



# A novel image segmentation algorithm based on neutrosophic similarity clustering



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## ARTICLE INFO

### Article history:

Received 17 June 2014

Received in revised form 22 August 2014

Accepted 29 August 2014

Available online 8 September 2014

### Keywords:

Image segmentation

Clustering analysis

Neutrosophic set

Similarity function

## ABSTRACT

Segmentation is an important research area in image processing, which has been used to extract objects in images. A variety of algorithms have been proposed in this area. However, these methods perform well on the images without noise, and their results on the noisy images are not good. Neutrosophic set (NS) is a general formal framework to study the neutralities' origin, nature, and scope. It has an inherent ability to handle the indeterminant information. Noise is one kind of indeterminant information on images. Therefore, NS has been successfully applied into image processing algorithms. This paper proposed a novel algorithm based on neutrosophic similarity clustering (NSC) to segment gray level images. We utilize the neutrosophic set in image processing field and define a new similarity function for clustering. At first, an image is represented in the neutrosophic set domain via three membership sets:  $T$ ,  $I$  and  $F$ . Then, a neutrosophic similarity function (NSF) is defined and employed in the objective function of the clustering analysis. Finally, the new defined clustering algorithm classifies the pixels on the image into different groups. Experiments have been conducted on a variety of artificial and real images. Several measurements are used to evaluate the proposed method's performance. The experimental results demonstrate that the NSC method segment the images effectively and accurately. It can process both images without noise and noisy images having different levels of noises well. It will be helpful to applications in image processing and computer vision.

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## 1. Introduction

Image segmentation is known as partitioning of a given image into multiple non over-lapping regions. Further, it is announced as a low-level image processing technique which transforms an image into one or more regions for high-level image description in terms of features, objects, and scenes [1–3]. So far, a variety of image segmentation algorithms have been proposed. Most image segmentation approaches are based on either discontinuity and/or homogeneity of the intensities. The discontinuity based approaches segment an image by detecting isolated points, lines and edges according to abrupt changes in intensities. Thresholding, edge detection, clustering and region growing and merging techniques can be seen in homogeneity based approaches [3]. However, these methods perform well on noise free images [4]; an accurate partitioning of noisy images is generally a very challenging

problem. For example, thresholding technique is sensitive to noise and ignores the spatial information. Region growing methods have several drawbacks such as over-segmentation and time-consuming. In addition, noises usually cause wrong edges in edge detection methods. Clustering methods suffer from over-segmentation [5], special on noisy images.

Recently, a new philosophy namely neutrosophy has been proposed for handling the indeterminate information [6,7]. It studies the origin, nature and scope of neutralities. Noise is one kind of indeterminant information on images. Therefore, neutrosophy has been successfully applied into image processing and computer vision applications [5,8–13]. Guo and Cheng [5] proposed a framework based on neutrosophic set (NS) for noise-resistant image segmentation. The image was transformed into NS domain depicted by three membership sets and an entropy criterion was employed to evaluate the indeterminacy. Two operators namely  $\alpha$ -mean and  $\beta$ -enhancement operators were employed for tuning the set indeterminacy. Finally, a clustering mechanism was used to performance the segmentation. The NS based image segmentation idea was then extended to color images by Karabatak et al. [8]. Karabatak et al. proposed entropy based indeterminate set and the

