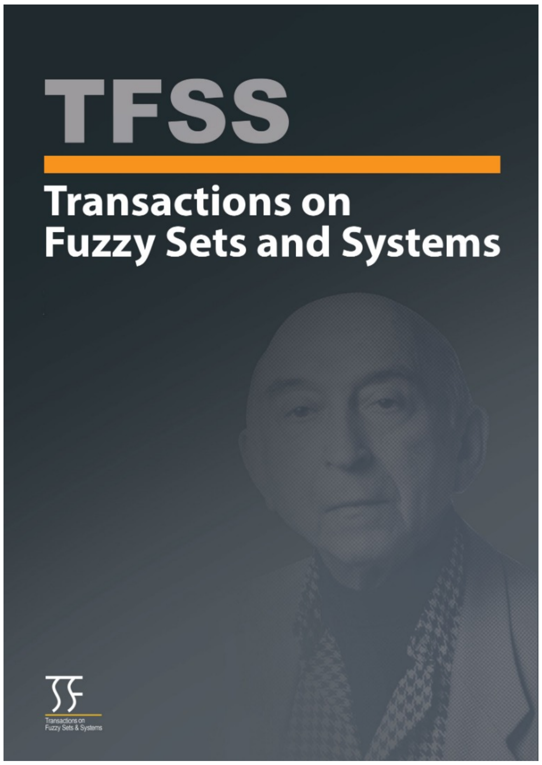
Transactions on Fuzzy Sets and Systems



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A Unique Edge Detection Strategy Employing Neutrosophic r-cut with Enhanced User Interference

Himangshu Nath, **Prasenjit Bal**, **Mithun Datta***

Abstract. Neutrosophic set (NS) theory provides a foundation for investigating the nature and implications of neutral elements within various conceptual frameworks. While NS offers a general framework, its practical application requires specific adaptations to suit particular domains. This research focuses on applying NS to the field of image segmentation. By representing images in the NS domain using truth (T), indeterminacy (I), and falsity (F) membership functions, we introduce a novel entropy measure to quantify image uncertainty. An r-cut-based segmentation method is developed to partition images effectively. Experimental results validate the proposed approach's ability to segment images across different values of r, demonstrating its robustness in handling both clean and noisy image conditions.

AMS Subject Classification 2020: 91B06; 94A08; 94A13
Keywords and Phrases: Neutrosophic Set, r-cut, Image Processing, Edge Detection.

1 Introduction

Neutrosophic set (NS) theory, introduced by Florentin Smarandache [1], offers a powerful framework for handling uncertainty and indeterminacy by considering truth, indeterminacy, and falsity membership degrees independently. This departure from traditional set theory has shown promise in various fields, including image processing.

Image segmentation, a fundamental task in computer vision, involves partitioning an image into distinct, semantically meaningful regions. While traditional segmentation techniques have demonstrated efficacy in certain scenarios, their performance often falters when confronted with the inherent ambiguity and uncertainty prevalent in real-world imagery. These challenges arise from factors such as noise, occlusions, and variations in illumination, rendering precise pixel-wise classification a formidable task. To address these limitations, this paper introduces a novel image segmentation framework grounded in neutrosophic set (NS) theory. By leveraging the ability of NS to model uncertainty, vagueness, and inconsistency, we propose a robust approach that effectively captures the complexities inherent in images. Some recent works on image processing and r-cut can be found in [2], [3], and [4]. Our contributions encompass the development of a novel NS-based entropy measure to quantify image uncertainty, enabling a more nuanced understanding of image content. Furthermore, we introduce an r-cut segmentation algorithm specifically tailored to the NS domain, providing a flexible and adaptive framework for image partitioning. The subsequent sections will delve into the theoretical underpinnings of our methodology, present experimental results validating its efficacy, and discuss the broader

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implications of our research. Some works on edge detection over the last years are done by Shrivakshan et al [5], Maini et al [6], Gao et al [7], Chen etal [8].

The r-cut segmentation method influences results by reducing false edges and enhancing real ones. Users can fine-tune edge strength based on different values of r. This method filters out high-indeterminacy pixels. It works across different image types and noise levels. By leveraging neutrosophic set theory and r-cut thresholds, the proposed method outperforms traditional edge detection techniques, offering greater flexibility and accuracy in segmentation results.

2 Motivation and Preliminaries

Edge detection is a fundamental task in image processing and computer vision. It plays a critical role in object recognition, segmentation, and feature extraction. However, traditional edge detection methods, such as Sobel, Prewitt, and Canny often face challenges when dealing with noisy images, poor illumination, and ambiguous edges. These methods struggle to differentiate between actual object boundaries and noise-induced artifacts, leading to inaccurate segmentation results. Limitations of Traditional Edge Detection Approaches Existing edge detection techniques rely on gradient-based or thresholding methods, which suffer from limitations like noise sensitivity, fixed thresholding, and uncertainty handling issues. Thus, there is a strong need for an approach that can handle image uncertainty effectively, reducing false detections while preserving meaningful edges. Neutrosophic Set (NS) theory provides a powerful mathematical framework to handle uncertainty, vagueness, and imprecision by incorporating three membership values such as truth ($\tilde{\mathcal{T}}$), indeterminacy ($\tilde{\mathcal{I}}$), and falsity ($\tilde{\mathcal{F}}$). This approach allows for a more flexible representation of pixel properties, enabling a better balance between edge preservation and noise reduction. While NS-based methods have been explored in image processing, an effective segmentation strategy tailored for edge detection was lacking. This paper introduces an r-cut-based segmentation framework, which:

- Offers user control over segmentation strength via the r threshold, allowing fine-tuned edge detection.
- Provides adaptive filtering of edges based on uncertainty.
- Reduces noise interference by discarding pixels with high indeterminacy.

