Comparative Analysis of mshEdgeGrayFT2 and Laplacian of Gaussian Method for Edge Detection in Grayscale Images

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ABSTRACT
Edge detection is a fundamental technique in image processing that can enhance the visual quality and readability of images by highlighting the boundaries and contours of objects, shapes, and features. It has many applications in various fields and domains, such as computer vision, machine learning, image analysis, pattern recognition, medical imaging, remote sensing, and art.Interval type-2 fuzzy logic is particularly useful for pattern recognition and image processing because it can manage the uncertainty in the gradient of an image and their aggregation. This uncertainty allows for the detection of edges that may be overlooked by conventional edge detection approaches. In this paper, we analysed fuzzy logic-based algorithms that aim to enhance the conventional edge detection methods.A fuzzy logic type-2 based approach, mshEdgeGrayFT2 is utilized for detecting edges in images. We compared the results with the fuzzy logic type-1 based mshEdgeGrayFT1algorithm and the Laplacian of Gaussian Edge Detector. The work demonstrates comparison analysis of different edges identified for different fuzzy parameters set for fuzzy logic type-1 based mshEdgeGrayFT1algorithm and fuzzy logic type-2 based mshEdgeGrayFT2 algorithm.

Keywords: Edge Detection, Fuzzy Logic Type-1, Fuzzy Logic Type-2, Gray Scale Images, Laplacian of Gaussian.

1. INTRODUCTION

Edges are significant in digital image analysis as they signify change in intensity within a digital image.These changes, or discontinuities, are abrupt and highlight the boundaries between different regions in an image.Edges also indicate the areas of discontinuity.This helps in image segmentation and object recognition[1].Over the years, numerous edge detection approaches have been developed, but the most frequent is to use first or second derivative.This leads to the classification of edge detection methods into gradient edge detectors and Laplacian methods or Gaussian edge detectors [2]. The gradient, a vector, denotes the strength of edge pixel through its magnitude and the direction of edges through its orientation. Based on variations in pixel intensities, pixels with high gradient values are identified as edges. "Roberts, Sobel and Prewitt" are gradient based edge detectors.The drawbacks of gradient based edge detectors include their sensitivity to noise, which affects the accuracy of edge detection and their orientations [3]. In Laplacian method, the process involves initially smoothing the image with a Gaussian filter, followed by applying the Laplacian to find the second derivative for enhancement.The final step involves detecting edges by locating zero crossings in the second derivative, which correspond to high peaks in the first derivative [4].Shrivakshanetal et al. [5] investigated edge detection techniques for Shark Fish Classification using gradient-based operators (Roberts, Sobel, Prewitt), Laplacian-based edge detectors, and the Canny edge detector, highlighting the increasing attention to edge detection in image processing. Gradient-based edge detection algorithms are sensitive to noise and use static kernel filters, limiting their adaptability to varying image conditions. The Canny algorithm, while effective, relies mainly on changing parameters like the Gaussian filter's standard deviation and thresholds, affecting performance based on these settings.Juneja et al. [6] presented the comparative analysis of different edge detection techniques by using threshold. In Sobel, Prewitt, and Robert's methods, threshold is applied to gradient function. In Laplacian of Gaussian (LoG) method, thresholding occurs on the zero-crossing slope after the image is processed with a LoG filter. After applying threshold, the Canny method uses the derivative of a Gaussian filter to calculate the gradient.Visually, the Sobel, Prewitt, and Robert's methods produce lower quality edge maps compared to the others. The Canny and LoG methods provide better image representations, with the Canny method being more effective at detecting both strong and weak edges, making it more suitable than the LoG method.

