Neutrosophic Sets and Systems, Vol. 28, 2019
University of New Mexico

Reduction of indeterminacy of gray-scale image in bipolar neutrosophic domain

Arulpandy P [1*] and Trinita Pricilla M [2]

[1]Department of Mathematics, Bannari Amman Institute of Technology, Erode, Tamilnadu, India.
Email: arulpandy002@gmail.com, arulpandy@bitsathy.ac.in.
[2]Department of Mathematics, Nirmala College for Woman, Coimbatore, Tamilnadu, India.
Email: abishai_kennet@yahoo.in

*Correspondence: Arulpandy P ; arulpandy002@gmail.com.

Abstract: Neutrosophy is a branch of philosophy introduced by Florentin Smarandache. Neutrosophic set (NS) is the derivative of neutrosophy; it is a powerful tool to handle uncertainty. Here we applied neutrosophic set to gray scale image domain for image analysis. Several authors contributed in neutrosophic image analysis and image processing. We propose a novel approach on representation of grayscale images in bipolar neutrosophic domain (BNS). The reduction of noise in images is one of the challenging task in every field. While we transform a grayscale image into bipolar neutrosophic domain, the indeterminacy degree of both positive and negative memberships are reduced significantly. Indeed, we extract some useful information from indeterminacy domain; it leads to perform image analysis and processing in noisy images in a better manner. We discuss the representation of medical images in bipolar neutrosophic domain with examples.

Keywords: Bipolar neutrosophic set, Image analysis, Neutrosophy, Digital image processing.

1. Introduction

Neutrosophy is one of the useful tool to handle uncertainty in real world problems. It is the extension of fuzzy theory. Neutrosophy is a branch of philosophy which was introduced by Florentin Smarandache [1-3]. Neutrosophy deals with origin, nature and scope of neutralities, as well as their interactions with different ideational spectra. Neutrosophy is the basis of neutrosophic sets (derivative of neutrosophy).

Neutrosophic set contains three parameters as true-membership degree, indeterminacy-membership degree and falsity-membership degree. These three membership degrees are independent and has range, a non-standard interval $\left]^{-}0,1^{+}\right[$. But for real life problems, non-standard interval is not applicable. Wang et al. [5] introduced single valued neutrosophic sets which is a neutrosophic set defined in the range [0, 1]. Later, Pinaki Majumdar et al. and Ali Aydogdu [6, 4] proposed some similarity and entropy measurements of single valued neutrosophic sets. In 2015, Deli et al. [7] introduced the concepts of bipolar neutrosophic sets (BNS) as an extension of neutrosophic sets. In 2016, Uluçay et al. [8] proposed some measures of similarities of bipolar neutrosophic sets.

Nowadays reduction of noise in images is difficult task in every field. Cheng and Guo [10] introduced the representation of image in neutrosophic domain and proposed image thresholding technique using neutrosophic domain. Guo and Cheng [11] proposed some concepts about image denoising through neutrosophic domain. Yanhui Guo and H.D. Cheng [9] introduced a new neutrosophic approach on image segmentation. A. A. Salama et al. [12, 14] proposed some image processing techniques using neutrosophic sets. G. Xu et al.[18] proposed image segmentation using TOPSIS method. Mohammed Abdel Basset et al. proposed some concepts of TOPSIS method for decision making problems in medical field [15, 19, 20, 22]. In 2017, Mumtaz Ali et al. introduced the concepts of bipolar neutrosophic soft sets which is a combined version of bipolar neutrosophic set and neutrosophic soft set. Arulpandy et al. [17] proposed some similarity and entropy measurements of bipolar neutrosophic soft sets. Several authors contributed to decision making and performance analysis using neutrosophic field [21, 23, 24].

In this paper, we proposed a novel approach on representation of any gray scale image in bipolar neutrosophic domain. In section 4, we applied our approach to MRI (Magnetic Resonance Image) medical images and discuss their nature with histogram representation. We analyze transformed images with some of the popular metrics Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE). In this transformation, the indeterminacy of both positive and negative membership degree is reduced significantly. This is the main advantage of this bipolar neutrosophic domain. Indeed, we extract useful information from original image through BNS domain; it is not available in neutrosophic domain.

