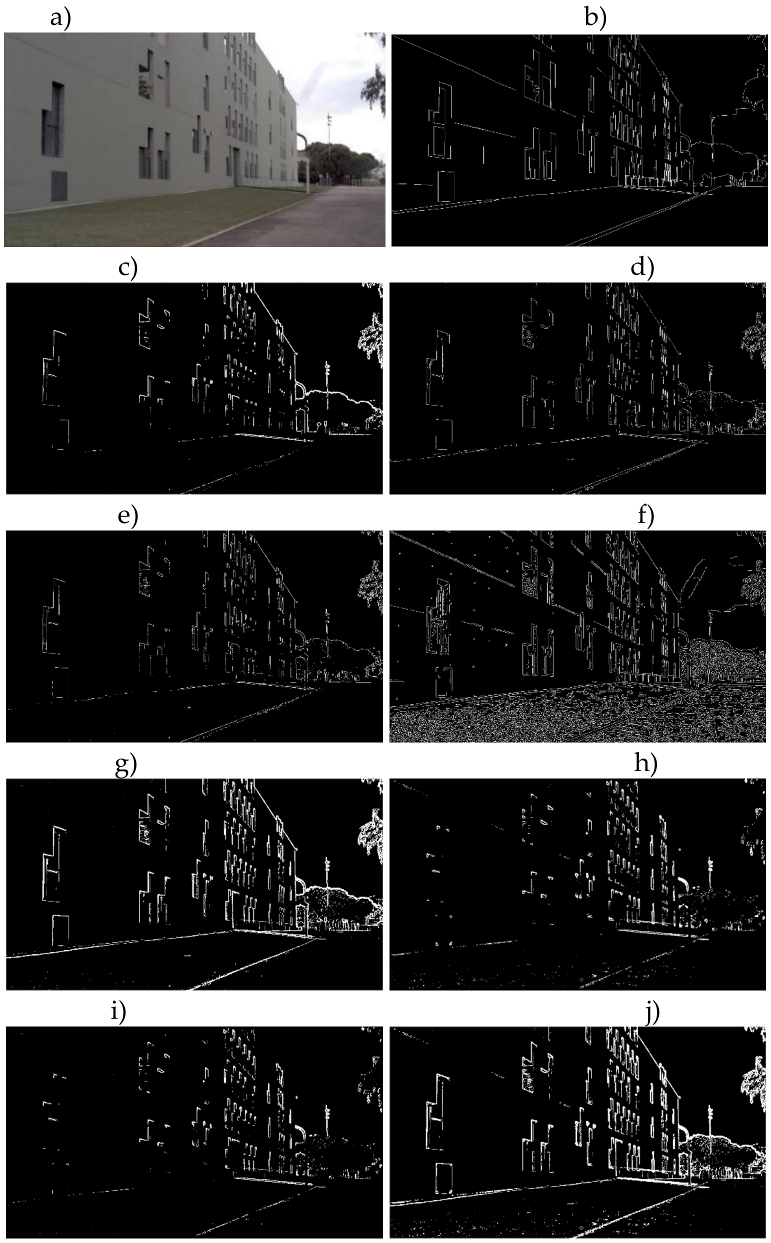

Figure 7. A visual comparison of different methods is given for an image from BIPED dataset. Original image and the ground truth for the image is given in a and b, respectively. Outputs of both classical and fuzzy methods are given as follows: c) Sobel filter, d) Prewitt filter, e) Roberts filter, f) Canny filter, g) Type-1 fuzzy method, h) Type-2 fuzzy method i) Hybrid 1 fuzzy method j) Hybrid 2 fuzzy method.