In recent years, edge detection algorithms based on fuzzy logic have gained significant attention due to their computational effectiveness and quick processing times. Furthermore, specialized methods have been developed to further enhance the edge detection performance. Russo [7] introduced the use of fuzzy inference for efficiently extracting edge features with strong noise robustness, the application of fuzzy theory in edge detection has gained increasing attention. Melin et al. [8] proposed an edge detection approach using an interval type-2 (IT2) fuzzy logic system based on the morphological gradient technique. This system employs Gaussian membership functions with dynamically calculated parameters based on image gradient values. Type reduction is performed using the centre of sets method. Simulations compared a type-1 fuzzy inference system and an IT2 FLS.The IT2 FLS achieves superior results due to its ability to model uncertainty in gradient values and gray ranges.Castillo et al. [9]explored the use of type-2 fuzzy systems in various image processing application,including segmentation, classification, filtering, and edge detection. The paper presents enormous applications by utilizing interval-value fuzzy sets, general type-2 fuzzy sets, and interval type-2 fuzzy sets, comparing themwith traditional type-1 fuzzy sets and other establishedmethodologies in the image processing literature**.** Baghbani et al. [10] proposed an edge detection method that utilized interval-valued fuzzy sets. In this approach, each pixel isassigned an interval membership derived from its intensity as well its neighbouring pixels.

Biswas et al. [11] developed an algorithm by utilizing type-2 fuzzy sets to handle uncertainties. This algorithm automatically calculates the threshold values required for segmenting gradient images using the classical Canny edge detection method. The method performs well on both benchmark and medical images, such as hand radiography images. Liu [12] introduced an efficient centroid type-reduction strategy for general type-2 fuzzy sets by utilizing α-plane representation and performing type-reduction on each α-plane. Simulations indicate that only a few resolution steps are typically required for the defuzzified value to converge to a precise value.Wu et al. [13] introduced a type-2 fuzzy set concept called the Footprint of Uncertainty (FOU). Their paper focuses on creating more high efficiency type-reducers. This type-reducer utilizes equivalent type-1 sets, which replicate the input-output mapping of a fuzzy logic system based on type-2.

The contribution of this paper is the comparison of two algorithms mshEdgeGrayFT1 and mshEdgeGrayFT2 withtheLaplacian of Gaussian operatorfor edge detection.The organization of the rest of the paper is as follows: Section 2 describes some basic concepts of Fuzzy type-1, Fuzzy type-2 and LoG operators. Experimental results and discussion have been done in Section 3. Section 4 concludes the research work.

2. METHODS

In this segment, some basic concepts related to this paper have been discussed.

2.1 Type-1 Fuzzy Logic System

Fuzzy logic, introduced by Lotfi Zadeh in the 1960s, is a type of logic designed to handle approximate rather than precise reasoning, unlike traditional binary logic. It is especially useful when dealing with ideas like uncertainty, imprecision, and vagueness. A Fuzzy Logic System (FLS) transforms crisp inputs into crisp outputs(Fig.1) consisting of four main components: the fuzzifier, rules, inference engine, and defuzzifier.

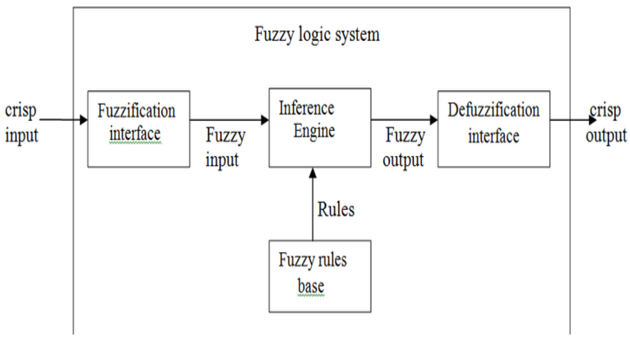


Fig 1. Fuzzy Logic Type-1 [14]

The fuzzifier converts crisp numbers into fuzzy sets, which are necessary to activate the rules using linguistic variables. The inference engine processes these fuzzy sets and manages how the rules are combined. Fuzzy logic type-1 handles the uncertainties which are related to Fuzzy Logic System (FLS) input and output values by using the crisp membership function. When the Fuzzy logic Type-1 membership functions are selected then all uncertainty is eliminated because membership functions are precise [14].

