

A Comparative Study on X-Ray image Enhancement Based on Neutrosophic Set

Nihal N. Mostafa¹ , Amit Krishan Kumar² , and Yasir Ali^{3,*} 

¹ Misr Higher Institute for Computer and Commerce, Computer Science Department; Nihal.nabil@fci.zu.edu.eg.

² Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam; amitkrishankumar@duytan.edu.vn

³ School of Automation, Beijing Institute of Technology, 100086, Beijing, 382082051@bit.edu.cn

Abstract: Medical image noise, ambiguity, and fuzziness pose challenges to the medical image analysis process. To lessen these problems, fuzzy sets are utilized; however, they frequently ignore the pixel's spatial context. The neutrosophic set (NS) is employed in picture denoising to get over these restrictions. Neutrosophic theory, in particular the NS Bilateral filter, NS Wiener filter, NS Median filter, NS gaussian filter, and NS rank-ordered filter, is covered in this paper. The Lung-cancer dataset of X-Ray images is used to assess the performance of different denoising techniques. The effectiveness of NS-based denoising techniques over conventional techniques is demonstrated through comparisons with other approaches, demonstrating the NS's function in X-ray image denoising.

Keywords: Neutrosophic Set, Medical Imaging, Neutrosophic Filters, Image Quality Assessment, Image Fusion, Image Segmentation

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1. Introduction

In recent years, the need to enhance medical images has increased rapidly. Image enhancement is a critical process for improving image quality and removing noise. The goal of image enhancement is to reduce additive noise while retaining as many important signal characteristics as possible. Enhancing images is a crucial method aimed at enhancing image quality and facilitating information retrieval, thus playing a significant role in various image processing tasks. This technique, known as image enhancement, serves as a preprocessing step utilized in feature identification, segmentation, analysis, registration, matching, classification, and other applications related to images. The primary obstacle lies in the task of devising a proficient algorithm capable of improving each image effectively amidst different environmental conditions [1].

Unfortunately, X-Ray images involve fuzziness, uncertain, and imprecise due to their low illumination; image processing relies heavily on direct enhancement. It removes unnecessary data that is unrelated to image processing tasks and highlights important or difficult-to-see features. Therefore, the only practical solution for these problems is to improve the quality of the noise image by using image denoising techniques[1].

Soft computing methodologies provide successful strategies for addressing uncertainty and imprecision across diverse domains, such as image processing and enhancement. There are several types, including fuzzy set (FS), intuitionistic fuzzy set (IFS), and neutrosophic set (NS). FS proposed by Zadeh [2] are widely used in image

processing and pattern recognition algorithms to deal with uncertainty and imprecision in images. FS theory is widely applied in many fields, one of which is medical image enhancement and denoising. Qingrong et al. [3] Proposed a contrast-enhancement technique for medical images that makes use of FS theory and the nonsub-sampled shearlet transform (NSST) to enhance the detail and definition of the image. Another proposed by Ahmed Fadil et al. [4] The fuzzy c-means clustering (FCM) technique is used to enhance medical images. There are two stages to the enhancement process. The proposed algorithm applies a cluster test to the image pixels. It then increases the difference in gray level between the various objects to achieve the enhancement purpose of the medical images. The concept of FS is expanded by IFS [5], which adds a degree of non-membership as an extra membership degree. This enables a more flexible representation of uncertainty. Tirupal et al. [6] proposed for the integration of multimodal medical images through the utilization of interval-valued intuitionistic fuzzy sets (IVIFS). According to Smarandache (2003), Neutrosophy defines knowledge as fuzziness and inaccuracy in data, including visuals. Noise in images is categorized as indeterminant information. The NS can effectively reduce noise in images during denoising, leading to improved performance [7]. This study explores several denoising methods performance under NS domain. The enhancement is obtained on X-Ray images. The applied filters to NS images were Bilateral filter, Wiener filter, Median filter, Gaussian filter, and rank-ordered filter. Consequently, the following are this paper's main contributions:

- Propose an enhancement approach based on NS that can deal with uncertainty by presenting a degree of indeterminacy.
- Compare different denoising techniques under NS domain.
- The image represented in the image is transformed into the NS domain, which is described by three membership sets: True (T), Indeterminacy (I), and False.
- We introduce a novel technique to convert from neutrosophic image to spatial domain.
- The enhancement is performed in each neutrosophic image (T, I, F) separately.

