NSS

Neutrosophic Sets and Systems, Vol. 58, 2023

University of New Mexico

A Novel Approach of Residue Neutrosophic Technique for Threshold Based Image Segmentation

Vinoth D[1] and Ezhilmaran Devarasan[2*]

Department of Mathematics, School of Advanced Sciences,

Vellore Institute of Technology, Vellore, India.

vinov002@gmail.com

*Correspondence: ezhilmaran.d@vit.ac.in;

Abstract. The Residue Neutrosophic Set *(RNS)* is a new idea in image additional pixel level. Our idea is to make an analysis based on the additional pixel amount. In recent decades, computer vision has revolutionized image analysis by researchers. Image segmentation is a more investigated topic in the science of computer vision. Neutrosophic is a sophisticated mathematical idea to solve a myriad of challenges. The objective is to invent a neutrosophic technique to execute image thresholding. In the article, the residue methodology was applied, which denotes the residual values of neutrosophic membership intensities. This article will explore a novel idea for image thresholding termed *RNS*. There will be three types of *RNS* techniques: minimum, average, and maximum. The concepts of existing thresholding techniques in neutrosophic solvation are considered in this proposal. This article adopts novel methodologies to provide an integrated visionary path segmentation methodology. Furthermore, the proposed technique reaches a better average accuracy score.

Keywords: Image segmentation, neutrosophic sets, neutrosophic image, residue neutrosophic, thresholding

1. Introduction

Massive investigative study challenges in computer vision and image analysis have emerged during this technological era. The mathematical principles entice everyone to strive to tackle difficulties and challenges. Lotfi Zadeh created the notion of fuzzy in 1965. It is a remarkable mathematical approach for solving most research difficulties. After a few decades, Krassimir Atanassov developed the extended fuzzy idea known as Intuitionistic fuzzy sets (IFS) in 1983. Smarandache later developed the more advanced concept of neutrosophic set (NS) in 1998 [22]. Obstacles must be approached with developed methods in our modernistic universe. In this sense, the neutrosophic theory should be the preferable strategy for discovering the difficulties hidden aspects. A neutrosophic set has three components: truth membership(T), indeterminacy membership(I), and falsity membership(F), according to the neutrosophic conception. In 2009, the first image segmentation in the neutrosophic domain was beginning it is one of the most challenging tasks in image processing and pattern recognition, it is used in a variety of applications including robot vision, object recognition, medical imaging, computer vision, etc [8]. Authors [19] classifies image segmentation approaches into three categories: threshold, edge, and region-based methods. The best segmentation results are usually obtained with a gray-level image.

In various scenario approaches, such as clustering, Support Vector Machine (SVM), segmentation made with fuzzy sets, IFS, and NS set. In this manner, image segmentation occurs in stages, but as the image has become more informative, the segmentation may exclude lower pieces of data. Considering these timeframes, we may lose the image's information. If the image is a fingerprint application, it is essential to give preference to every little feature. Instead, it is critical not to lose any of the image's information when executing image analysis. The proposal focuses on reducing the loss of information in the threshold images. We approached the NS domain intending to segment the aim of segmenting images based on the residue value of the neutrosophic intensities, so we developed a novel approach called the RNS idea to try to accomplish the objective. Existing image segmentation algorithms, such as binary threshold, binary inverse threshold, TRUNC threshold, To zero threshold, and To zero inverse threshold, will be applied to the modified RNS image. When dealing with the specified neutrosophic collection, the amalgamation results of any image should have more information than the others, according to RNS segmentation. Precision, recall score, and $F1$ score is used to evaluate performance.

The article section 1 provides a brief overview of the concepts in this section of the article. The section 2 collects research on image segmentation and neutrosophic concept development from the literature. The essential preliminaries of the neutrosophic set carry in section 3. Perhaps the next section 4, expands on the definitions of the proposed approaches and discusses the algorithm. In section 5, we perform an experimental study of the concept and produce a result. Finally, section 6 examines the suggested methodologies conclusion and future scope.