2. Preliminaries

Definition 1. [1, 2, 3] Let X be the universe of discourse contains x . A Neutrosophic set $NS(A)$ is defined by $NS(A) = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\}$. Where $T_A(x), I_A(x), F_A(x)$ represents truth-membership degree, indeterminacy-membership degree and falsity-membership degree respectively. Here $T_A(x), I_A(x), F_A(x) : X \to]^-0, 1^+[$ along with the following condition

$$^-0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3^+.$$

Example. Let $X = \{x_1, x_2, x_3\}$ be the universal set. Here, x_1, x_2, x_3 represents capacity, trustworthiness and price of a machine, respectively. Then $T_A(x), I_A(x), F_A(x)$ gives the degree of 'good service', degree of indeterminacy, degree of 'poor service' respectively. The neutrosophic set is defined by $NS(A) = \{\langle x_1, 0.3, 0.4, 0.5\rangle, \langle x_2, 0.5, 0.2, 0.3\rangle, \langle x_3, 0.7, 0.2, 0.2\rangle\}$ where $^-0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3^+$.

Definition 2. [4,5,6] Single valued neutrosophic set(SVNS) is the immediate result of neutrosophic set if it is defined over standard unit interval [0,1] instead of the non-standard unit interval $]^-0, 1^+[$. A single valued neutrosophic set SVNS (A) is defined by $SVNS(A) = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\}$ where $T_A(x), I_A(x), F_A(x) : X \to [0,1]$ such that $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.

Definition 3. [7, 8] Let X be the universal set which contains arbitrary points x. A bipolar neutrosophic set (BNS) $BNS(A)$ is defined by

$$BNS(A) = \{\langle x, T_A^+(x), I_A^+(x), F_A^+(x), T_A^-(x), I_A^-(x), F_A^-(x)\rangle : x \in X\}$$

Where

$T_A^+, I_A^+, F_A^+ : E \to [0,1]$ (Positive membership-degrees)

$T_A^-, I_A^-, F_A^- : E \to [-1,0]$ (Negative membership-degrees)

Such that

$$0 \leq T_A^+(x) + I_A^+(x) + F_A^+(x) \leq 3, \quad -3 \leq T_A^-(x) + I_A^-(x) + F_A^-(x) \leq 0.$$

Example. Let $X = \{x_1, x_2, x_3\}$ be the universal set. A bipolar neutrosophic set (BNS) is defined by

$$A = \{\langle x_1, 0.3, 0.4, 0.5, -0.2, -0.4, -0.1\rangle, \langle x_2, 0.5, 0.2, 0.3, -0.2, -0.7, -0.5\rangle, \langle x_3, 0.7, 0.2, 0.2, -0.5, -0.4, -0.5\rangle\}$$

Where $0 \le T_A^+(x) + I_A^+(x) + F_A^+(x) \le 3$ and $-3 \le T_A^-(x) + I_A^-(x) + F_A^-(x) \le 0$. Also $T_A^+(x), I_A^+(x), F_A^+(x) \to [0,1]$ and $T_A^-(x), I_A^-(x), F_A^-(x) \to [-1,0]$.

3. Grayscale image in bipolar neutrosophic domain

Neutrosophy has wide range of applications in science and engineering. In particular, it is very useful in fields such as Data analytics, financial market, Social network analysis, Quantum theory, robotics in terms of decision making problems. In this section, we discuss about the applications of neutrosophic sets in image analysis. In 2008, H.D Cheng and Yanhui guo[10] introduced the representation of grayscale image in neutrosophic domain. After that, so many papers have been published about neutrosophic image such as image denoising, image thresholding, image segmentation etc.

3. 1. Image in neutrosophic domain

Let X be a universe of discourse, W be the set contained in X, which is composed by bright pixels. A neutrosophic image P_{NS} is characterized by three subset T, I and F. A pixel P in an image is described as P(T, I, F) and belongs to W in the following way: it is *t*% true , *i* % indeterminate and *f* % false in the bright pixel set, where *t* varies in T, *i* varies in I and *f* varies in F. Each component has a value in [0, 1].

Pixel P(i,j) in the image domain is transformed into neutrosophic domain $P_{NS}(i,j) = T(i,j), I(i,j), F(i,j)$, where $T(i,j), I(i,j), F(i,j)$ represents probabilities belonging to white set, indeterminate set and non-white set, respectively, which are defined as:

$$T(i,j) = \frac{\bar{g}(i,j) - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}}, \quad I(i,j) = \frac{\delta(i,j) - \delta_{min}}{\delta_{max} - \delta_{min}}, \quad F(i,j) = 1 - T(i,j) = \frac{\bar{g}_{max} - \bar{g}(i,j)}{\bar{g}_{max} - \bar{g}_{min}}$$

Where $\bar{g}(i,j)$ represents mean intensity of pixel in some neighborhoods in W. Here,

$$g(i,j) = \frac{1}{W \times W} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} g(m,n)$$

$$\delta(i,j) = |g(i,j) - \bar{g}(i,j)|$$

$$\delta_{max} = max\delta(i,j) \qquad \delta_{min} = min\delta(i,j).$$

Example 1. We consider the original Lena image and represent it in neutrosophic domain as follows:

Figure 1. Original Lena image.