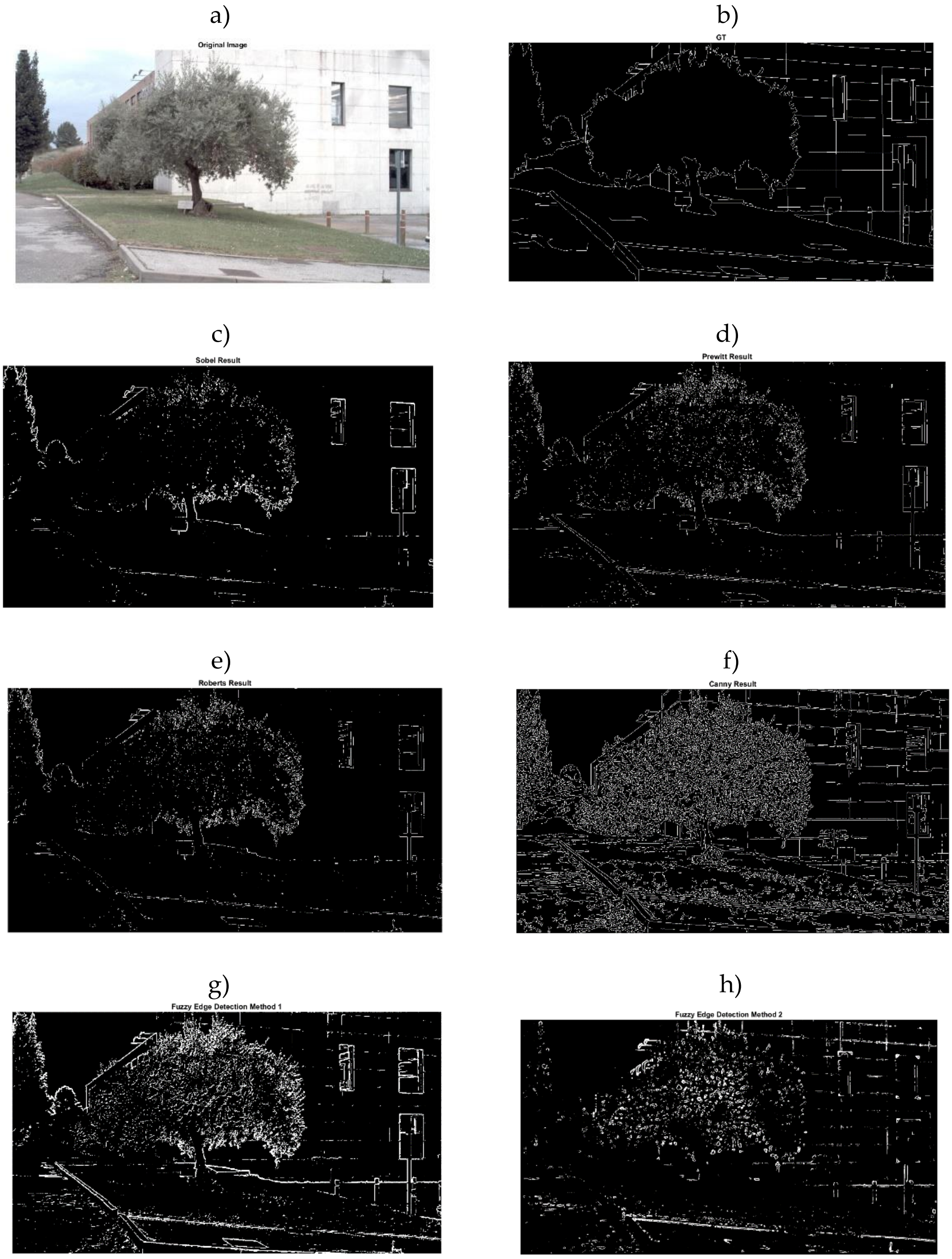

Figure 8. A visual comparison of the second image from BIPED dataset. The original image is provided in a, the ground truth image is provided in b. The following are the results of the fuzzy and classical methods: Type-1 fuzzy method (c), Sobel filter (d), Prewitt filter (e), Roberts filter (f), Canny filter (g), and Type-2 fuzzy method (h).