This approach bridges the gap between theoretical NS concepts and practical edge detection applications which makes image segmentation more robust and versatile. The motivation behind this study is to introduce a more effective and adaptable edge detection strategy that overcomes the challenges of traditional methods. By leveraging neutrosophic set theory and r-cut filtering, this approach enables better edge segmentation with enhanced noise resistance, making it valuable for applications in medical imaging, remote sensing, object recognition, etc. Let us now discuss some preliminary concepts which are essential for this article.

Definition 2.1. [9] *We assume that a non-empty set which is $\mathcal{X}$. Then a fuzzy set (FS) α is a set having the form $\alpha = \left\{(x, \tilde{\mathcal{T}}_\alpha(x)) : x \in \mathcal{X}\right\}$ where the function $\tilde{\mathcal{T}}_\alpha : \mathcal{X} \to$ [0,1] is called the membership function and $\tilde{\mathcal{T}}_\alpha(x)$ is called the degree of membership of each element $x \in \mathcal{X}$.*

Definition 2.2. [10] *We assume that a non-empty set which is $\mathcal{X}$. An Intuitionistic Fuzzy Set (IFS) α is an set having the form $\alpha = \left\{(x, \tilde{\mathcal{T}}_\alpha(x), \tilde{\mathcal{F}}_\alpha(x)) : x \in \mathcal{X}\right\}$ where the functions $\tilde{\mathcal{T}}_\alpha : \mathcal{X} \to [0,1]$ and $\tilde{\mathcal{F}}_\alpha : \mathcal{X} \to [0,1]$ denote the degree of membership (namely $\tilde{\mathcal{T}}_\alpha(x)$) and the degree of non-membership (namely $\tilde{\mathcal{F}}_\alpha(x)$) of each element $x \in \mathcal{X}$ to the set α respectively and $0 \leq \tilde{\mathcal{T}}_\alpha(x) + \tilde{\mathcal{F}}_\alpha(x) \leq 1$ for each $x \in \mathcal{X}$.*

Definition 2.3. [1] *A neutrosophic set (NS) which is α on the universal crisp set $\mathcal{X}$ can be defined as $\alpha = \{(x, \tilde{\mathcal{T}}_\alpha(x), \tilde{\mathcal{I}}_\alpha(x), \tilde{\mathcal{F}}_\alpha(x)) : x \in \mathcal{X}\}$, where $\tilde{\mathcal{T}}_\alpha, \tilde{\mathcal{I}}_\alpha, \tilde{\mathcal{F}}_\alpha : \mathcal{X} \to]^{-}0, 1^{+}[$ are functions such that the condition*

$\forall x \in \mathcal{X}$, $^{-}0 \leq \tilde{\mathcal{T}}_\alpha(x) + \tilde{\mathcal{I}}_\alpha(x) + \tilde{\mathcal{F}}_\alpha(x) \leq 3^{+}$ is satisfied. Here $\tilde{\mathcal{T}}_\alpha, \tilde{\mathcal{I}}_\alpha, \tilde{\mathcal{F}}_\alpha$ represent the truth membership function, indeterminacy membership function and falsity membership function respectively of the element $x \in U$.

Definition 2.4. [11] *Let α be a neutrosophic subset of $\mathcal{X}$ defined by $\alpha = \{(x, \tilde{\mathcal{T}}_\alpha(x), \tilde{\mathcal{I}}_\alpha(x), \tilde{\mathcal{F}}_\alpha(x)) : x \in \mathcal{X}\}$. For any $r \in [0,1]$, the weak r-cut of α may be defined by two types:*
***Type 1**: $\alpha_r = \{x : x \in \mathcal{X}$, either $\tilde{\mathcal{T}}_\alpha(x), \tilde{\mathcal{I}}_\alpha(x) \geq r$ or $\tilde{\mathcal{F}}_\alpha(x) \leq 1-\alpha\}$*
***Type 2**: $\alpha_r = \{x : x \in \mathcal{X}$, either $\tilde{\mathcal{T}}_\alpha(x) \geq r, \tilde{\mathcal{I}}_\alpha(x) \leq r$ or $\tilde{\mathcal{F}}_\alpha(x) \leq 1-\alpha\}$*
and the strong r-cut is defined by
***Type 1**: $\alpha_r = \{x : x \in \mathcal{X}$, either $\tilde{\mathcal{T}}_\alpha(x), \tilde{\mathcal{I}}_\alpha(x) > r$ or $\tilde{\mathcal{F}}_\alpha(x) < 1-\alpha\}$*
***Type 2**: $\alpha_r = \{x : x \in \mathcal{X}$, either $\tilde{\mathcal{T}}_\alpha(x) > r, \tilde{\mathcal{I}}_\alpha(x) < r$ or $\tilde{\mathcal{F}}_\alpha(x) < 1-\alpha\}$*