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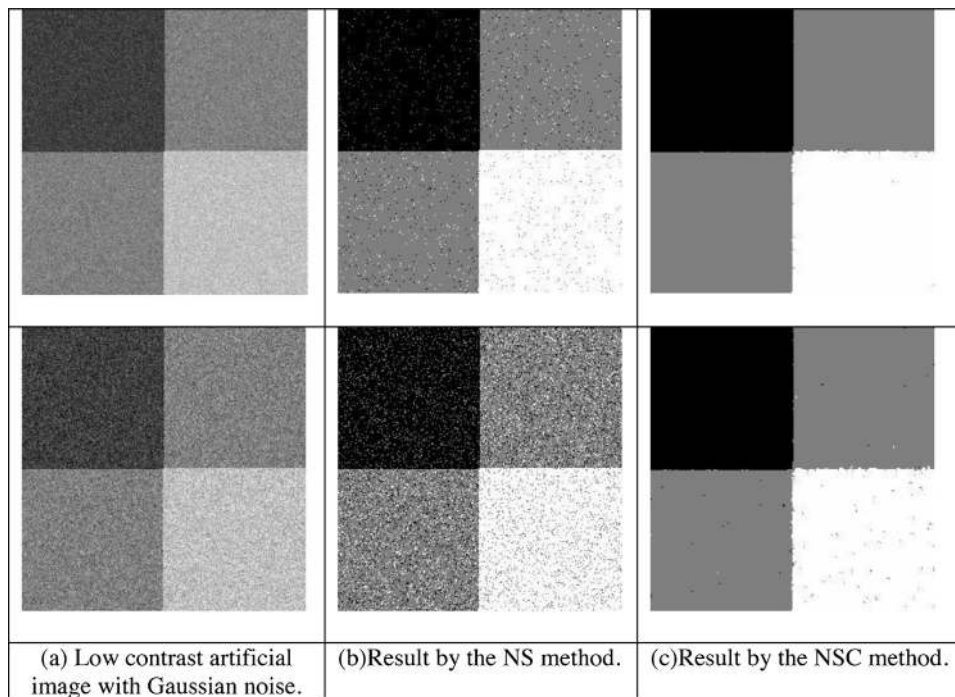


Fig. 1. Performance comparison on a low contrast artificial noisy image.

$\alpha$ -mean operator was replaced with  $\alpha$ -median operator to alleviate the blurring effect of the mean operator. A fully automatic NS and wavelet transform based color texture image segmentation approach was proposed in Ref. [9]. The wavelet transform was applied to each channel of the color image and vertical and horizontal details were extracted for subsequent processes. Then, the NS based segmentation approach was applied to the detail images. Energy features were calculated and concatenated for forming the feature matrix. Finally,  $\gamma$ -K-means clustering algorithm was used for segmentation. Zhang et al. [10] used NS and watershed method for image segmentation. A  $T$  membership of the NS was defined via  $S$ -function. The input image was transformed to neutrosophic domain and neutrosophic logic was applied for obtaining a binary image. Then the watershed technique was applied to obtain the segmentation results. An unsupervised method, which synthesized the NS and mean-shift, was proposed in Ref. [11]. The proposed algorithm adopted the mean-shift clustering in NS domain to segment images, which makes it possible to detect constructions with a consistent threshold. Ling et al. [12] proposed an unsupervised color image segmentation algorithms based on NS. The centers of image clusters were determined by using color information in RGB color space. The neutrosophic indeterminacy was defined by using spatial information in CIE ( $L^*u^*v^*$ ) color space. The color and spatial information were integrated by the neutrosophy approach. Recently, Guo and Sengur [13] proposed filtering in NS domain and level set theory for image segmentation. A newly defined filter was employed to reduce the indeterminacy of the image in the NS domain and the level set algorithm was used to extract the objects' boundaries automatically.

Based on the reviewed literature, it is evident that NS is an open area for further image segmentation applications. Therefore, in this paper, we propose a new image segmentation technique based on neutrosophic similarity clustering (NSC). We utilize the NS and define a new similarity function for clustering. At first, an image is represented in the NS domain via three membership subsets  $T$ ,  $I$  and  $F$ . Then, a new similarity function, neutrosophic similarity function (NSF) is defined and employed in the objective

function of the clustering analysis. Finally, the new defined clustering algorithm segments the pixels on the image into different groups. Experiments have been conducted on a variety of artificial and real images. Several measurements are used to evaluate and compare the proposed method's performance. The experimental results demonstrate that the NSC method segment the images effectively and accurately. It is able to process both images without noise and noisy images having different levels of noises well.

The paper is organized as follows. Section 2 describes the proposed method which contains clustering analysis and image segmentation method. Section 3 discusses the experimental results and comparisons, and the conclusions are drawn in Section 4.

## 2. Proposed method

### 2.1. Clustering analysis

Clustering can classify similar samples into the same group [15]. Let  $X = \{X_i, i = 1, 2, \dots, n\}$  be a data set, and  $x_i$  be a sample. The goal of clustering is to find a partition  $C = \{C_1, C_2, \dots, C_m\}$ , which satisfies:  $X = \bigcup_{i=1}^m C_i, C_i \neq \Phi$  for  $i = 1, 2, \dots, m, C_i \cap C_j = \Phi$  for  $i, j = 1, 2, \dots, m; i \neq j$ .