2.2. Type-2 Fuzzy Logic System

TheType-2 Fuzzy Logic System (FLS), introduced by Lotfi Zadeh in 1975, enhances traditional fuzzy logic by incorporating fuzzy membership functions that are themselves fuzzy. Unlike Type-1 fuzzy sets as shown in Fig.2, which have crisp membership grades within[0, 1], Type-2 fuzzy sets feature membership grades that are subsets within [0,1]. These three-dimensional sets include a "Footprint of Uncertainty" adding degrees of freedom to effectively model and manage uncertainties. Although advantageous for scenarios where precise membership functions are difficult to define, Type-2 FLSs are computationally intensive and may not be ideal for some real-time applications [15].

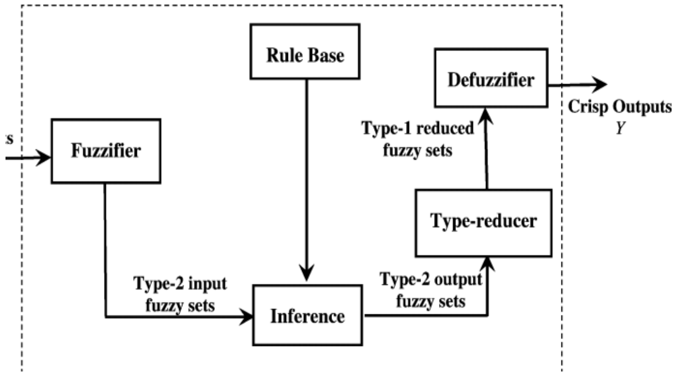


Fig 2. Fuzzy Logic Type-2 [15].

2.3. Laplacian of Gaussian (LoG)

The Laplacian Gaussian edge detector can remove the noise and give the smoothness of any gray image with a higher sigma value. It calculates the second-order derivatives of gray images which are used to identify the edge pixels and any abrupt change in those taken images. This edge detector is also known as the Marr-Hildreth edge detector. Particularly, Laplacian filters are very sensitive to noise, so firstly they work on the smoothness of images.

The Laplacian process is given in equation (1):

$$L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \qquad (1)$$

To find an approximate discrete convolution mask,several methods are available that minimise the effect of Laplacian. One of them is given below:

$$\begin{pmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

For negative Laplacian, centre pixel is negative and the other pixels are positive, for positive Laplacian, centre pixel is positive and the othersare negative. The Gaussian filter can be derived by equation (2), which is the combination of both the Laplacian and Gaussian functions [16].

$$LoG\ (x,y)=\frac{1}{\pi\sigma^4}1-\frac{x^2+y^2}{2\sigma^2}\ e^{\frac{x^2+y^2}{2\sigma^2}} \qquad (2)$$

3. RESULTS AND DISCUSSION

In this segment, the comparative analysis of fuzzy logic-based edge detection algorithms mshEdgeGrayFT1,mshEdgeGrayFT2 and LoGhave been done for gray scale images.For experiments, we used three gray scale jpg images namely Einstein (182×186), Camera Man (203× 249) and City Building (270×148) as shown in Fig 3.

In algorithm mshEdgeGrayFT1, firstly, we take a gray scale image and remove the noise from the image by using Gaussian filter and then mask the image. In fuzzy inference system (FIS), two inputs are taken as difference of two consecutive column(diff Column) and rows(diff Row) of a masked image. A Fuzzy rule base was created to identify and display the edge pixels. The Mamdani inference approach was employed for defuzzification, and the centroid method was used to determine the system's output. For

mshEdgeGrayFT2 algorithm, the same technique used in mshEdgeGrayFT1 was implemented for a direct comparison of results of these two algorithms.
We used the Laplacian of Gaussian (LoG) edge detector to identify the edges in the image (**edgeImage_log)**. Additionally, edges were identified using the **mshEdgeGrayFT1**and **mshEdgeGrayFT2** algorithms. A comparative analysis is shown in Fig. 4.