3 Case Study and Results

3.1 Case Study

Edge detection is a fundamental concept in image processing, used to identify the location and presence of edges by analyzing changes in image intensity. Various computational techniques are employed to detect edges, primarily by assessing variations in gray levels. However, edge detection methods can be sensitive to noise, often generating rapid responses to its presence. As a crucial component in image analysis, edge detection plays a pivotal role in pattern recognition, image segmentation, and scene interpretation. It functions as a filtering mechanism designed to extract edge points, which typically manifest as sudden changes in image brightness.

In image processing, edges are regarded as a unique class of singularities. Mathematically, singularities in a function are characterized by discontinuities where the gradient approaches infinity. Since image data is inherently discrete, edges within an image are commonly defined as the local maxima of the gradient.

Edges predominantly occur at the boundaries between objects, between primitives, or between objects and the background. These boundaries often appear as discontinuities in the reflected intensity. Edge detection methodologies focus on identifying changes in single-pixel intensity values within grayscale images to delineate these transitions.

Edge detection techniques are widely utilized for measuring, detecting, and locating variations in grayscale images. Edges serve as fundamental features in an image, representing the most distinct and informative structures within an object. The identification of edges and lines provides critical insights into an object's overall structure. Consequently, edge extraction is a vital process in computer graphics, image processing, and feature extraction applications.

Difference of pixel values with point $\tilde{P}_{i,j}$ is determined by $|\tilde{P}_{i,j} - \tilde{P}_{i-1,j-1}|$, $|\tilde{P}_{i,j} - \tilde{P}_{i-1,j}|$, $|\tilde{P}_{i,j} - \tilde{P}_{i-1,j+1}|$, $|\tilde{P}_{i,j} - \tilde{P}_{i,j-1}|$, $|\tilde{P}_{i,j} - \tilde{P}_{i+1,j-1}|$, $|\tilde{P}_{i,j} - \tilde{P}_{i+1,j}|$, $|\tilde{P}_{i,j} - \tilde{P}_{i+1,j+1}|$.

The maximum difference indicated the maximum chance of the existence of an edge at that point. So we take the true membership value as $\tilde{\mathcal{T}}_{i,j} = max\{|\tilde{P}_{i,j} - \tilde{P}_{i-1,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i-1,j}|, |\tilde{P}_{i,j} - \tilde{P}_{i-1,j+1}|, |\tilde{P}_{i,j} - \tilde{P}_{i,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i,j+1}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j+1}|\}$.

In the conventional sense, (1-true membership) represents the false membership. But false membership is also a membership where a maximum of non-difference of pixel values of all neighboring points indicates the absence of an edge. So we take the false membership value as $\tilde{\mathcal{F}}_{i,j} = max\{1-|\tilde{P}_{i,j} - \tilde{P}_{i-1,j-1}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i-1,j}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i-1,j+1}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i,j-1}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i,j+1}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i+1,j-1}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i+1,j}|, 1-|\tilde{P}_{i,j} - \tilde{P}_{i+1,j+1}|\}$.

Meanwhile, the greatest difference of all the differences creates the **hesitancy** about the existence of an edge. So we take the **indeterminacy** membership value as $\tilde{\mathcal{I}}_{i,j} = max\{|\tilde{P}_{i,j} - \tilde{P}_{i-1,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i-1,j}|, |\tilde{P}_{i,j} - \tilde{P}_{i-1,j+1}|, |\tilde{P}_{i,j} - \tilde{P}_{i,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i,j+1}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j+1}|\} - min\{|\tilde{P}_{i,j} - \tilde{P}_{i-1,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i-1,j}|, |\tilde{P}_{i,j} - \tilde{P}_{i-1,j+1}|, |\tilde{P}_{i,j} - \tilde{P}_{i,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i,j+1}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j-1}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j}|, |\tilde{P}_{i,j} - \tilde{P}_{i+1,j+1}|\}$.

For the computational scheme, we choose the following figure 1 as the subject of the experiment whose neighborhood of the point $\tilde{P}_{245,245}$ is given in table 1 .