2. **Related Work**

Sengur et al. [20] achieved the neutrosophic strategies for color texture image segmentation in 2011. Neutrosophic similarity clustering made a significant contribution by [9] Yanhui Guo et al. Later the same author suggested a new method called Breast ultrasound image segmentation in the article [10]. Koundal [13] in 2017 successfully performed neutrosophic clustering segmentation with noisy data on many instances. Many academics are still aiming to enhance the effectiveness of K-means clustering, which is still a universal approach for unsupervised classifications. In 2018, the authors [16] discovered a better method for picture segmentation in the neutrosophic image domain. In the same year, authors [15] suggested neutrosophic c-means clustering kernel metric-based image segmentation local information. The article [6] focuses on computer vision of neutrosophic images, which performs using nine distinct classifiers for image classification with an accuracy of 98.4%. Elays et al. [18] was implementing the cost function to boost the accuracy of degrees of the membership clustering algorithms. Yanhui et al. [11] implemented neutrosophic c-means clustering and an adaptive region expanding technique. The objective function was solved using the Lagrange multiplier approach in the paper [14], which focused on a single-valued neutrosophic set as a restricting minimization issue. The neutrosophic clustering method Amira et al. [1] approaches skin lesion detection histogram-based clustering estimation algorithm. Romualdas et al. [3] introduced a weighted aggregated sum product assessment approach in 2019 that was ranked using an edge detection algorithm. In digital image processing, Samarandachec [24] proposed using offsets and off uniforms for segmentation and edge detection. Jing et al. [28] provide a novel particle swarm optimization method for neutrosophic images based on fuzzy c-means. By including single valued (SV) trapezoidal neutrosophic numbers in all of the objective function and constraint parameters, the neutrosophic complex programming *(NCP)* process is classified. The objective of the difficult programming challenge is to improve the applicability of SV trapezoidal neutrosophic numbers in new decision-making scenarios [12]. This method advantage of more adaptable and realistic in a real-world situation. In the realm of psychological research, the concepts of single-valued neutrosophic N soft set (SVNNSS) and quasi-hyperbolic discounting intertemporal single-valued neutrosophic N soft set (QHDISVNNSS) are employed to demonstrate student's mental state through observation. Neutrosophic numbers are utilized to represent values in counseling sessions, ensuring no loss of information. The focus of the counselor is on individuals with mental health issues, using SVNNSS and QHDISVNNSS due to their higher susceptibility to emotional distress [25].

3. Preliminaries

3.1. *Neutrosophic set*

Definition 3.1. Let A be an universe of data, the element in A denoted by a, then the neutrosophic set (NS), of the object A is in the form [5, 22]

$$A = \{(a, T_A(a), I_A(a), F_A(a)\}$$

where the neutrosophic membership functions $T, I, F : A \rightarrow]^{-}0, 1^{+}[$ define respectively the degrees of truth, indeterminacy and the falsity of the element $a \in A$ to the set condition.

$$^{-}0 \leq T_A(a) + I_A(a) + F_A(a) \leq 3^{+}$$

Definition 3.2. (Basic properties) [21, 23]

(1) **Complement**

The complement of A is represented as A^c where

$$A^c = \{a, F_A(a), 1 - I_A(a), T_A(a)\}$$

(2) **Intersection**

Let A, B be two sets then the neutrosophic intersection is represented as $A \cap B$ where

$$A \cap B = \{a, \min(T_A(a), T_B(a)), \max(I_A(a), I_B(a)), \max(F_A(a), F_B(a))\}$$

(3) **Union**

Let A, B be two sets then the neutrosophic union is represented as $A \cup B$ where

$$A \cup B = \{a, \max(T_A(a), T_B(a)), \min(I_A(a), I_B(a)), \min(F_A(a), F_B(a))\}$$