(a) **(b)** **(c)**

Figure 2. Neutrosophic domain images of Original Lena image.

(a) T domain (b) I domain (c) F domain

Above images represents truth-membership domain, indeterminacy domain and false-membership domain of original Lena image respectively. We mainly focus on truth-membership domain for image analysis along with indeterminacy domain. Truth-membership domain is correlated with indeterminacy domain.

3. 2. Image in bipolar neutrosophic domain

Now we introduce grayscale image representation in bipolar neutrosophic domain. Main advantage of this representation is, when we transform image into bipolar neutrosophic domain, the indeterminacy degree get reduced. Indeed, we extract some useful information from indeterminacy degree in bipolar neutrosophic domain which is not available in neutrosophic domain. We used MATLAB 2010 version for this transformation. The following steps are involved in this representation:

1. Load the original image. Convert this into grayscale if it is RGB color image.
2. Represent image in pixel domain.
3. Find the median pixel value of entire image.
4. Consider pixels above the median value as foreground image and below the median value as background image.
5. Set the window size (size of neighborhood) to find local mean value. In our case, we take 3x3-neighborhood.
6. Transform image into bipolar neutrosophic domain by taking positive memberships for foreground pixels and negative memberships for background pixels.

We use the following membership values to transform any grayscale image to bipolar neutrosophic domain. Since the elements are pixels of an image, we use only unsigned integer to represent the membership functions. A pixel in bipolar neutrosophic domain is represented by

$$P_{BNS}(i,j) = \{T^{+}(i,j), I^{+}(i,j), F^{+}(i,j), T^{-}(i,j), I^{-}(i,j), F^{-}(i,j)\}.$$

Here

$$T^{+}(i,j) = \frac{\bar{g}(i,j) - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}} \qquad I^{+}(i,j) = \frac{\delta(i,j) - \delta_{min}}{\delta_{max} - \delta_{min}}$$

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

$$T^{-}(i,j) = \frac{\hat{g}(i,j) - \hat{g}_{min}}{\hat{g}_{max} - \hat{g}_{min}} \qquad I^{-}(i,j) = \frac{\delta(i,j) - \delta_{min}}{\delta_{max} - \delta_{min}}$$
$$F^{-}(i,j) = 1 - T^{+}(i,j) = \frac{\hat{g}_{max} - \hat{g}(i,j)}{\hat{g}_{max} - \hat{g}_{min}}$$

Where $\bar{g}(i,j)$ represents mean intensity of foreground pixel in some neighborhood W and $\hat{g}(i,j)$ represents the mean intensity of background pixel in some neighborhood in W^{*}.

Here

$$g(i,j) = \frac{1}{W \times W} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} g\,(m,n)$$
$$g(i,j) = \frac{1}{W^{*} \times W^{*}} \sum_{m=i-w^{*}/2}^{i+w^{*}/2} \sum_{n=j-w^{*}/2}^{j+w^{*}/2} g\,(m,n)$$
$$\delta(i,j) = |g(i,j) - \bar{g}(i,j)|$$
$$\delta(i,j) = |g(i,j) - \hat{g}(i,j)|$$
$$\delta_{max} = max\delta(i,j) \qquad \delta_{min} = min\delta(i,j).$$

Example 2. Consider the original Lena image in the previous example. The following image shows the image in bipolar neutrosophic domain.