Among clustering methods, the K-means algorithm is widely used and more efficient [15]. It is important to define the object function for a clustering analysis method. Each cluster should be as compact as possible. The objective function of K-means is defined as:

$$J_C = \sum_{j=1}^m \sum_{i=1}^{n_j} \|X_i - Z_j\| \quad (1)$$

$$Z_j = \frac{1}{n_j} \sum_{X_i \in C_j} X_i \quad (2)$$

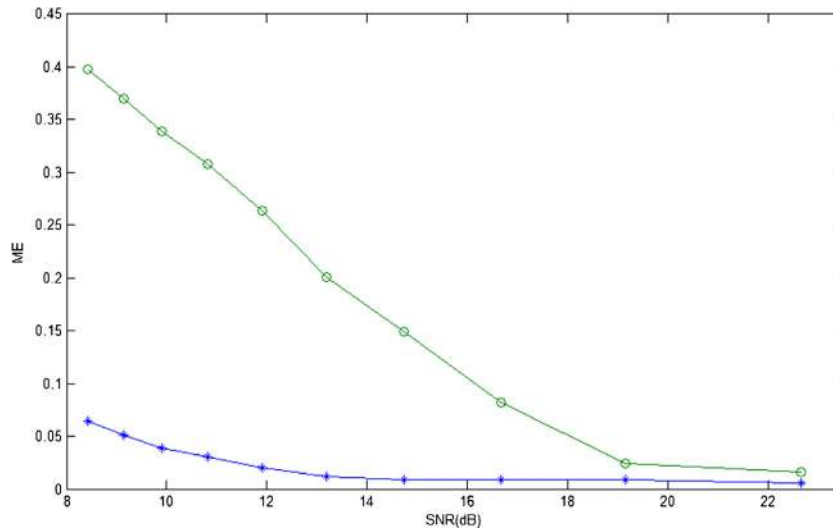


Fig. 2. The relation between SNR and ME. \*: NSC method, O: NS method.

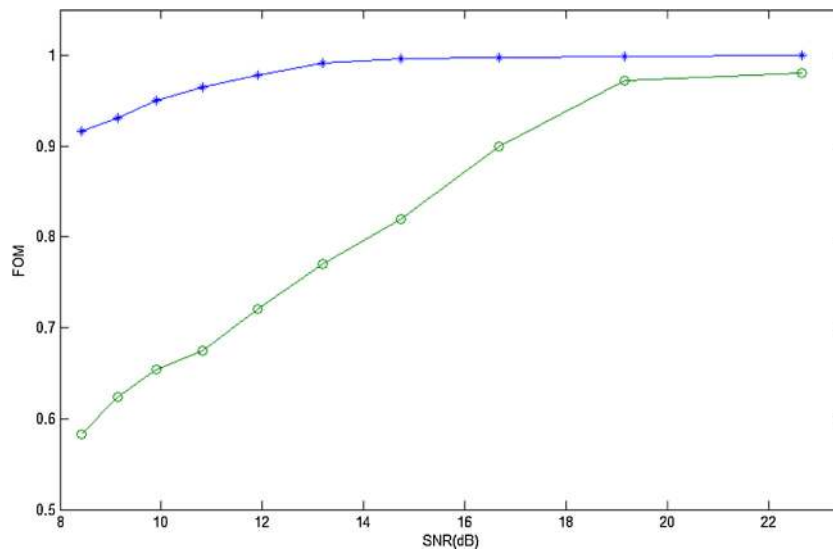


Fig. 3. The relation between SNR and FOM. \*: NSC method, O: NS method.

where  $Z_j$  is the center of the  $j$ th cluster,  $m$  is the total number of clusters and  $n_j$  is the number of pixels in the  $j$ th cluster.