Definition 3.3. Let A be a nonempty set, the single valued neutrosophic set $(SVNS)$ is defined as [5, 26]

$$A = \{(a, T_A(a), I_A(a), F_A(a)\}$$

where their membership functions are $T, I, F : A \rightarrow]^{-}0, 1^{+}[$ denotes respectively the degrees of truth, indeteminacy and falsity of the element $a \in A$ to the set values.

$$0 \leq T_A(a) + I_A(a) + F_A(a) \leq 3$$

3.2. *Image Neutosophic sets*

Definition 3.4. A neutrosophic image P_{NS} is charecterized with neutrosophic membership functions which are T, I, F where P_{NS} are the intensities of the image. Universally for neutrosophic image approach is gray intensities of the image. The image neutrosophic set is defined as [5, 7]

$$P_{NS}A(i, j) = \{T_A(i, j), I_A(i, j), F_A(i, j)\} \tag{1}$$

In general the arithmetic mean is consider as truth membership values and the standard deviation of the image is consider as indeterminacy membership. The neutrosophic transformation intensity of the image is define by the following formulae

$$\begin{aligned} T_A(i,j) &= \frac{\bar{p}(i,j) - \bar{p}\min}{\bar{p}\max - \bar{p}\min} \\ \bar{p}_A(i,j) &= \frac{1}{w * w} \sum_{m=i-\frac{w}{2}}^{m=i+\frac{w}{2}} \sum_{n=j-\frac{w}{2}}^{n=j+\frac{w}{2}} p(m,n) \\ I_A(i,j) &= \frac{\delta(i,j) - \delta\min}{\delta\max - \delta\min} \\ \delta_A(i,j) &= abs(p(i,j) - \bar{p}(i,j)) \\ F_A(i,j) &= 1 - T_A(i,j) \end{aligned}$$

where $\bar{p}_A(i,j)$ denotes the pixel mean in the region $w{*}w$ and w is generally $w = 2n{+}1, \ (n \geq 1)$.

Definition 3.5. The entropy of the neutrosophic image is defined as follows [7]

$$En_{NS} = En_T + En_I + En_F \tag{2}$$

where

$$\begin{aligned} En_T &= -\sum_{i=\min(T)}^{\max(T)} p_T(i)\ln p_T(i) \\ En_I &= -\sum_{i=\min(I)}^{\max(I)} p_I(i)\ln p_I(i) \\ En_F &= -\sum_{i=\min(F)}^{\max(F)} p_F(i)\ln p_F(i) \end{aligned}$$

p refers that the probability of the membership functions.

4. **Proposed method**

We will approach a different technique for the neutrosophic image segmentation which is based on the value of global neutrosophic image data. This contains three types of approaches which are the minimum value of universal image set based, the maximum value of image set based, and the average value of global image set. In the classical method generally, the piece-wise linear transformation means is used to transform the set into the neutrosophic domain. This proposal focused on the minimum or maximum or mean values of the entire image data. While approaching this technique it may possibly the image data is turned from *SVNS* to *NS*. Entering deal with this scenario proposal recommend that the residue technique to handle an affirmative concept. Here *SVNS* can be denoted as *NS* for comprehensive understanding while approaching the method. The complete architecture of the proposed method is shown in Figure 1.

Definition 4.1. Let $\wp(m,n)$ be an image data with m,n dimensions, the neutrosophic membership components of the image data T,I,F are modified as the classical method with the alteration of $\wp_{\min}$, $\wp_{\max}$ which are known as minimum, maximum value of the global image data.

$$_{\min}NS_{\wp(i,j)} = \{T_{\wp(i,j)} + I_{\wp(i,j)} + F_{\wp(i,j)}\} \tag{3}$$

$$\begin{aligned} \text{where } T_{\wp(i,j)} &= \frac{\wp_{(i,j)} - \wp_{\min}}{\wp_{\max} - \wp_{\min}} \\ I_{\wp(i,j)} &= \sqrt{1 - (T^2_{\wp(i,j)} + F^2_{\wp(i,j)})} \\ F_{\wp(i,j)} &= 1 - T_{\wp(i,j)} \end{aligned}$$