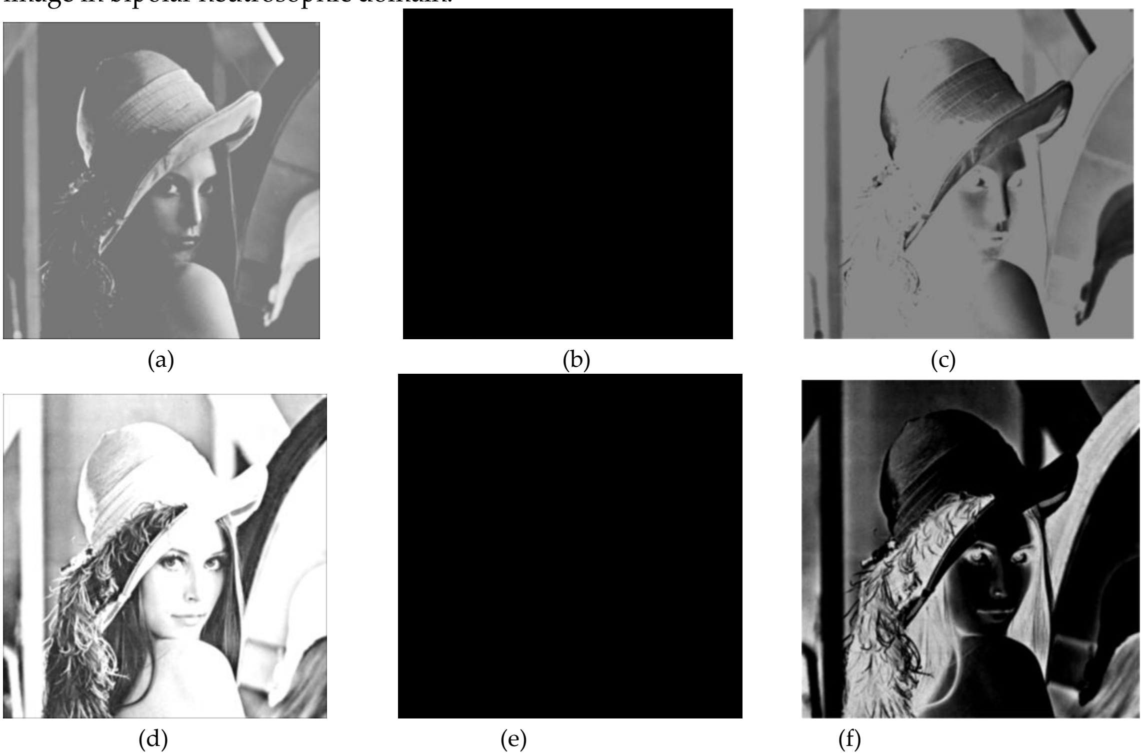


Figure 3. Bipolar neutrosophic representation of lena image (fig 1.)
(a) T+ domain, (b) I+ domain, (c) F+ domain, (d) T- domain, (e) I- domain, (f) F- domain

Note that in the above images, I- domain and I+ domain images looks identical and black in color. It means both images contained only black pixels (pixels which has value zero). So from this we eliminate the indeterminacy of both positive and negative membership domains. The following histogram images shows that the gray level distribution of each images in BNS domain.

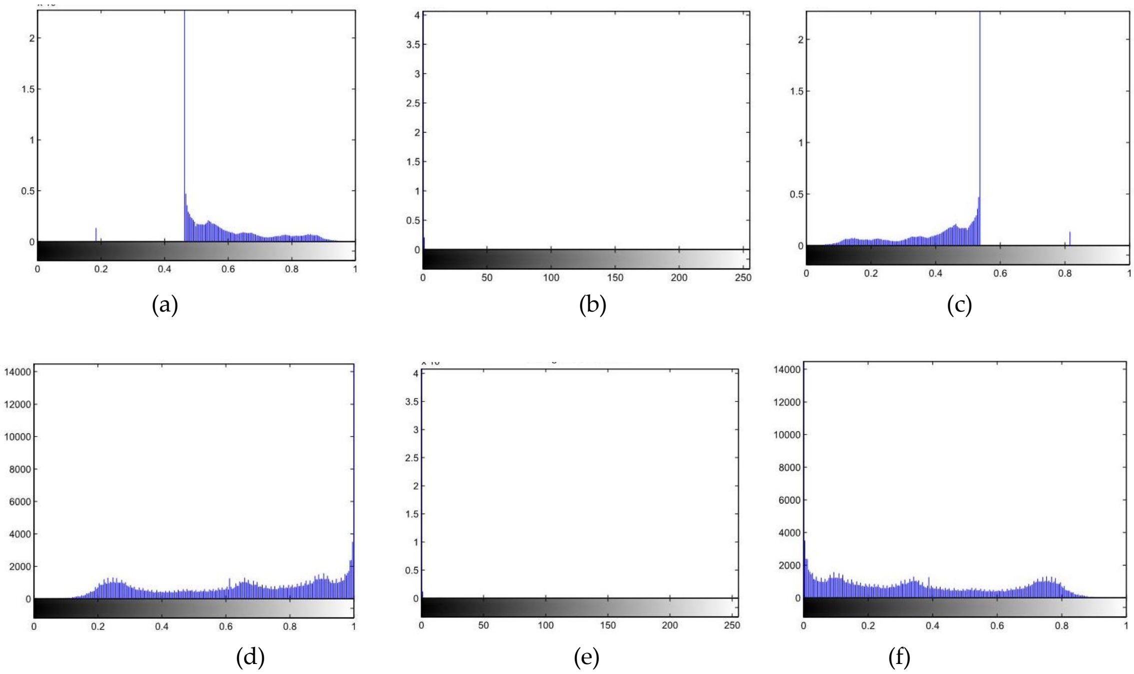


Figure 4. Histogram of transformed images (Fig 3.)
(a) Histogram of T+ , (b) Histogram of I+ , (c) Histogram of F+ , (d) Histogram of T- , (e) Histogram of I- , (f) Histogram of F- .