The remainder of the paper is divided as follows. Section 2 presents the related work. Section 3 presents preliminaries for Neutrosophic theory and denoising technique. Section 4 presents the steps of the proposed approach. Section 5 presents experimental results. Section 6 illustrates the conclusion and future directions of this proposal.

2. Background and Literature

In this section we introduce several studies that utilize NS for image enhancement. Many studies investigated the effect of neutrosophic in of medical images enhancement. Salama et al. [8] presented a technique for enhancing medical images by removing noise and improving contrast using three enhancing transforms. The technique embeds images into a neutrosophic fuzzy domain, mapping them into three levels of trueness, falseness, and indeterminacy. The technique outperforms four other systems for leukemia detection and classification, with an accuracy of 98%. The system uses various algorithms and filters to process images, extract features like color and texture, and uses k-means for segmentation and SVM for classification.

Chaira [9] proposed a new image enhancement method using NS, which can handle indeterminant information, reducing image uncertainty. The method converts images into neutrosophic domains using three membership degrees: truth, indeterminacy, and false. A neutrosophic divergence score (NDS) is then suggested to improve image brightness and highlight fine structures. A modified histogram hyperbolization is used to enhance the final image. The method's performance is evaluated qualitatively and quantitatively with recent methods, with experiments conducted on various mammogram images.

Hu et al.[10] introduced the NeutSS-PLP method which is a novel approach for polyp region extraction in colonoscopy images. A short connected saliency detection network with neutrosophic enhancement has been obtained. The method enhances specular reflection detection in colonoscopy images, utilizing local and global threshold criteria and two-level short connections. Experimental results show improved performance compared to state-of-the-art networks and semantic segmentation networks for colorectal polyp region extraction.

Another study introduced a new medical image enhancement method using type-2 neutrosophic set (T2NS) and α -mean and β -enhancement operations. The method aims to improve contrast and gray levels in X-ray images. The method uses six membership functions to obtain a neutrosophic domain for gray level images. Enhancement operations evaluate the change in gray levels, reducing entropy values to minimize image uncertainty. The enhanced images undergo image de-neutrosophication to convert them to grayscale images. The output images are compared with enhanced images achieved under a single-valued neutrosophic set domain [11].

Speckle noise, which is essentially a random value multiplied by image intensities, is another issue with US images. In order to lessen speckle noise, Koundal et al. [12] suggested a method based on the Kuan filter as well as the Lee filter under the NS domain.

Nakagami distribution and applied gamma variation [13]. Bharti et al. proposed a method for liver image enhancement based on the NS similarity score (NSS) [14]. An additional proposal sought to improve ultrasound images by optimizing the NLM algorithm, which is based on the weighted function [15]. Shahin et al. [16] suggested a method for using NSS to improve the quality of an RGB image. A unique technique for improving dermoscopic images was presented by Ashour et al. [17]. This method relies on the optimized indeterminacy filter (OIF), which uses genetic algorithms (GAs) to optimize the indeterminacy filter. A different study presented a method based on NS and the salp swarm algorithm (SSA) under several criteria to enhance the dark areas in skeletal images [18]. In the non-medical domain, Bhat and Koundal presented a novel method for improving fused images using stationary wavelet transform and multi-focus image fusion under the neutrosophic domain [19]. Al Ghamdi and Al Shehri added another contribution to image fusion within the neutrosophic domain. Their method seeks to enhance the monitoring system by improving the image and extracting significant features from an infrared image [20]. Several research have been undertaken to investigate various approaches for improving the enhancement of medical images. In this context, the neutrosophic approach of X-Ray image denoising methods such as NS Bilateral filter, NS Wiener filter, NS Median filter, NS gaussian filter, and NS rank-ordered filter are discussed for denoising X-Ray images with.

3. Preliminaries

3.1. Image under Neutrosophic domain

A neutrosophic image P_{NS} is characterized by three membership sets (T, I, F), A pixel P in the image is described as P(T,I,F) and belongs to W_{in} in the following way: It is t true in the set, i indeterminate in the set, and f false in the set, where t varies in T, I varies in I and f varies in F. Then, the pixel $P(i,j)$ in the image space is transformed into the NS space $P_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\}$, where $T(i,j)$, $I(i,j)$ and $F(i,j)$ are the probabilities belong to white pixels set, indeterminate set and non white pixels set respectively[21] :

$$T(i, j) = \frac{\bar{g}(i, j) - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}} \tag{1}$$

$$\bar{g}(i, j) = \left(\frac{1}{win \times win} \right) \sum_{m=a-\frac{win}{2}}^{a+\frac{win}{2}} \sum_{n=i-\frac{win}{2}}^{i+\frac{win}{2}} g(m, n) \tag{2}$$

$$F(i, j) = 1 - T(i, j) \tag{3}$$

$$\delta(i, j) = abs(g(i, j) - \bar{g}(i, j)) \tag{4}$$

$$I(i, j) = \frac{\delta(i, j) - \delta_{min}}{\delta_{max} - \delta_{min}} \tag{5}$$