The residue neutrosophic set's minimum method is defined as

$$_{\min}RNS_{\wp(i,j)} = (\tau_{\min}) \mod (L) \tag{4}$$

$$\tau_{\min} = {}_{\min}NS_{\wp(i,j)} \times L$$

Definition 4.2. Let $\wp(m,n)$ be an image data with m,n dimensions, the neutrosophic membership components of the image data T,I,F are modified as the classical method with the alteration of $\wp_{\min}$, $\wp_{\max}$ which are known as minimum, maximum value of the global image data.

$$_{\max}NS_{\wp(i,j)} = \{T_{\wp(i,j)} + I_{\wp(i,j)} + F_{\wp(i,j)}\} \tag{5}$$

$$\begin{aligned} \text{where } T_{\wp(i,j)} &= \frac{\wp_{\max} - \wp_{(i,j)}}{\wp_{\max} - \wp_{\min}} \\ I_{\wp(i,j)} &= \sqrt{1 - (T^2_{\wp(i,j)} + F^2_{\wp(i,j)})} \\ F_{\wp(i,j)} &= 1 - T_{\wp(i,j)} \end{aligned}$$

The residue neutrosophic set's maximum method is defined as

$$_{\max}RNS_{\wp(i,j)} = (\tau_{\max}) \mod (L) \tag{6}$$

$$\tau_{\max} = {}_{\max}NS_{\wp(i,j)} \times L$$

Definition 4.3. Let $\wp(m,n)$ be an image data with m,n dimensions, the neutrosophic membership components of the image data T,I,F are modified as the classical method with the alteration of $\wp_{\min}$, $\wp_{\max}$, $\wp_{avg}$ which are known as minimum, maximum value, average value of the global image data.

$$_{\text{avg}}NS_{\wp(i,j)} = \{T_{\wp(i,j)} + I_{\wp(i,j)} + F_{\wp(i,j)}\} \tag{7}$$

$$\text{where } T_{\wp(i,j)} = \frac{\wp_{(i,j)} - \wp_{\text{avg}}}{\wp_{\max} - \wp_{\min}}$$
$$I_{\wp(i,j)} = \sqrt{1 - (T^2_{\wp(i,j)} + F^2_{\wp(i,j)})}$$
$$F_{\wp(i,j)} = 1 - T_{\wp(i,j)}$$

The residue neutrosophic set's average method is defined as

$$_{\text{avg}}RNS_{\wp(i,j)} = (\tau_{\text{avg}}) \mod (L) \tag{8}$$

$$\tau_{\text{avg}} = {}_{\text{avg}}NS_{\wp(i,j)} \times L$$

Algorithm:

Step 1: Convert the image as L gray scale image.

Step 2: Make that L image to neutosophic domain with any one of the equation 3 or 5 or 7 using the membership formulae.

Step 3: Transform the NS to any one of RNS domain

Step 4: Apply the segmentation methods for the transformed RNS.

Step 5: Detect the hidden pattern of the image

A single intensity values contain in standard image analysis. The proposed method, on the other contrary, can analyze the three membership intensity values. As a result, the analysis is more trustworthy than the traditional way. The image characteristics were retrieved at a consistent level using these thresholding methods. As a result, we may lower the image's indeterminacy for various thresholding values. This character will aid us in classifying the image with convincing processing and analysis in the future. There is no need to find or fix a threshold value.

5. Expirement and Result

Table 1. The employed metrics for quantitative evaluation.