3. 3. Entropy of image in bipolar neutrosophic domain

Bipolar neutrosophic image entropy is defined as sum of entropies of all subsets $T^+, I^+, F^+, T^-, I^-, F^-$, which is used to evaluate the distribution of pixels in bipolar neutrosophic domain. $En_{BNS} = En_{T^+} + En_{I^+} + En_{F^+} + En_{T^-} + En_{I^-} + En_{F^-}$.

Here

$$En_{T^+} = -\sum p_{T^+}(i) \ln p_{T^+}(i)$$
$$En_{I^+} = -\sum p_{I^+}(i) \ln p_{I^+}(i)$$
$$En_{F^+} = -\sum p_{F^+}(i) \ln p_{F^+}(i)$$
$$En_{T^-} = -\sum p_{T^-}(i) \ln p_{T^-}(i)$$
$$En_{I^-} = -\sum p_{I^-}(i) \ln p_{I^-}(i)$$
$$En_{F^-} = -\sum p_{F^-}(i) \ln p_{F^-}(i).$$

4. Bipolar neutrosophic representation of medical image

Nowadays image denoising is the challenging task in every field. Especially, in medical field, it is very useful for X-ray images, MRI images, CT images, Ultra sound images etc. In this section, we take MRI scan brain image and transform it to BNS domain and analyze various parameters.

Consider the following brain MRI image.

Figure 5. MRI Brain image

The following image shows the brain image in bipolar neutrosophic domain.

(a) (b) (c)

(d) (e) (f)

Figure 6. Bipolar neutrosophic representation of MRI brain images as

(a) T+ domain, (b) I+ domain, (c) F+ domain, (d) T- domain, (e) I- domain, (f) F- domain

From the above images, we can clearly see that the variations between each images. Every image has some useful information. We may neglect indeterminate images I+ and I-, since it has only black pixels. Peak Signal-to-noise Ratio (PSNR) values mostly used to find the noise level in the transformed image and we can check similarity level between original image and transformed image. PSNR value is calculated using the following formula:

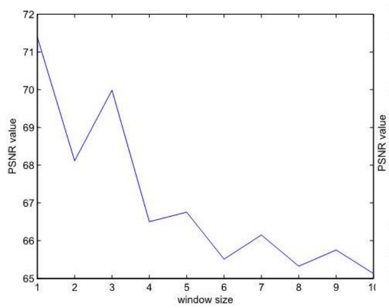
$$PSNR = -10log\left[\frac{\sum_{i=0}^{i=H-1}\sum_{j=0}^{j=W-1}[A(i,j) - A'(i,j)]^2}{M \times N \times 255^2}\right].$$

Here, the local mean average determines the variations in the transformed image. Local mean average of an image is depend on the window size (neighborhood size) which is used in the local mean average. Here, we analyze the PSNR value of the original image and images in the transformed domain for different neighborhood sizes.

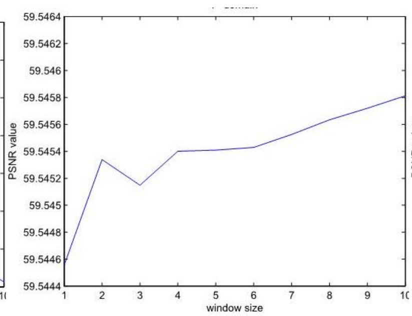
Window Size	**T+ domain**	**I+ domain**	**F+ domain**	**T- domain**	**I- domain**	**F- domain**
1x1	71.393	59.544	50.173	54.816	59.544	51.039
2x2	68.115	59.545	51.579	54.868	59.545	51.121
3x3	69.987	59.545	51.275	54.924	59.545	51.160
4x4	66.502	59.545	51.758	54.950	59.545	51.199
5x5	66.755	59.545	51.632	54.990	59.545	51.228
6x6	65.509	59.545	51.877	55.018	59.545	51.261
7x7	66.151	59.545	51.744	55.055	59.545	51.287
8x8	65.323	59.545	51.916	55.077	59.545	51.320
9x9	65.752	59.545	51.819	55.107	59.545	51.346
10x10	65.128	59.545	51.955	55.127	59.545	51.377

Table 1. PSNR values of brain image in BNS domain associated with different neighborhood windows.