Where the pixels in the window have $\bar{g}(i, j)$ local mean (LMV), and $\delta(i, j)$ implies the absolute value of difference among intensity $g(i, j)$ and its $\bar{g}(i, j)$.

3.2. Neutrosophic entropy

The entropy of an image is used to determine the distribution of grey levels. If the entropy is at its highest, the intensities have equal probability. If the entropy is low, the intensity distribution is not uniform. Neutrosophic entropy of an image is defined as the sum of the entropies of three subsets: I, T, and F [21]:

$$Entropy_{NS} = Entropy_T + Entropy_I + Entropy_F \tag{6}$$

$$Entropy_T = - \sum_{j=\min\{T\}}^{\max\{T\}} P_T(i) \ln P_T(i) \tag{7}$$

$$Entropy_I = - \sum_{j=\min\{I\}}^{\max\{I\}} P_I(i) \ln P_I(i) \tag{8}$$

$$Entropy_F = - \sum_{j=\min\{F\}}^{\max\{F\}} P_F(i) \ln P_F(i) \tag{9}$$

Where the entropies are $Entropy_T, Entropy_I,$ and $Entropy_F$ for T, I, and F, respectively. And $P_T(i), P_I(i),$ and $P_F(i)$ are the probabilities of elements in I, T, and F respectively, whose values equal to i.

4. Neutrosophic set-based X-Ray image denoising

For NS-based X-Ray image denoising, the noisy X-Ray image is transferred to the NS domain that is defined by true, indeterminacy, and false subsets, which are symbolized as T, I, and F, respectively. Entropy is used to measure its indeterminacy. In the present work, the filtering operator is performed on T and F to reduce the indeterminacy set and obtain the denoised image, as illustrated in **Figure 1**. In this study, Five NS-based denoising approaches including NS Bilateral filter, NS Wiener filter, NS Median filter, NS gaussian filter, and NS rank-ordered filter were proposed.

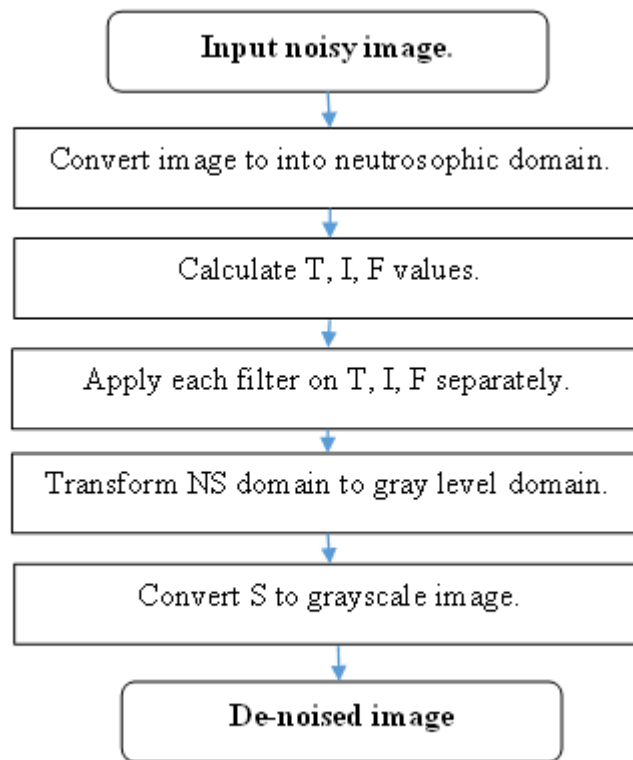


Figure 1 Summary of the proposed approach.

Step 1. Find the grayscale image

Each pixel in RGB is converted to the grayscale image range from 0–255, where image has $H \times W$ size.

Step 2. Calculate the LMV of [gray scale image](#).