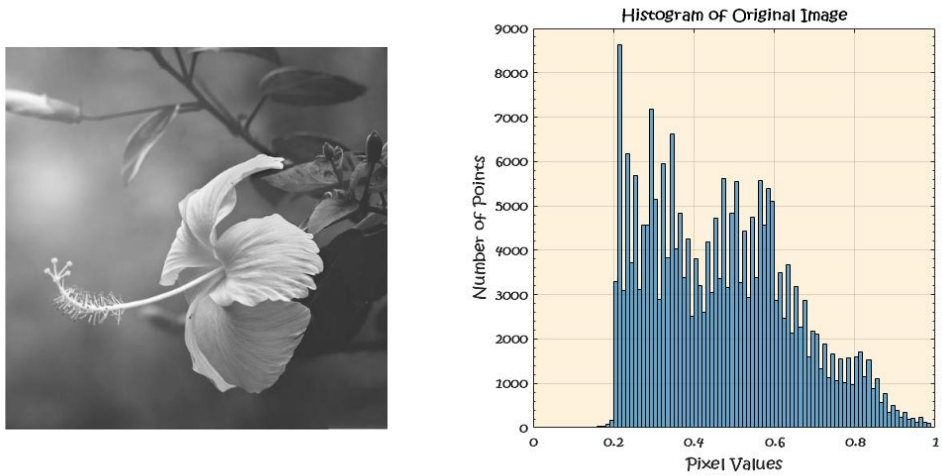


Figure 1: Original Image with Histogram

So, $|\tilde{P}_{245,245} - \tilde{P}_{244,244}| = 0.0196$, $|\tilde{P}_{245,245} - \tilde{P}_{244,245}| = 0.0588$, $|\tilde{P}_{245,245} - \tilde{P}_{244,246}| = 0.0509$, $|\tilde{P}_{245,245} - \tilde{P}_{245,244}| = 0.0432$, $|\tilde{P}_{245,245} - \tilde{P}_{245,246}| = 0.0274$, $|\tilde{P}_{245,245} - \tilde{P}_{246,244}| = 0.0745$, $|\tilde{P}_{245,245} - \tilde{P}_{246,245}| = 0.0393$, $|\tilde{P}_{245,245} - \tilde{P}_{246,246}| = 0.0039$.

Table 1: Neighborhood of the point $\tilde{P}_{245,245}$

Neighborhood of $\tilde{P}_{245,245}$	C244	C245	C246
R244	0.6471	0.6863	0.6784
R245	0.5843	0.6275	0.6549
R246	0.5530	0.5882	0.6236

Thus, $\tilde{\mathcal{T}}_{i,j} = \tilde{\mathcal{T}}(\tilde{P}_{245,245}) = Max\{0.0196, 0.0588, 0.0509, 0.0432, 0.0274, 0.0745, 0.0393, \ 0.0039\} = 0.0745$.
$\tilde{\mathcal{F}}_{i,j} = \tilde{\mathcal{F}}(\tilde{P}_{245,245}) = Max\{1 - 0.0196, 1 - 0.0588, 1 - 0.0509, 1 - 0.0432, 1 - 0.0274, 1 - 0.0745, 1 - 0.0393, 1 - 0.0039\} = 0.9961$.
$\tilde{\mathcal{I}}_{i,j} = \tilde{\mathcal{I}}(\tilde{P}_{245,245}) = Max\{0.0196, 0.0588, 0.0509, 0.0432, 0.0274, 0.0745, 0.0393, \ 0.0039\} - Min\{0.0196, 0.0588, 0.0509, 0.0432, 0.0274, 0.0745, 0.0393, \ 0.0039\} = 0.0706$.

Continuing in this way, we find the true membership, false membership, and indeterminacy for the existence of an edge at each point of the image (neglecting the first row, last row, first column, and last column). For the reader's convenience, we show the true membership, false membership, and indeterminacy for the existence of an edge at 100 neighboring points which is again validated by graphical representation in tables 2, 3, 4 and figures 2, 3 and 4 respectively.

Table 2: Truth membership values of $\tilde{P}_{241,241}$ to $\tilde{P}_{250,250}$

$\tilde{\mathcal{T}}_{i,j}$	C241	C242	C243	C244	C245	C246	C247	C248	C249	C250
R241	0.1176	0.0902	0.0745	0.0627	0.0549	0.0667	0.0275	0.0353	0.0314	0.0235
R242	0.0902	0.0863	0.0902	0.0549	0.0667	0.0824	0.0784	0.0392	0.0353	0.0078
R243	0.0863	0.0902	0.0941	0.0863	0.0824	0.0784	0.0706	0.0667	0.0471	0.0196
R244	0.0588	0.0941	0.0863	0.1059	0.1020	0.0706	0.0667	0.0471	0.0588	0.0392
R245	0.0235	0.0745	0.1059	0.1020	0.0745	0.0667	0.0431	0.0588	0.0510	0.0471
R246	0.0196	0.0275	0.0510	0.0745	0.0667	0.0471	0.0510	0.0510	0.0471	0.0471
R247	0.0235	0.0314	0.0275	0.0314	0.0471	0.0510	0.0549	0.0588	0.0314	0.0471
R248	0.0314	0.0431	0.0510	0.0314	0.0314	0.0549	0.0588	0.0392	0.0627	0.0314
R249	0.0431	0.0510	0.0314	0.0314	0.0314	0.0235	0.0235	0.0627	0.0392	0.0275
R250	0.0196	0.0235	0.0314	0.0314	0.0314	0.0314	0.0235	0.0392	0.0275	0.0353