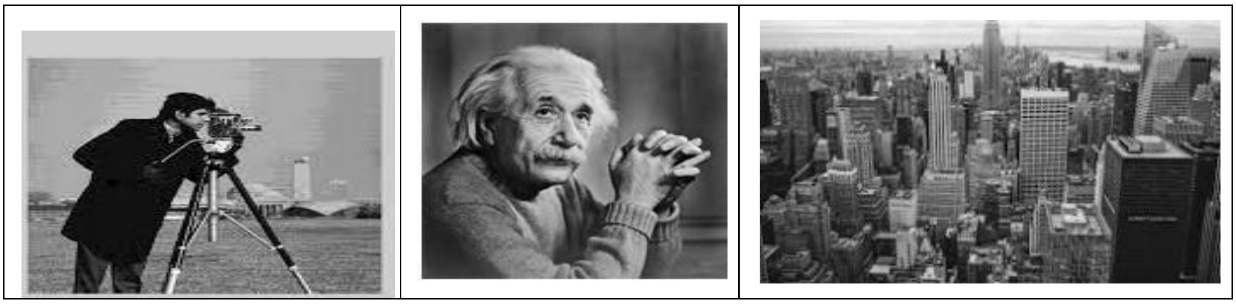


Fig 3. Original gray images of different size

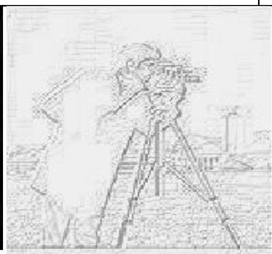
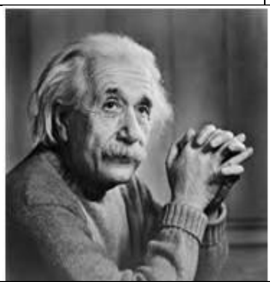