### 2.2. Neutrosophic similarity function

A neutrosophic set can be defined as: let  $A = \{A_1, A_2, \dots, A_m\}$  be a set of alternatives in neutrosophic set, and  $C = \{C_1, C_2, \dots, C_n\}$  be a set of conditions. The alternative  $A_i$  at the  $C_j$  condition is denoted as  $\{T_{C_j}(A_i), I_{C_j}(A_i), F_{C_j}(A_i)\}/A_i$ , where  $T_{C_j}(A_i)$ ,  $I_{C_j}(A_i)$  and  $F_{C_j}(A_i)$  are the membership values to the true, indeterminance and false set at the  $C_j$  condition.

A similarity function is proposed to evaluate the similarity degree between two elements in neutrosophic set [16]:

$$S_{C_j}(A_m, A_n) = \frac{T_{C_j}(A_m)T_{C_j}(A_n) + I_{C_j}(A_m)I_{C_j}(A_n) + F_{C_j}(A_m)F_{C_j}(A_n)}{\sqrt{T_{C_j}^2(A_m) + I_{C_j}^2(A_m) + F_{C_j}^2(A_m)} \sqrt{T_{C_j}^2(A_n) + I_{C_j}^2(A_n) + F_{C_j}^2(A_n)}} \quad (3)$$

The ideal element in NS can identify the best alternative. The ideal alternative  $A^*$  is denoted as:  $\{T_{C_j}^*(A_i), I_{C_j}^*(A_i), F_{C_j}^*(A_i)\}/A_i^*$ . The similarity to the ideal alternative is computed as:

$$S_{C_j}(A_i, A^*) = \frac{T_{C_j}(A_i)T_{C_j}(A^*) + I_{C_j}(A_i)I_{C_j}(A^*) + F_{C_j}(A_i)F_{C_j}(A^*)}{\sqrt{T_{C_j}^2(A_i) + I_{C_j}^2(A_i) + F_{C_j}^2(A_i)} \sqrt{T_{C_j}^2(A^*) + I_{C_j}^2(A^*) + F_{C_j}^2(A^*)}} \quad (4)$$

An image is defined in the NS as: let  $U$  be a universe, BP be a bright pixel set in  $U$ , and an image  $I_m$  described using NS is called neutrosophic image  $I_{NS}$ . A neutrosophic image  $I_{NS}$  is depicted using subsets  $T, I$  and  $F$ . According to the definition of neutrosophic image, a pixel  $P(x, y)$  is interpreted in the neutrosophic set domain:  $P_{NS}(x, y) = \{T(x, y), I(x, y), F(x, y)\}$ .  $T(x, y)$ ,  $I(x, y)$  and  $F(x, y)$  represent memberships belonging to bright pixel set, indeterminate set and non-bright pixel set, respectively. Using the intensity criterion, they are defined as:

$$T_{C_g}(x, y) = \frac{g(x, y) - g_{\min}}{g_{\max} - g_{\min}} \quad (5)$$

$$I_{C_g}(x, y) = 1 - \frac{Gd(i, j) - Gd_{\min}}{Gd_{\max} - Gd_{\min}} \quad (6)$$

$$F_{C_g}(x, y) = 1 - T_{C_g}(x, y) \quad (7)$$

where  $g(x, y)$  and  $Gd(x, y)$  are the intensity value and gradient value at the position of  $(x, y)$  on the image. Then, a similarity value is calculated to identify the degree to the ideal object under intensity condition.  $g_{\min}$  and  $g_{\max}$  are minimum and maximum intensity values, respectively.  $Gd_{\min}$  and  $Gd_{\max}$  are



Fig. 4. Comparison results on "Lake" image.

minimum and maximum of the gradient value in the image.

$$S_{C_g}(P(x, y), A^*) = \frac{T_{C_g}(x, y)T_{C_g}(A^*) + I_{C_g}(x, y)I_{C_g}(A^*) + F_{C_g}(x, y)F_{C_g}(A^*)}{\sqrt{T_{C_g}^2(x, y) + I_{C_g}^2(x, y) + F_{C_g}^2(x, y)} \sqrt{T_{C_g}^2(A^*) + I_{C_g}^2(A^*) + F_{C_g}^2(A^*)}} \quad (8)$$

To make the segmentation results robust to noise, we integrate two new conditions, local mean intensity criterion  $C_m$  and local homogeneity criterion  $C_h$ , into the neutrosophic similarity function.