For $H \times W$ gray image, the LMV of pixel can be achieved using a filter that operates over the image pixels. The filter averages the value of neighbor pixels for each pixel. In our study, the window filter is 5×5 size.

Step 3. Describe the maximum and minimum values of LMV.

Step 4. Calculate T, I, and F in NS.

After computing T, I, and F via Eqs. (1)–(5), each pixel in an image is represented in the form of $P_{NS}(H, W) = \{T(H, W), I(H, W), F(H, W)\}$

Step 5. Image enhancement under the NS domain

This step is obtained using Bilateral filter, Wiener filter, Median filter, gaussian filter, and rank-ordered filter individually on each T, I, F subsets.

Step 6. Convert from neutrosophic domain to gray scale domain.

In this step we combine T, I, F in one matrix using score function which defined in [22], then using the following equation for spatial domain conversion [23]:

$$\hat{F}(n) = \bar{g}_{min} + (\bar{g}_{max} - \bar{g}_{min}) \cdot F(n) \quad (10)$$

Where $F(n)$ is the results from score function in [22]. The algorithm procedure of our approach is summarized in Algorithm 1 and represented in [Figure 1](#).

Algorithm 1. X-Ray enhancement approach based on NS.

Input: Grayscale image with pixels ranging from [0–255].
for \forall pixels in grayscale image **do**
 Represent each pixel into NS domain (Equations (1)–(5)).
 Perform denoising operations on T,I,F separately.
 Represent image from the NS domain to grayscale level.
End

Experimental results

This section involves the radiology image dataset overview, evaluation metrics, of the NS-based enhancement proposed .

Dataset Overview

The database includes 154 conventional chest radiographs with a lung nodule (100 malignant and 54 benign nodules) and 93 radiographs without a nodule which were digitized by a laser digitizer with a 2048x2048 matrix size (0.175-mm pixels) and a 12-bit gray scale (no header, big-endian raw data) [24].

Performance Evaluation Metrics

Our proposed work is evaluated based on PSNR, SNR, SSIM, to indicates the effectiveness of our approach.

Peak- signal-to-noise-ratio (PSNR): Independent evaluation metric, it assesses the maximum image value with the noise distorting value that affects the image. The higher PSNR indicates a higher quality image [25]. It is represented as:

$$PSNR = 10 \log \left[\frac{\sum_{a=0}^{H-1} \sum_{b=0}^{W-1} (I(x, z) - I_d(x, z))^2}{H \times W \times 255^2} \right] \quad (11)$$

Since H and W is the height and width of gray image, $I(x, z)$ and $I_d(x, z)$ are the main and enhancement image with pixels a, b respectively.

Signal-to-Noise Ratio (SNR): The ratio of enhanced image variance and the error variance between original image and enhances image [26]. It is represented as:

$$PSNR = 10 \log_{10} \left(\frac{\sigma_F^2}{\sigma_E^2} \right) \quad (12)$$

Since σ_F and σ_E is the noise-free image variance and the error variance respectively.

Structural Similarity Index (SSIM): Since PSNR is not the suitable, the SSIM is considered the effective way to estimate the error depending on visual sense. It measures the similarity structure between main image and enhanced image[25]. It is represented as:

$$SSIM(x, z) = \frac{(2\mu_a\mu_b + Z_1)(2\sigma_{ab} + Z_2)}{(\mu_a^2 + \mu_b^2 + Z_1)(\sigma_a^2 + \sigma_b^2 + Z_2)} \quad (13)$$

Since Z_1 and Z_2 are constant, $Z_1 = (D_1S)^2$ and $Z_2 = (D_2S)^2$, $D_1, D_2 \ll 1$ is small constant and S is a dynamic range of pixel values. Also, μ_a and μ_b are obtained the mean intensity, and σ_a and σ_b is standard deviation that can be represented as:

$$\sigma_{ab} = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_x)(z_i - \mu_z) \quad (14)$$

Mean squared error (MSE): is a risk function that measures the average squared difference between estimated and actual values. It is often strictly positive due to randomness or inaccuracies in estimators [26]. This can be represented as

$$\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (15)$$

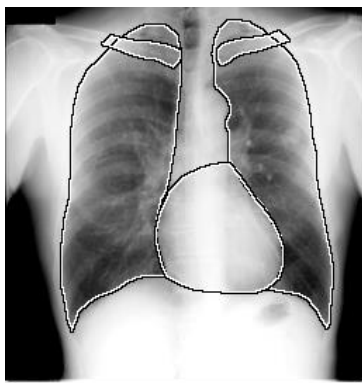
Where n is the number of data point, y_i is observed value, and \hat{y}_i is predicted value.