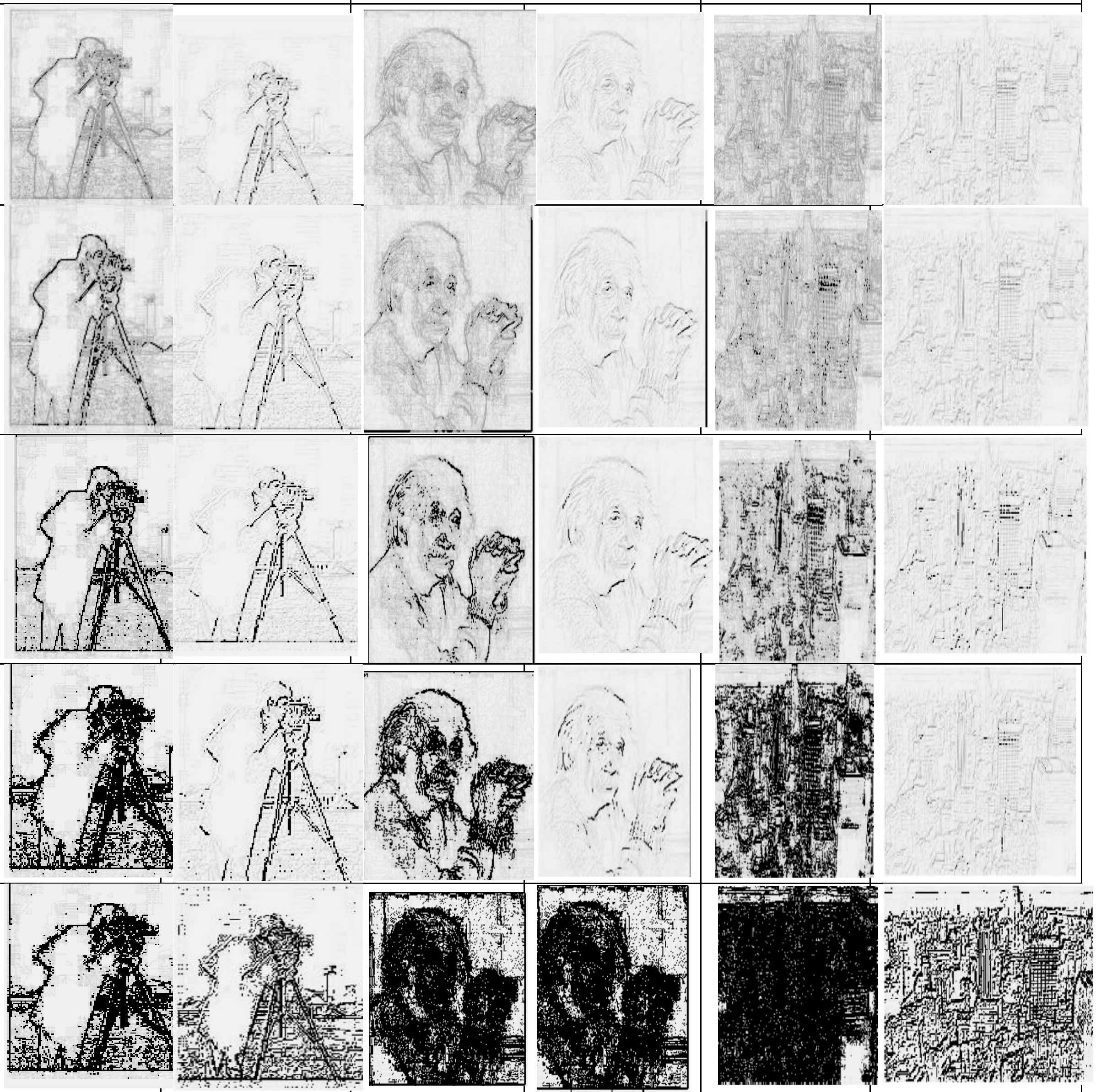
Name	Original image	**edgeImage_log**	**edgeImage_type1**	**edgeImage_type2**
Camera Man				
Einstein				
City Building				