The neutrosophic set using the local mean intensity  $C_m$  is defined as:

$$T_{C_m}(x, y) = \frac{g_m(x, y) - g_{m \min}}{g_{m \max} - g_{m \min}} \quad (9)$$

$$g_m(x, y) = \frac{1}{w \times w} \sum_{m=x-w/2}^{x+w/2} \sum_{n=y-w/2}^{y+w/2} g(m, n) \quad (10)$$

$$I_{C_m}(x, y) = 1 - \frac{Gd_m(i, j) - Gd_{m \min}}{Gd_{m \max} - Gd_{m \min}} \quad (11)$$

$$F_{C_m}(x, y) = 1 - T_{C_m}(x, y) \quad (12)$$

where  $g_m(x, y)$  and  $Gd_m(x, y)$  are the intensity value and gradient magnitude value at the position of  $(x, y)$  on the image after mean filter processing.  $g_{m \min}$  and  $g_{m \max}$  are the minimum and maximum of the intensity on the image after mean filter processing, and  $Gd_{m \min}$  and  $Gd_{m \max}$  are the minimum and maximum of the gradient magnitude value on the image after mean filter processing, respectively.

The neutrosophic set under the local homogeneity condition  $C_h$  is also defined as:

$$T_{C_h}(x, y) = \frac{H(x, y) - H_{\min}}{H_{\max} - H_{\min}} \quad (13)$$

$$I_{C_h}(x, y) = 1 - \frac{Gd_h(i, j) - Gd_{h \min}}{Gd_{h \max} - Gd_{h \min}} \quad (14)$$

$$F_{C_h}(x, y) = 1 - T_{C_h}(x, y) \quad (15)$$

$$H(x, y) = \text{TEM}(g(x, y)) \quad (16)$$

where  $H(x, y)$  is the homogeneity value at  $(x, y)$ , which is depicted as the filtering result with the texture energy measures (TEM) filters [14].  $Gd_h(x, y)$  is the gradient value on  $H(x, y)$ .