Metrics	**Formula**
Sensitivity	True Positive/(True Positive/False Negative)
Specificity	True Negative/(True Negative + False Positive)
Precision	True Positive/(True Positive + False Positive)
Recall	True Positives / (True positive + False negative)
$F1$ score	(2 * Precision * Recall) / (Precision + Recall)
Accuracy	(True Positive + True Negative)/Total samples

For the experiment, we used an Intel(R) Core(TM) i5 processor with 16GB of RAM and a 64-bit operating system. The programing tool to be used is Python. A fingerprint image was

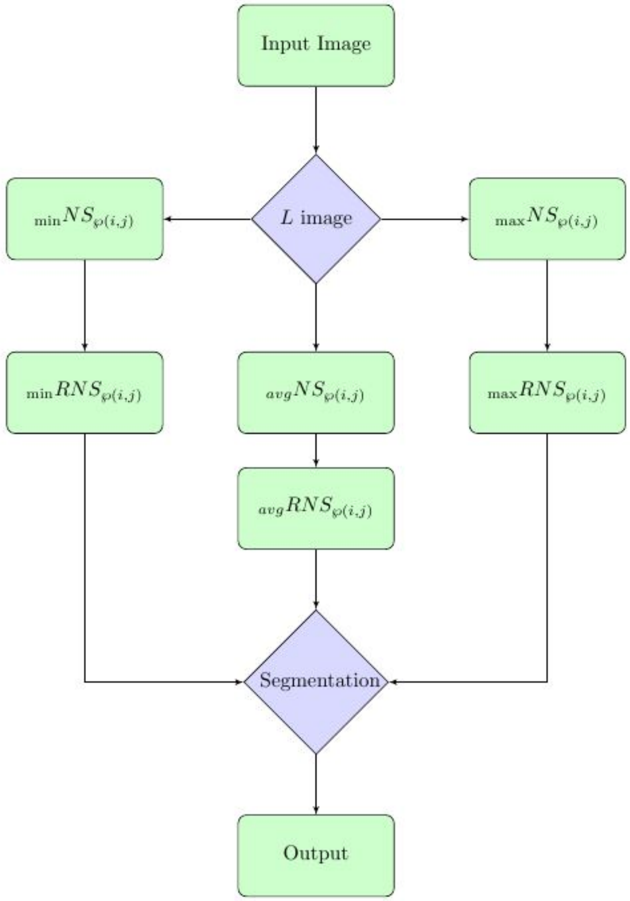
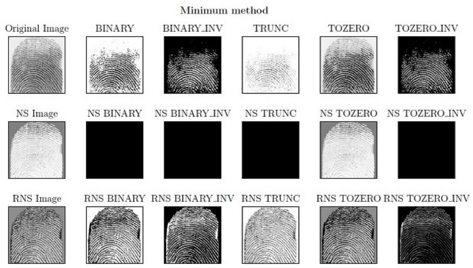
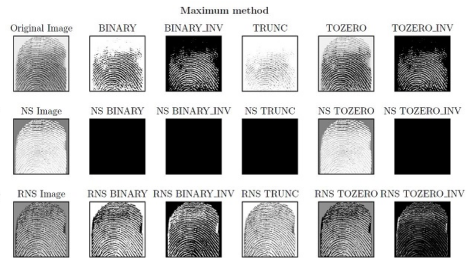


FIGURE 1. Residue neutrosophic set image segmentation architecture

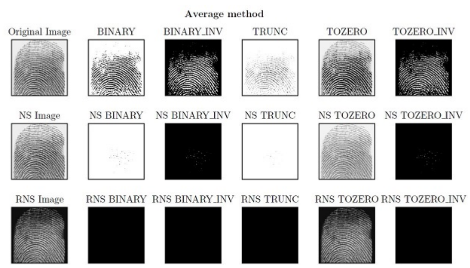
collected from the [2] for the experiment analysis suggestion. Because the primary purpose of acquiring a fingerprint image contains more information than the image itself, it is critical to analyze it without losing the data. In this regard, the suggested method compares favorably to existing segmentation methods. Each image was resized to 250×250 for the segmentation analysis, and the segmentation pixel was set to $\alpha = 128$. Figure 2 shows the images that resulted. Apart from the example, some segmentation fails in NS and RNS however, if we emphasize avoiding the loss of image information for segmentation, any of the three given approaches should be a superior proposal for different scenarios. The proposal's further tasks will be based on the failed scenario. The Table 1 calculates the performance evaluation of the methods. For the evaluation of the resulted image and measurements, a single sample image is shown, The performance evaluation is shown in Figure 3. Table 2 tabulates the results of each segmentation method resulted for the metrics. It is calculating by metric formulae with concept of confusion matrix.