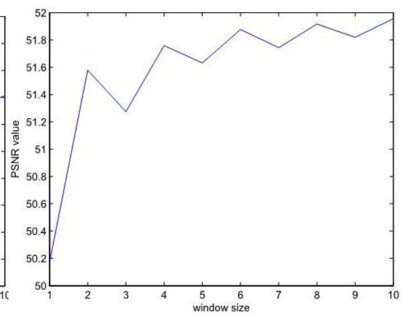
Following plots shows the variations in PSNR values when we increase the size of the window in local mean average.



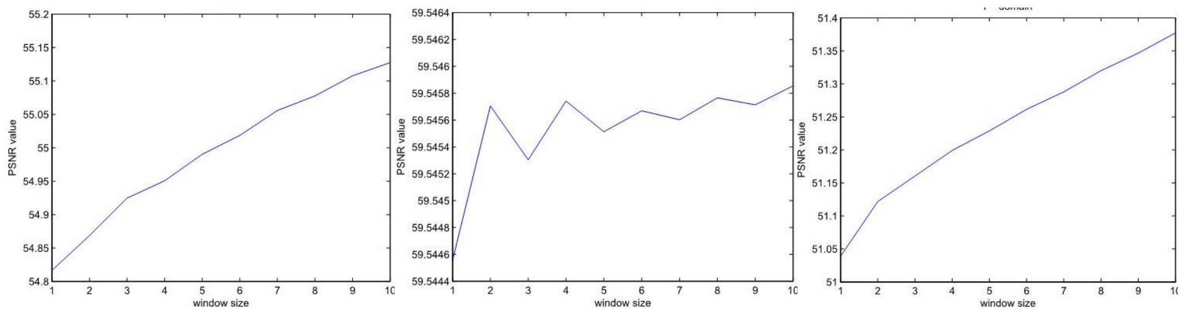
(a)



(b)



(c)



(d) (e) (f)

Figure 7. Comparison of PSNR values and neighborhood window size in (a) T+ domain, (b) I+ domain, (c) F+ domain, (d) T- domain, (e) I- domain, (f) F- domain

Mean Square Error (MSE) is another parameter to check the quality of transformed image. MSE is calculated using the following formula:

$$MSE = \frac{\sum_{i=0}^{i=H-1}\sum_{j=0}^{j=W-1}[A(i,j) - A'(i,j)]^2}{M \times N}.$$

Following table shows that the mean square error between original image and transformed images with different window size.

Window Size	T+ domain	I+ domain	F+ domain	T- domain	I- domain	F- domain
1x1	0.00472	0.07221	0.62480	0.21449	0.07221	0.51189
2x2	0.01003	0.07220	0.45200	0.21194	0.07220	0.50223
3x3	0.00652	0.07220	0.48482	0.20922	0.07220	0.49778
4x4	0.01455	0.07220	0.43370	0.20797	0.07219	0.49336
5x5	0.01373	0.07220	0.44652	0.20609	0.07220	0.49000
6x6	0.01829	0.07220	0.42206	0.20475	0.07220	0.48633
7x7	0.01577	0.07220	0.43519	0.20300	0.07220	0.48337
8x8	0.01909	0.07220	0.41824	0.20198	0.07219	0.47981
9x9	0.01729	0.07220	0.42767	0.20059	0.07220	0.47688
10x10	0.01996	0.07219	0.41447	0.19968	0.07219	0.47353

Table 2. MSE values of brain image in BNS domain associated with different neighborhood windows.

Following plots shows the variations in MSE when we increase the window size.