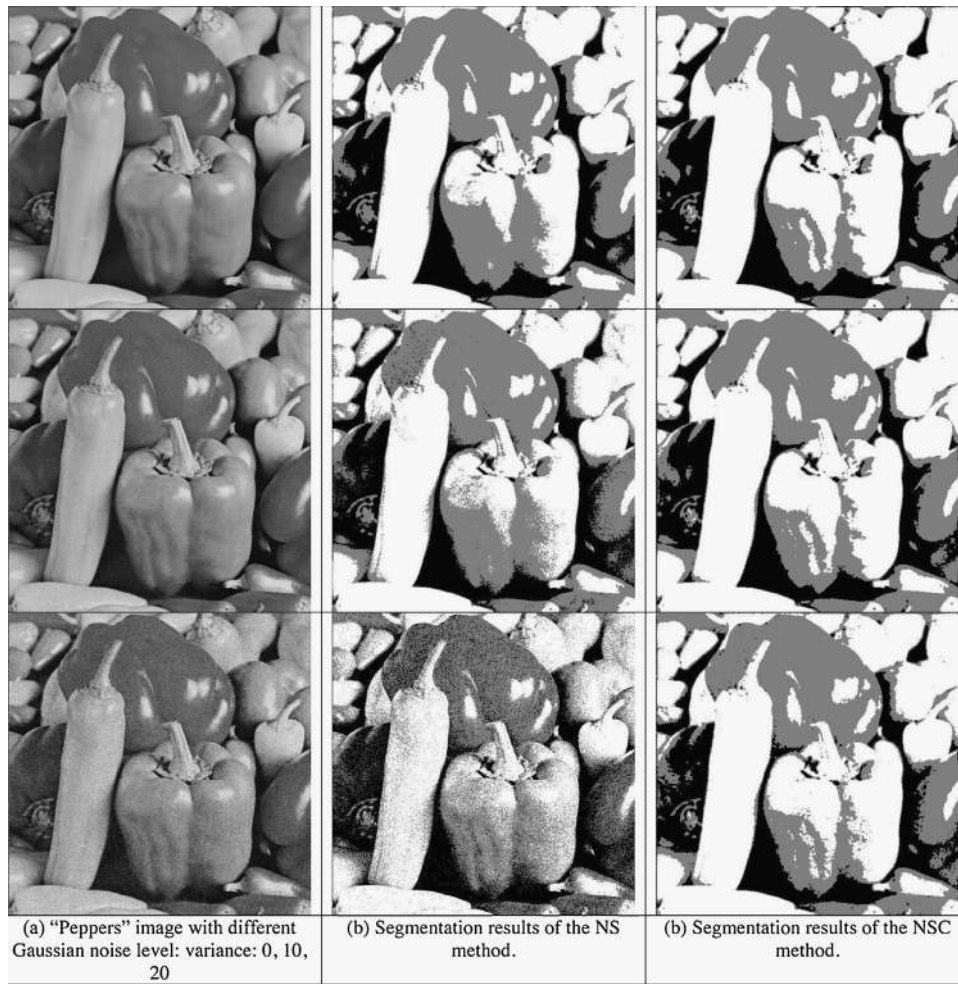


Fig. 5. Comparison results on “Peppers” image.

Two NSF<sub>s</sub> to the ideal alternative are defined as:

$$S_{C_a}(P(x, y), A^*) = \frac{T_{C_a}(x, y)T_{C_a}(A^*) + I_{C_a}(x, y)I_{C_a}(A^*) + F_{C_a}(x, y)F_{C_a}(A^*)}{\sqrt{T_{C_a}^2(x, y) + I_{C_a}^2(x, y) + F_{C_a}^2(x, y)}\sqrt{T_{C_a}^2(A^*) + I_{C_a}^2(A^*) + F_{C_a}^2(A^*)}} \quad (17)$$

$$S_{C_h}(P(x, y), A^*) = \frac{T_{C_h}(x, y)T_{C_h}(A^*) + I_{C_h}(x, y)I_{C_h}(A^*) + F_{C_h}(x, y)F_{C_h}(A^*)}{\sqrt{T_{C_h}^2(x, y) + I_{C_h}^2(x, y) + F_{C_h}^2(x, y)}\sqrt{T_{C_h}^2(A^*) + I_{C_h}^2(A^*) + F_{C_h}^2(A^*)}} \quad (18)$$

The value of  $A^*$  under three conditions are same as:  $\{T_{C_j}^*(A_i), I_{C_j}^*(A_i), F_{C_j}^*(A_i)\} / A_i^* = \{1, 0, 0\} / A^*$ .

The average value of  $S_{C_g}$ ,  $S_{C_m}$  and  $S_{C_h}$  is defined as the final neutrosophic similarity function as:

$$NSF(x, y) = \frac{S_{C_g}(x, y) + S_{C_a}(x, y) + S_{C_h}(x, y)}{3} \quad (19)$$

### 2.3. Image segmentation based on neutrosophic similarity clustering

A novel clustering method, neutrosophic similarity clustering (NSC) is proposed to segment the pixels in image by using an optimum partition with minimizing the object function.

The new objective function is defined as:

$$J_{NKC} = \sum_{l=1}^K \sum_{x=1}^H \sum_{y=1}^W ||NSF(x, y) - Z_l||^2 \quad (20)$$

$$Z_l = \frac{1}{n_l} \sum_{(x,y) \in C_l} NSF(x, y) \quad (21)$$

The steps in the NSC algorithm can be summarized as follows:

- Step 1: Convert the image into NS domain;
- Step 2: Compute the NSF values under three conditions;
- Step 3: Calculate the object function using the NSF;
- Step 4: Select the partition with minimized the object function value;
- Step 5: Segment the image using the optimum partition result.

### 3. Experimental results and discussions

We have tested the proposed algorithm using different images, and compared its performance with those of newly developed



Fig. 6. Comparison results on “Woman” image.

algorithms. In the experiments, we compare the NSC method with a published method based on NS [5].

### 3.1. Performance on artificial images

We use artificial images to compare the NSC method and NS method visually, and then evaluate their results quantitatively. In Ref. [5], several artificial images having two intensities and impaired by different levels of noise were employed to evaluation the performance of the NS method.

To identify the performance difference of the NS and NSC methods, we employ an artificial image having two gray levels (64 and 128) impaired by different levels of Gaussian noise to test the performance of two segmentation methods. Fig. 1(a) shows the synthetic images having Gaussian noise, whose mean values are 0 and standard variance values are 15 and 30, respectively. Fig. 1(b) and (c) are the results by the NS and NSC methods, respectively. From the results in Fig. 1, the NSC method achieved the better performances than those of the NS algorithm.