(a)

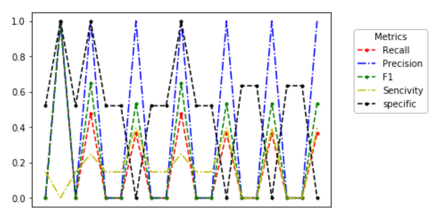


(b)

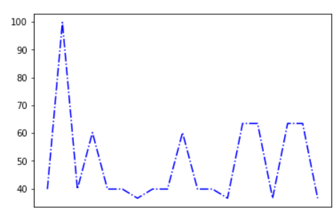


(c)

FIGURE 2. The resulted images of the proposed methods: (a) ${}_{min}RNS$ method image segmentation; (b) ${}_{max}RNS$ method image segmentation; (c)${}_{avg}RNS$ method image segmentation.



(a)



(b)

FIGURE 3. This is a figure of evaluation metrics: (a) Recall, precision, $F1$-score, sensivity, specific; (b) Accuracy.

TABLE 2. Table of performance evaluation.

Method	Recall	Precision	F1-score	Sensitivity	Specificity	Accuracy
$_{min}RNS$	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{min}RNS$ Binary	0.994040	1.000000	0.997011	0.00137	1.000000	99.7808
$_{min}RNS$ Binary INV	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{min}RNS$ TRUNC	0.478574	0.999956	0.647336	0.24896	0.999932	60.1648
$_{min}RNS$ ToZero	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{min}RNS$ ToZero INV	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{max}RNS$	0.365616	1.000000	0.535459	0.39649	0.000000	36.5616
$_{max}RNS$ Binary	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{max}RNS$ Binary INV	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{max}RNS$ TRUNC	0.478574	0.999956	0.647336	0.24896	0.999932	60.1648
$_{max}RNS$ ToZero	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{max}RNS$ ToZero INV	0.000068	0.000044	0.000053	0.14753	0.521426	39.8352
$_{avg}RNS$	0.365616	1.000000	0.535459	0.39649	0.000000	36.5616
$_{avg}RNS$ Binary	0.000000	0.000000	0.000000	0.00000	0.634384	63.4384
$_{avg}RNS$ Binary INV	0.000000	0.000000	0.000000	0.00000	0.634384	63.4384
$_{avg}RNS$ TRUNC	0.365616	1.000000	0.535459	0.39649	0.000000	36.5616
$_{avg}RNS$ ToZero	0.000000	0.000000	0.000000	0.00000	0.634384	63.4384
$_{avg}RNS$ ToZero INV	0.000000	0.000000	0.000000	0.00000	0.634384	63.4384

6. Conclusion

The article proposed three kinds of novel approaches to the neutrosophic image segmentation technology in this proposal. Our focus was to use neutrosophic sets to segment without losing information, and the idea succeeded with a better result. The use of these procedures is preferred solvation, especially for fingerprint images. Researchers can see from the analysis that the $_{min}RNS$ Binary segmentation method works exceptionally well in comparison to the other approaches. The TRUNC segmentation methodology, which focuses on the $_{max}RNS$ method, is preferred. When compared to the $_{min}RNS$ and $_{max}RNS$ methods, $_{avg}RNS$ performs poorly. Binary segmentation is a great way to approach neutrosophic thresholding binarization $_{min}RNS$. Since it can able to generalize the results for a collection of image sets if the image features are constant. These qualities are extremely beneficial when it comes to image processing and categorization. We will use this knowledge feature to apply these principles to machine learning approaches in order to achieve better outcomes. Because of the residue approach, the segmented picture features are always constant. In this way, this article produces the neutrosophic thresholding with better results for the samples.

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Received: June 3, 2023. Accepted: Sep 30, 2023