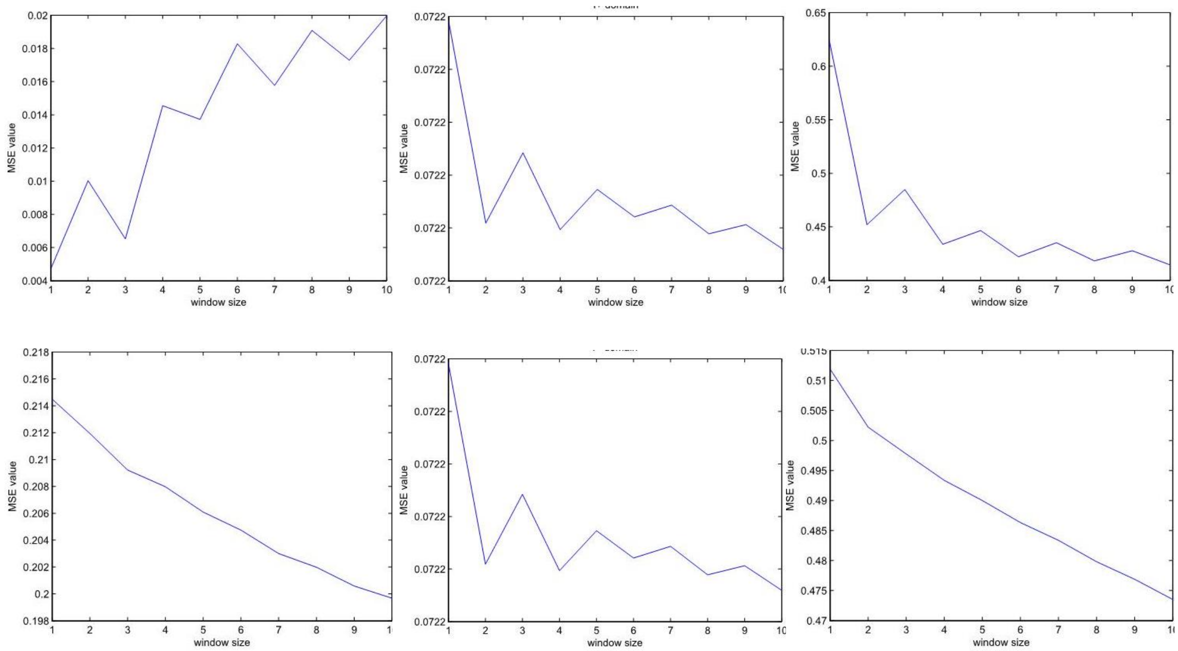


Figure 8. Comparison of PSNR values and neighborhood window size in (a) T+ domain, (b) I+ domain, (c) F+ domain, (d) T- domain, (e) I- domain, (f) F- domain.

The following table shows the entropies of each images in bipolar neutrosophic domain. It represents the uncertainty level of a gray-scale image. Particularly, higher entropy value means, it gives more detailed information about the image; likewise, lower entropy value means, it gives less information. Roughly speaking, higher entropy represents distribution level high intensity pixels and lower entropy represents distribution level of low intensity pixels.

	T+ domain	**I+ domain**	**F+ domain**	**T- domain**	**I- domain**	**F- domain**
Entropy Value	4.5872	0.0258	4.5872	3.9005	0.0361	3.9005

Table 3. Entropy values of brain image in BNS domain

	T domain	**I domain**	**F domain**
Entropy Value	6.0492	3.9579	6.0492

Table 4. Entropy values of brain image in NS domain

From the above Table 3 and Table 4. we can clearly see that the variations of entropy values between neutrosophic domain and bipolar neutrosophic domain. Entropy values of indeterminacy domain in bipolar neutrosophic domain is significantly reduced when compared to neutrosophic domain. So we conclude that our bipolar neutrosophic domain of gray scale image performed well.

5. Conclusions

A new technique to represent gray scale image in bipolar neutrosophic domain is proposed. While the image is transformed into bipolar neutrosophic domain, the indeterminacy degree of both positive and negative membership domain is reduced significantly. So this transformation gives more useful information compared to neutrosophic domain. Further, we discussed about the gray level distribution of images in bipolar neutrosophic domain through histogram. Selection of neighborhood window is important in this transformation. Large window gives best transformation, but we lose essential information of original image. We compared most popular metrics PSNR and MSE for our transformed images associated with different neighborhood sizes. PSNR and MSE both are useful parameters to determine the quality of gray-scale images by analyzing distribution of gray levels. Our future work will include image analysis and image processing through bipolar neutrosophic domain.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Florentin Smarandache, Neutrosophy: A new branch of philosophy, Multiple valued logic: An international journal, 8(2002), 297-384.
2. Florentin Smarandache, A unifying field in logics neutrosophic logic, Neutrosophy, Neutrosophic Set, Neutrosophic Probability, 3rd ed. American Research Press, 2003.
3. Florentin Smarandache, Neutrosophic set: A generalization of the intuitionistic fuzzy set, International Journal of Pure and Applied Mathematics, 24(2005), 3, 287-297.
4. Ali Aydogdu, On similarity and entropy of Single valued neutrosophic sets, Gen. Math. Notes, 29(2015), 1, 67-74.
5. Haibin wang, Florentin Smarandache, Yanqing Zhang and Rajshekar Sunderaraman. Single Valued Neutrosophic sets, Proceedings in Technical serise and applied Mathematics, 2012.
6. Pinaki Majumdar and Syamal Kumar Samanta. On similarity and entropy of Neutrosophic sets, Journal of Intelligent and Fuzzy Systems, 26(2014), 3, 1245-1252.
7. Irfan Deli, Mumtaz Ali and Florentin Smarandache, Bipolar Neutrosophic Sets and Their Application Based on Multi-Criteria Decision Making Problems, Proceedings of the 2015 International Conference on Advanced Mechatronic Systems, Beijing, China, August, 22-24, 2015.
8. Vakkas Ulucay, Irfan Deli and Mehmet Sahin, Similarity measures of Bipolar neutrosophic sets and their applications to multiple criteria decision making, Neural Computing and Applications, 29(2018), 3, 739-748.
9. Yanhui Guo and H.D. Cheng, New neutrosophic approach to image segmentation, Pattern Recognition, 42(2009), 5, 587-595.
10. H. D. Cheng and Yanhui Guo, A new Neutrosophic approach to image thresholding, New Mathematics and Natural Computation, 4(2008), 3, 291-308.
11. Y. Guo and H.D. Cheng, A new neutrosophic approach to image denoising, New Mathematics and Natural Computation, 5(2009),3, 653-662.
12. A. A. Salama, Florentin Smarandache and Mohamed Eisa, introduction to image processing via neutrosophic techniques, Neutrosophic Sets and Systems, 5(2014), 59-64.