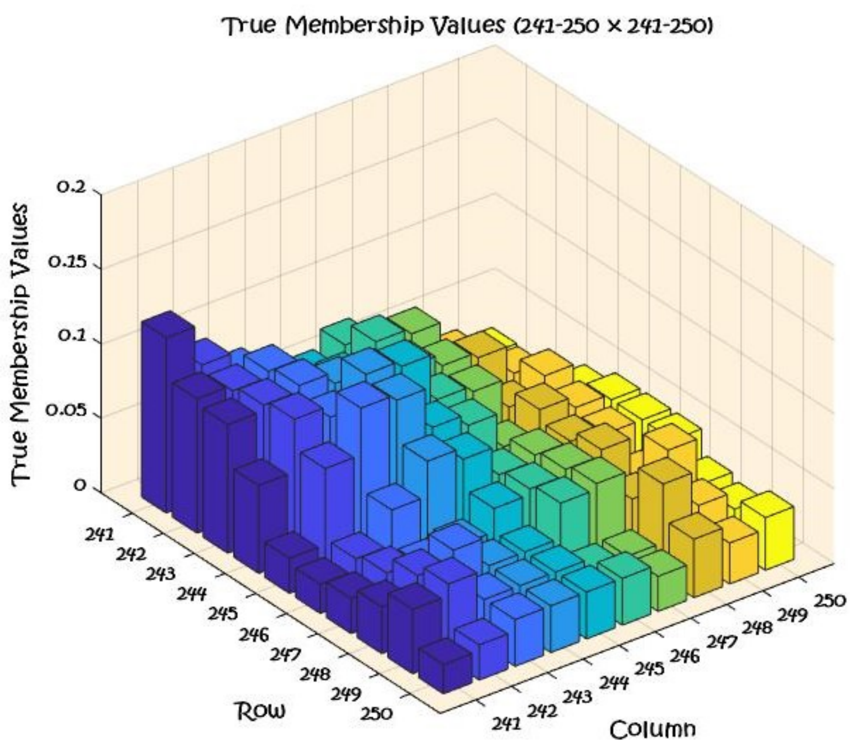


Figure 2: True Membership Values for $241 - 250 \times 241 - 250$.

Table 3: False membership values of $\tilde{P}_{241,241}$ to $\tilde{P}_{250,250}$

$\tilde{\mathcal{F}}_{i,j}$	C241	C242	C243	C244	C245	C246	C247	C248	C249	C250
R241	0.9882	1	0.9922	0.9961	0.9922	1	1	0.9922	0.9961	0.9961
R242	1	0.9882	1	0.9961	0.9882	0.9961	1	09922.	1	1
R243	0.9882	1	0.9843	0.9922	1	0.9882	1	1	0.9961	1
R244	0.9961	0.9961	0.9922	0.9843	1	0.9922	0.9922	1	1	0.9961
R245	0.9961	0.9961	0.9961	0.9961	0.9961	0.9961	0.9961	0.9922	1	0.9961
R246	1	0.9961	0.9961	0.9961	0.9961	1	0.9961	0.9961	0.9961	1
R247	1	0.9922	0.9961	1	0.9922	0.9922	1	0.9961	1	1
R248	1	1	0.9961	0.9961	1	0.9961	1	0.9882	0.9961	1
R249	1	1	1	1	0.9961	1	0.9961	1	0.9922	1
R250	1	0.9922	0.9961	0.9882	0.9961	0.9961	1	1	0.9922	0.9961

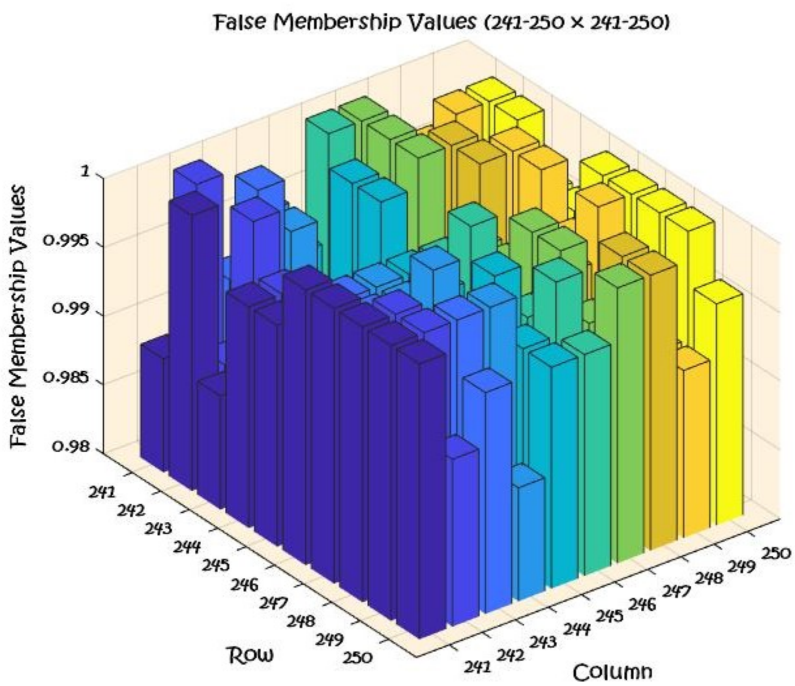


Figure 3: False Membership Values for $241 - 250 \times 241 - 250$

Table 4: Indeterminacy membership values of $\tilde{P}_{241,241}$ to $\tilde{P}_{250,250}$