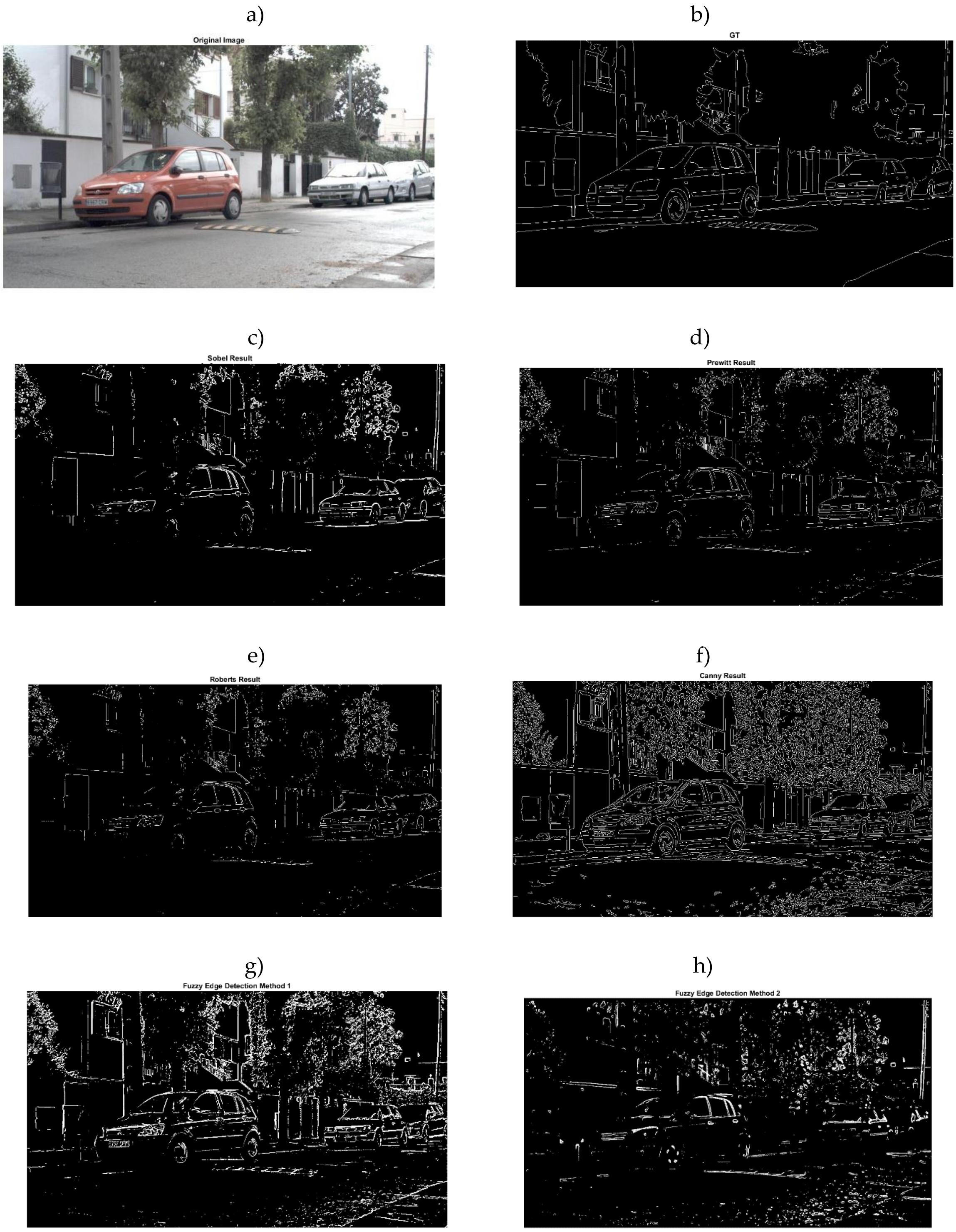

Figure 9. A visual comparison of the third image from the BIPED dataset. The original image is provided in a, the ground truth image is provided in b. The following are the results of the fuzzy and classical methods: Type-1 fuzzy method (c), Sobel filter (d), Prewitt filter (e), Roberts filter (f), Canny filter (g), and Type-2 fuzzy method (h).

6. CONCLUSION

Edge detection is one of the critical subjects in computer vision and has many application areas such as object detection. In this paper, several classical methods that are Sobel, Prewitt, Roberts, and Canny, and two of the fuzzy logic-based edge detection methods that use the type-1 fuzzy inference system and type-2 fuzzy inference system were implemented. Also, results of hybrid fuzzy methods which are obtained with "AND" and "OR" operators using outputs of type-1 and type-2 fuzzy methods are provided. The results were compared by using two datasets which are STARE blood vessels from retinal images and BIPED street and car images. Results were analyzed quantitatively and qualitatively. For quantitative assessment, PSNR, SSIM, and MSE image metrics were calculated for each method on both datasets. The type-2 fuzzy method outperformed on the STARE retinal image dataset while the Roberts method outperformed the BIPED street image dataset. In terms of visual quality, the hybrid-1 fuzzy method worked well on the BIPED data set following the Roberts method then the type-2 fuzzy method comes after the hybrid-1 fuzzy method.

For medical images, we choose the type-2 fuzzy approach, which may also be applied to street images. For more general images, the hybrid-1 fuzzy technique was adopted. Conclusion: Based on the selected image quality measures, we have discovered that the type-2 fuzzy approach is the best for identifying blood vessels, and Robert is the best for street images.

Declaration of Competing Interest

There is no competing interest.

Funding / Acknowledgements

There is no funding for the research.

Acknowledgments

I would like to thank Ismail Yener and Dursun Ali Ekinci for their contributions.

REFERENCES

[1] S. Yunhong, Y. Shilei, Z. Xiaojing, and Y. Jinhua, "Edge Detection Algorithm of MRI Medical Image Based on Artificial Neural Network," in *Procedia Computer Science*, Elsevier B.V., 2022, pp. 136–144. doi: 10.1016/j.procs.2022.10.021.

[2] M. C. Shin, D. B. Goldgof, and K. W. Bowyer, "Comparison of edge detector performance through use in an object recognition task," *Computer Vision and Image Understanding*, vol. 84, no. 1, pp. 160–178, 2001, doi: 10.1006/cviu.2001.0932.

[3] C. I. Gonzalez, P. Melin, and O. Castillo, "Edge detection method based on general type-2 fuzzy logic applied to color images," *Information (Switzerland)*, vol. 8, no. 3, Aug. 2017, doi: 10.3390/info8030104.