Fig 4. Edge images are generated by using different edge operator

The edges identified by the mshEdgeGrayFT1algorithm (edgeImage_type1)show clearer and more defined edges. In contrast, the edges identified by the mshEdgeGrayFT2 algorithm (edgeImage_type2) appear smoother and slightly less defined because of its ability to handle more uncertainty. As a result, both algorithms mshEdgeGrayFT1 and mshEdgeGrayFT2
detected more edges as compared to the Laplacian of Gaussian edge detector, due to their ability to handle uncertainty and noise without requiring a hard threshold for edge detection.Next,the analysis of algorithm mshEdgeGrayFT1 and mshEdgeGrayFT2 according to different range of membership values has been shown in Fig.5.



Range of membership value	Images					
	Camera Man		Einstein		City Building	
0.5-1.0						
0.6-1.0						
0.7-1.0						
0.8-1.0						
0.9-1.0						
	edgeImage_type1	**edgeImage_type2**	**edgeImage_type1**	**edgeImage_type2**	**edgeImage_type1**	**edgeImage_type 2**

Fig 5. Comparison of identified edges by using mshEdgeGrayFT1 and mshEdgeGrayFT2 according to different range of membership values

Using a larger range of membership values, the detected edges appear clearer and more precise because the system is effectively capturing more significant transitions in pixel intensity.But with a smaller range of membership values, only pixels with very specific intensity differences are considered part of an edge. Consequently, the edges may appear less clear or even missing, as the system may not capture more subtle transition.Next, we identified the number of edge pixels using the mshEdgeGrayFT1and mshEdgeGrayFT2 algorithms for different ranges of membership values [0.5-1], as shown in Table 1.In some ranges of membership values, the number of edge pixels was the same for both algorithms. However, in other ranges, the mshEdgeGrayFT2 algorithm detected a greater number of edge pixels as compared to the mshEdgeGrayFT1algorithm, due to the handling of uncertainty in Fuzzy Type-2.Various evaluation parameters, including PSNR, MSE, and L2RAT, were used to assess the similarity between the edge images identified using LoG, mshDetectGrayFT1 and mshEdgeGrayFT2 algorithm as presented in Table1. PSNR and MSE represent the peak signal-to-noise ratio and mean square error between two edge images, i.e. edgeImage_log and edgeImage_type1. Additionally, PSNR and MSE were also used to compare the similarity between edgeImage_log and edgeImage_type2.

Table 1. Comparative analysis of performance parameters for defined ranges of membership values

Images	Range of member ship value	**mshEdgeGrayFT1**				**mshEdgeGrayFT2**			
		No. of edge pixels	PSNR	MSE	L2RAT	No. of edge pixels	PSNR	MSE	L2RAT
City Building	0.5-1.0	39957	3.545	28742.284	1.575	39957	3.439	29454.766	1.696
	0.6-1.0	39793	3.512	28960.349	1.573	39898	3.427	29533.063	1.695
	0.7-1.0	38141	3.198	31132.682	1.535	39466	3.339	30141.240	1.685
	0.8-1.0	32516	2.433	37130.882	1.368	38049	3.071	32058.257	1.368
	0.9-1.0	19730	1.722	43735.882	0.884	26320	1.880	42167.837	1.188
Einstein	0.5-1.0	33850	3.641	28114.815	1.609	33800	3.526	28866.025	1.698
	0.6-1.0	33177	3.577	28530.211	1.596	33231	3.480	29174.118	1.688
	0.7-1.0	32481	3.454	29350.230	1.578	32937	3.437	29469.291	1.681
	0.8-1.0	30033	3.021	32426.535	1.493	32480	3.339	30139.368	1.665
	0.9-1.0	20836	2.214	39048.719	1.082	26462	2.542	36207.200	1.391
Camera Man	0.5-1.0	50499	1.658	44389.376	3.785	50501	1.579	45198.326	3.914
	0.6-1.0	50230	1.632	44653.158	3.777	50314	1.561	45383.744	3.909
	0.7-1.0	49316	1.551	45486.467	3.741	49876	1.521	45810.281	3.892
	0.8-1.0	47327	1.395	47160.424	3.639	49248	1.471	46340.724	3.860
	0.9-1.0	41784	1.131	50105.205	3.272	44964	1.189	49442.265	3.571

A low PSNR and high MSE indicate a greater difference in the edge pixels between edgeImage_log and edgeImage_type2. In ranges, where the difference of edge pixels is less, the PSNR value is high and MSE is low. Throughout the comparison, it is evident that variations in the number of edge pixels impact the values of the evaluation parameters.

4. CONCLUSION

This paper presents the comprehensive comparison of the algorithm mshEdgeGrayFT1 and mshEdgeGrayFT2 by using fuzzy logic for detecting number of edge pixelsaccording to different range of membership value. The algorithm involves various steps, from preprocessing the image with Gaussian filter to create a fuzzy inference system for edge detection. The work focuses on evaluating various metrices such as PSNR, MSE and L2RAT foredge Image_log with edgeImage_type1 and edge Image_type2. Also, we compared the algorithmmshEdgeGrayFT1 and mshEdgeGrayFT2with the widely used Laplacian of Gaussian edge detector method. As a result, the algorithms mshEdgeGrayFT1 and mshEdgeGrayFT2 show greater number of edge pixels. The researcher can use the algorithm pixels mshEdgeGrayFT2for hiding data in edge pixels.

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Conflict of Interest
"The authors declare that they have no conflicts of interest.

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