$\tilde{\mathcal{I}}_{i,j}$	C241	C242	C243	C244	C245	C246	C247	C248	C249	C250
R241	0.1059	0.0902	0.0667	0.0588	0.0471	0.0667	0.0275	0.0275	0.0275	0.0196
R242	0.0902	0.0745	0.0902	0.0510	0.0549	0.0784	0.0784	0.0314	0.0353	0.0078
R243	0.0745	0.0902	0.0784	0.0784	0.0824	0.0667	0.0706	0.0667	0.0431	0.0196
R244	0.0549	0.0902	0.0784	0.0902	0.1020	0.0627	0.0588	0.0471	0.0588	0.0353
R245	0.0196	0.0706	0.1020	0.0980	0.0706	0.0627	0.0392	0.0510	0.0510	0.0431
R246	0.0196	0.0235	0.0471	0.0706	0.0627	0.0471	0.0471	0.0471	0.0431	0.0471
R247	0.0235	0.0235	0.0235	0.0314	0.0392	0.0431	0.0549	0.0549	0.0314	0.0471
R248	0.0314	0.0431	0.0471	0.0275	0.0314	0.0510	0.0588	0.0275	0.0588	0.0314
R249	0.0431	0.0510	0.0314	0.0314	0.0275	0.0235	0.0196	0.0627	0.0314	0.0275
R250	0.0196	0.0157	0.0275	0.0196	0.0275	0.0275	0.0235	0.0392	0.0196	0.0314

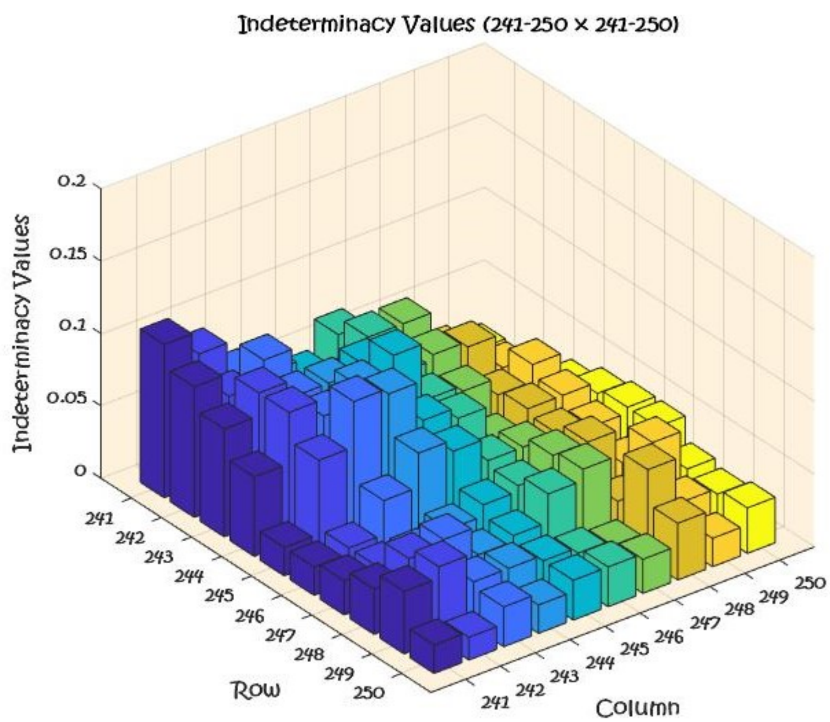


Figure 4: Indeterminacy Values for $241 - 250 \times 241 - 250$

Here in figure 5 and table 5 we have shown the truth ($\tilde{\mathcal{T}}$), indeterminacy ($\tilde{\mathcal{I}}$), and falsity ($\tilde{\mathcal{F}}$) values which are filtered by r-cut for r=0.05.