13. H. D Cheng, Y. Guot, Y. Zhang, A Novel Image Segmentation Approach Based on Neutrosophic Set And Improved Fuzzy CMeans Algorithm, New Mathematics and Natural Computation,Vol. 7(2011), 1, 155-171.

14. A. A. Salama, Florentin Smarandache and Hewayda ElGhawalby, Neutrosophic approach to Grayscale image domain, Neutrosophic sets and systems, 21(2018), 13-19.

15. Mohamed Abdel-Basset, Gunasekaran Manogaran, Abduallah Gamal and Florentin Smarandache A Group Decision Making Framework Based on Neutrosophic TOPSIS Approach for Smart Medical Device Selection, Journal of Medical Systems, 43(2019), 2, 19-41.

16. Mumtaz Ali, Le Hoang Son, Irafan Deli and Nguyen Dang Tien. Bipolar neutrosophic soft sets and applications in decision making, Journal of Intelligent and Fuzzy Systems, 33(2017), 6, 4077-4087.

17. P. Arulpandy and M. Trinita Pricilla Some similarity and entropy measurements of bipolar neutrosophic soft sets, Neutrosophic sets and systems, 25(2019), 1, 174-194.

18. G. Xu, S. Wang, T. Yang, W. Jiang A Neutrosophic Approach Based on TOPSIS Method to Image Segmentation, International Journal of Computer Communications and control, 13(2018), 6, 1047-1061.

19. Abdel-Baset, M., Victor Chang, Abduallah Gamal, and Florentin Smarandache. "An integrated neutrosophic ANP and VIKOR method for achieving sustainable supplier selection: A case study in importing field." Computers in Industry 106 (2019): 94-110.

20. Mohamed Abdel-Basset, Saleh, Abduallah Gamal and Florentin Smarandache An approach of TOPSIS technique for developing supplier selection with group decision making under type-2 neutrosophic number Applied Soft Computing, 77(2019), 438-452

21. Mohamed Abdel-Basset, Cheng V and Abduallah Gamal Evaluation of the green supply chain management practices: A novel neutrosophic approach Computers in Industry, 108(2019), 210-220

22. Nabeeh N. A.,Mohamed Abdel-Basset, El-Ghareeb H. A. and Aboelfetouh A. Neutrosophic multi-criteria decision making approach for iot-based enterprises IEEE Access, 7(2019), 59559-59574

23. Mohamed Abdel-Basset, Nabeeh N. A., El-Ghareeb H. A., and Aboelfetouh A. Utilising neutrosophic theory to solve transition difficulties of IoT-based enterprises Enterprise Information Systems, 2019, 1-21

24. Abdel-Basset, Mohamed, Rehab Mohamed, Abd El-Nasser H. Zaied, and Florentin Smarandache. "A Hybrid Plithogenic Decision-Making Approach with Quality Function Deployment for Selecting Supply Chain Sustainability Metrics." Symmetry 11, no. 7 (2019): 903.

25. Abdel-Basset, Mohamed, Asmaa Atef, and Florentin Smarandache. "A hybrid Neutrosophic multiple criteria group decision making approach for project selection." Cognitive Systems Research 57 (2019): 216-227.

Received: March 13, 2019. Accepted: August 15, 2019