[4] P. Melin, O. Mendoza, and O. Castillo, "An improved method for edge detection based on interval type-2 fuzzy logic," *Expert Syst Appl*, vol. 37, no. 12, pp. 8527–8535, 2010, doi: 10.1016/j.eswa.2010.05.023.

[5] Y. Becerikli and T. M. Karan, "LNCS 3512 - A New Fuzzy Approach for Edge Detection," in *LNCS*, Springer-Verlag, 2005, pp. 943–951.

[6] L. Hu, H. D. Cheng, and M. Zhang, "A high performance edge detector based on fuzzy inference rules," *Inf Sci (N Y)*, vol. 177, no. 21, pp. 4768–4784, Nov. 2007, doi: 10.1016/j.ins.2007.04.001.

[7] M. E. Yüksel, “Edge detection in noisy images by neuro-fuzzy processing,” *AEU - International Journal of Electronics and Communications*, vol. 61, no. 2, pp. 82–89, Feb. 2007, doi: 10.1016/j.aeue.2006.02.006.

[8] C. C. Kang and W. J. Wang, “A novel edge detection method based on the maximizing objective function,” *Pattern Recognit*, vol. 40, no. 2, pp. 609–618, Feb. 2007, doi: 10.1016/j.patcog.2006.03.016.

[9] O. Mendoza, P. Melin, and G. Licea, “A New Method for Edge Detection in Image Processing Using Interval Type-2 Fuzzy Logic,” Institute of Electrical and Electronics Engineers (IEEE), Apr. 2008, pp. 151–151. doi: 10.1109/grc.2007.115.

[10] F. Jacquey, F. Comby, and O. Strauss, “Fuzzy edge detection for omnidirectional images,” *Fuzzy Sets Syst*, vol. 159, no. 15, pp. 1991–2010, Aug. 2008, doi: 10.1016/j.fss.2008.02.022.

[11] N. Mathur, S. Mathur, and D. Mathur, “A Novel Approach to Improve Sobel Edge Detector,” in *Procedia Computer Science*, Elsevier B.V., 2016, pp. 431–438. doi: 10.1016/j.procs.2016.07.230.

[12] F. Orujov, R. Maskeliūnas, R. Damaševičius, and W. Wei, “Fuzzy based image edge detection algorithm for blood vessel detection in retinal images,” *Applied Soft Computing Journal*, vol. 94, Sep. 2020, doi: 10.1016/j.asoc.2020.106452.

[13] Z. Wang and A. C. Bovik, “Mean squared error: Lot it or leave it? A new look at signal fidelity measures,” *IEEE Signal Process Mag*, vol. 26, no. 1, pp. 98–117, 2009, doi: 10.1109/MSP.2008.930649.

[14] J. Erfurt, C. R. Helmrich, S. Bosse, H. Schwarz, D. Marpe, and T. Wiegand, “A Study of The Perceptually Weighted Peak Signal-To-Noise Ratio (Wpsnr) For Image Compression,” in *2019 IEEE International Conference on Image Processing (ICIP) : September 22-25, 2019, Taipei International Convention Center (TICC), Taipei, Taiwan*, IEEE Signal Processing Society, 2019.

[15] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: From error visibility to structural similarity,” *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, Apr. 2004, doi: 10.1109/TIP.2003.819861.

[16] R. Sun *et al.*, “Survey of Image Edge Detection,” *Frontiers in Signal Processing*, vol. 2, Mar. 2022, doi: 10.3389/frsip.2022.826967.

[17] D. Ziou and S. Tabbone, “Edge detection techniques: An overview’ Article ·,” 1998. [Online]. Available: https://www.researchgate.net/publication/312890367

[18] G. T. Shrivakshan and C. Chandrasekar, “A Comparison of various Edge Detection Techniques used in Image Processing,” 2012. [Online]. Available: www.IJCSI.org

[19] D. Ma, “Theory of edge detection,” 1980. [Online]. Available: https://royalsocietypublishing.org/

[20] X. Wang, “Laplacian operator-based edge detectors,” *IEEE Trans Pattern Anal Mach Intell*, vol. 29, no. 5, pp. 886–890, May 2007, doi: 10.1109/TPAMI.2007.1027.

[21] J. Canny, “A Computational Approach to Edge Detection,” *IEEE Trans Pattern Anal Mach Intell*, no. 6, 1986.

[22] A. Hoover, V. Kouznetsova, and M. Goldbaum, “Locating Blood Vessels in Retinal Images by Piecewise Threshold Probing of a Matched Filter Response,” *IEEE Trans Med Imaging*, vol. 19, no. 3, 2000.

[23] X. Soria, E. Riba, and A. Sappa, “Dense Extreme Inception Network: Towards a Robust CNN Model for Edge Detection.” [Online]. Available: https://github.com/xavysp/DexiNed