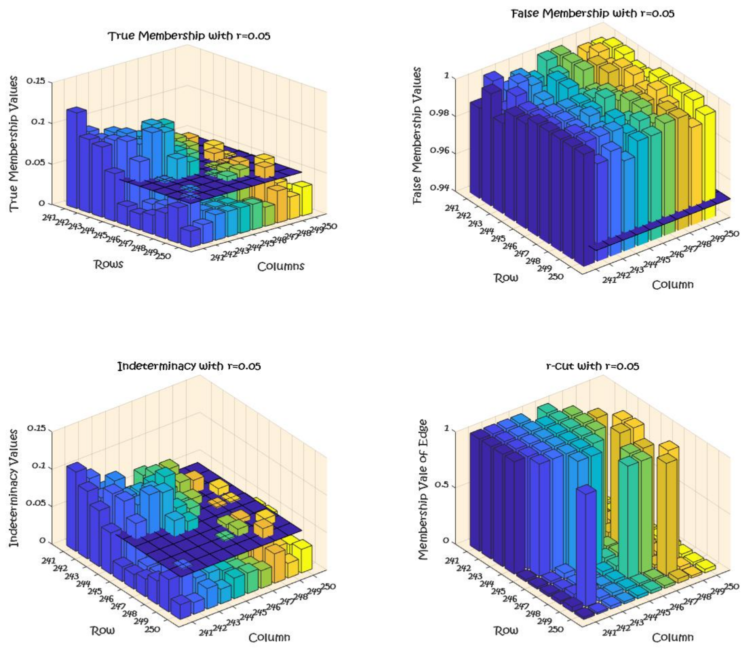


Figure 5: Filter by r-cut, where $r = 0.05$

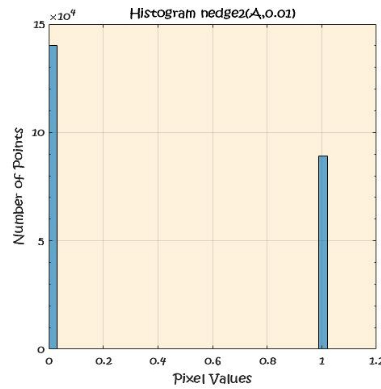
Table 5: Existence of Edge with 0.05-cuts for $\tilde{P}_{241,241}$ to $\tilde{P}_{250,250}$

$\tilde{\mathcal{T}}_{i,j}$	C241	C242	C243	C244	C245	C246	C247	C248	C249	C250
R241	1	1	1	1	0.0471	1	0.0275	0.0275	0.0275	0.0196
R242	1	1	1	1	1	1	1	0.0314	0.0353	0.0078
R243	1	1	1	1	1	1	1	1	0.0431	0.0196
R244	1	1	1	1	1	1	1	0.0471	1	0.0353
R245	0.0196	1	1	1	1	1	0.0392	1	1	0.0431
R246	0.0196	0.0235	0.0471	1	1	0.0471	0.0471	0.0471	0.0431	0.0471
R247	0.0235	0.0235	0.0235	0.0314	0.0392	0.0431	1	1	0.0314	0.0471
R248	0.0314	0.0431	0.0471	0.0275	0.0314	1	1	0.0275	1	0.0314
R249	0.0431	1	0.0314	0.0314	0.0275	0.0235	0.0196	1	0.0314	0.0275
R250	0.0196	0.0157	0.0275	0.0196	0.0275	0.0275	0.0235	0.0392	0.0196	0.0314

3.2 Results

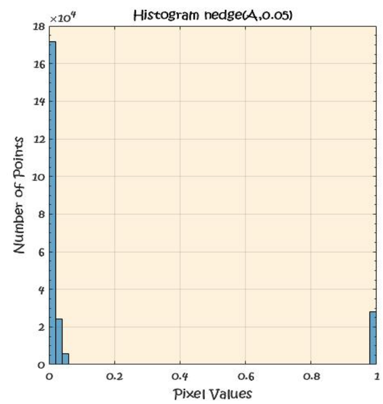
We have discussed the impact of edge detection outcomes for different values of r (r=0.01, 0.05, 0.20, and 0.50) in figure 6. The corresponding histograms provide a quantitative perspective on the variations in detected edges. The comparison of results across multiple images validates the adaptability of the proposed method in handling noise and preserving critical structures.

1(a)



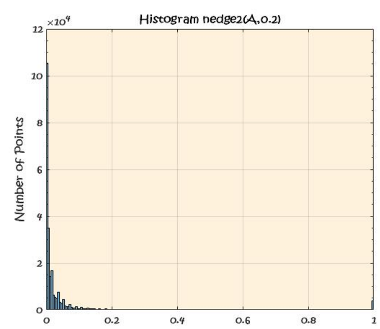
1(b)

2(a)

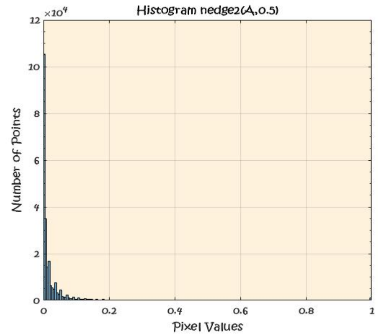


2(b)

3(a)



3(b)

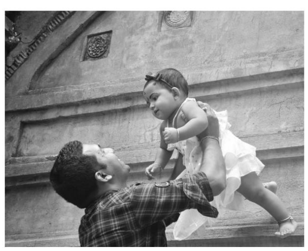


4(a) 4(b)

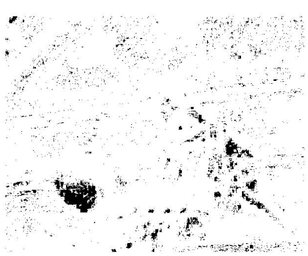
Figure 6: r-cut filters and corresponding histograms while $r = 0.01(1(a),1(b))$, $r = 0.05(2(a),2(b))$, $r = 0.20(3(a),3(b))$, $r = 0.50(4(a),4(b))$