5.1. Statistical results

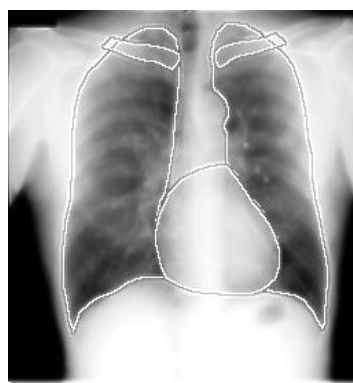
For statistical analyses, the PSNR, SNR, SSIM and MSE values are defined for the X-Ray image enhancement. These statistical analyses are achieved by comparing the NS Bilateral filter, NS Wiener filter, NS Median filter, NS gaussian filter, and NS rank-ordered filter denoising filters. The values of PSNR, SNR, SSIM and MSE are shown in **Table 1**.

Table.1 The average of the evaluation metrics of NS Bilateral filter, NS Wiener filter, NS Median filter, NS gaussian filter, and NS rank-ordered filter.

	NS Bilateral filter	NS Wiener Filter	NS Median filter	NS Gaussian filter	NS rank-ordered filter
PSNR	19.6669	19.4146	17.3378	18.6515	18.9969
SNR	16.6748	16.4225	14.3457	15.6594	16.0048
SSIM	0.88197	0.87687	0.79302	0.87166	0.8665
MSE	29.846	31.3175	25.4278	31.3045	28.4104
Entropy	18.3161	18.5561	17.2943	18.4004	17.4105



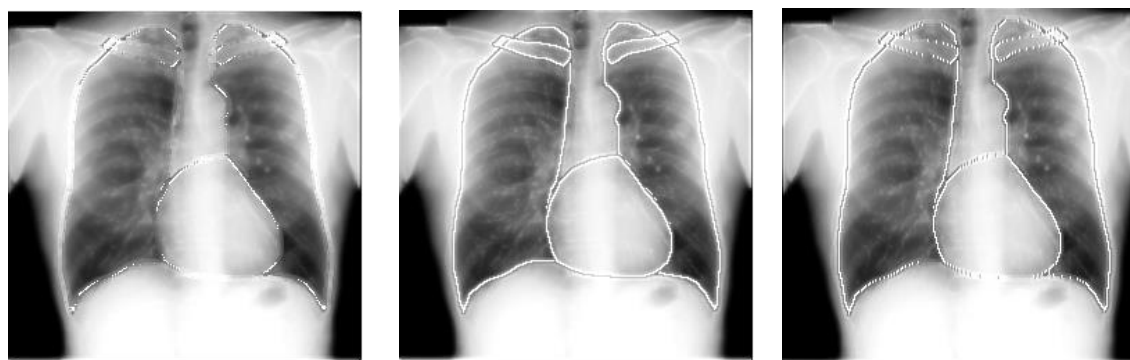
(a)



(b)



(c)



(d)

(e)

(f)

Fig.2 Denoising results of X-Ray image (a) original image, (b) NS imbilatfilt filter, (c) NS wiener filter, (d) NS median filter, (e) NS Gaussian filter, and (f) NS rank-order filter.

6. Conclusion

In this paper, an investigation for medical image enhancement based on NS has been introduced. The applicability of the image enhancement under the NS domain was demonstrated on X-ray images. The NS Bilateral filter, NS Wiener filter, NS Median filter, NS gaussian filter, and NS rank-ordered filter denoising filters were applied into the NS domain. Then converting the neutrosophic image to spatial domain using neutrosophic number score function and conversion Equation (20). In our approach, NS was obtained to transform the grayscale X-ray image to the NS domain and measure uncertainties using NS entropy. The proposed approach achieved enhancement in X-ray images with five denoising operations. The experiments were presented on 247 different benchmark X-rays of chest infections. The performance of the enhancement was evaluated using PSNR, SNR, SSIM, and MSE metrics. The experimental results of X-Ray image enhancement indicate the effectiveness of NS Bilateral filter approach over other denoising filters. In the future, more efforts are needed to find more efficient techniques to convert from neutrosophic domain to spatial domain.

Supplementary Materials

Not applicable.

Author Contributions

All Authors contributed equally to this work.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

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Data Availability Statement

Not applicable.

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