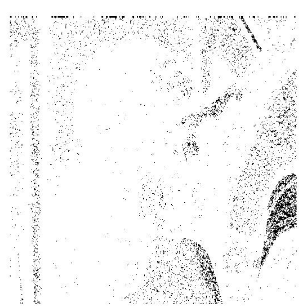
3.3 More Results

It is better to validate a result with more than one object. So we include the following results shown in figure 7:



1(a) 1(b)





2(a) 2(b)

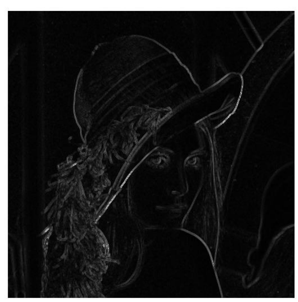
3(a)

3(b)

4(a)

4(b)

5(a)



5(b)

Figure 7: r-cut filters while $r = 0.01$(2(a),2(b)), $r = 0.05$(3(a),3(b)), $r = 0.20$(4(a),4(b)), $r = 0.50$(5(a),5(b))

4 Comparison, Advantages and Conclusion

4.1 Comparison with Existing Methods

To assess the practical significance of our method, we compared our results with existing edge detection techniques, such as:

1. Sobel Operator - Detects edges using gradient magnitude but is highly sensitive to noise.

2. Canny Edge Detection - Provides improved edge localization but requires careful parameter tuning.

3. Prewitt Operator - Detects edges using gradient magnitude with simpler kernels than Sobel but can still be sensitive to noise.

The results indicate that our proposed r-cut strategy offers a more flexible approach to edge detection, allowing users to fine-tune results based on specific application needs.

The amount of improvement depends on the image under consideration and only the value of r. The amount of improvement has been calculated as per the amount of edge points obtained and the pixel value of each point which are shown in table 6 and figure 8.

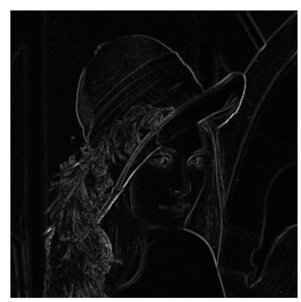
Table 6: Percentage of additional edges acquired in comparison to prior methods

r-cut value	Improvement in comparison to Sobel method	Improvement in comparison to Canny method	Improvement in comparison to Prewitt method
0.05	859.11%	254.13%	867.91%
0.2	142.84%	10.37%	144.96%
0.5	70.11%	37.22%	71.60%



Sobel Filter Canny Filter Prewitt Filter





Neutrosophic Filter eith

$r = 0.05$ $r = 0.2$ $r = 0.5$

Figure 8: Comparison among several edge detection methods

4.2 Advantages and limitations

The r-cut-based segmentation method introduced in this paper offers several key advantages:

- **Effective Uncertainty Handling** Unlike traditional edge detection methods, r-cut incorporates truth ($\tilde{\mathcal{T}}$), falsity ($\tilde{\mathcal{F}}$), and indeterminacy ($\tilde{\mathcal{I}}$) values, allowing for more accurate edge representation in complex images.

- **Adaptive Edge Detection** The method provides user-controlled segmentation based on the r threshold, enabling fine or coarse edge extraction depending on application needs.
- **Noise Resilience** By filtering out high-indeterminacy pixels, the r-cut method reduces false edges caused by noise, improving segmentation in real-world images.
- **Better Structural Preservation** It maintains important edge details while removing irrelevant variations, making it useful for medical imaging, satellite imagery, and object recognition.
- **Flexible and Scalable** The approach can be applied to various image types (grayscale, high-resolution, noisy images) without extensive parameter tuning.

Despite its advantages, the r-cut-based segmentation method also presents certain limitations and challenges that need to be addressed for improved performance.

- **Sensitivity to r-value Selection** The effectiveness of segmentation heavily depends on choosing the right r threshold. An inappropriate value of r may lead to over-segmentation (too many edges) or under-segmentation (missing important details).
- **Limited Generalization to Color Images** The method primarily works on grayscale images, and its direct applicability to RGB or multispectral images is not explored in this study.
- **Lack of Automatic Optimization-** The current approach requires manual tuning of the r parameter. An adaptive or machine learning-based approach could enhance its efficiency for different image conditions.

Future work could introduce adaptive or machine learning-based approaches to automatically determine optimal r values.

5 Conclusion

This paper introduces a novel image segmentation technique based on neutrosophic sets. By representing images using three membership values (truth, falsity, and indeterminacy), we define a new entropy measure to quantify uncertainty within the neutrosophic domain. A robust r-cut segmentation method is proposed to effectively partition images. Experimental results demonstrate the superior performance of our approach on both clean and noisy images, suggesting its potential for broader applications in image processing and pattern recognition.

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