The results on the second synthetic image with low contrast show the NSC method performs better than NS method on the synthetic images with two different noise levels. A lot of pixels in Fig. 1(b) are identified in wrong classes, while they are classified correctly by NSC method in Fig. 1(c).

To evaluate the segmentation results for artificial images quantitatively, we utilize a metric: misclassification error measure (ME) [17,18], to measure the segmentation performances. The ME depicts the percentage of background points wrongly grouped to

foreground set, and object points wrongly grouped to background set [17,18]:

$$ME = 1 - \frac{|B_O \cap B_T| + |F_O \cap F_T|}{|B_O| + |F_O|} \quad (22)$$

where  $F_o$  and  $B_o$  are the object and background sets on the ground truth image.  $F_T$  and  $B_T$  are the object and background sets on the result image.  $|\bullet|$  denotes the elements' number in the set. The ME defines a metric of the mis-grouped points between the ground truth image and the test image.

Another metric figure of merit (FOM) proposed by Pratt [19] is also utilized to evaluate the difference between the methods' results with the ideal segmentation result quantitatively:

$$FOM = \frac{1}{\max(N_I, N_A)} \sum_{k=1}^{N_A} \frac{1}{1 + \beta d^2(k)} \quad (23)$$

where  $N_I$  and  $N_A$  are the numbers of the object points and the ideal object pixels, respectively.  $d(k)$  is the distance from the  $k$ th actual point to the nearest segmented result point.  $\beta$  is a constant, and set as 1/9 in Pratt's paper [19]. The greater the FOM, the better the segmentation results are.

The quality of the noisy image is measured using the signal to noise ratio (SNR):

$$SNR = 10 \log \left[ \frac{\sum_{r=0}^{H-1} \sum_{c=0}^{W-1} Im(r, c)}{\sum_{r=0}^{H-1} \sum_{c=0}^{W-1} (Im(r, c) - \ln(r, c))^2} \right] \quad (24)$$



Fig. 7. Comparison results on "Lena" image.

where  $In(r, c)$  and  $Im(r, c)$  are the intensities of pixel  $(r, c)$  in the noisy and original images, respectively.

The values of ME are plotted at different SNR levels in Fig. 2. It demonstrates the NSC method archives lower MEs at all SNRs. All ME values of the NSC method are smaller than 0.065, and all values of NS method are higher than those of the NSC method. The NSC algorithm achieves the optimum performance with  $ME=0.0057$  which is nearly equal to zero when SNR is 20.67 dB, while NS obtains the optimum value with  $ME=0.016$ . Meanwhile, the values of FOM of NS are bigger than those of NSC at most SNR levels. The average value of FOM of NSC and NS are 0.9724 and 0.7698, respectively. The values of FOM are plotted at different SNR levels in Fig. 3.

### 3.2. Performance on real world images

A great number of real world images are employed to measure the NSC method's performance. Eight representative images are selected to demonstrate the effectiveness and robustness of the NSC method against the various noise levels. These images are "Lake", "Peppers", "Woman", and "Lena", respectively. In Figs. 4–7, the first row lists the original images without noise and the results of NS and NSC method on them. The second and third rows demonstrate the results on the noisy images with different Gaussian noise variances. The experimental results demonstrate that the results by NSC method exhibits visually better quality than those of NS

method. The results of the NSC method eliminate noise effect and most pixels are segmented into the right groups, while the NS methods are affected severely by the noise on the real images.

Fig. 4 is a scene image of a lake. In the original image, both NS and NSC methods obtain similar segmentation results. The ground and the lake surface are correctly segmented. For the second and third rows, the image is corrupted by noises and the NS method yields many misclassified pixels in the ground and water surface. There are also several numbers of misclassified pixels on the sky region. The superiority of the proposed NSC method can be seen in the result of the "Peppers" image which is depicted in Fig. 5. The surface of peppers and the boundaries between peppers are segmented correctly by NS method, while the NSC method obtains better results. In Fig. 5, it is obvious that our proposal obtains better results for all noise variance levels than the NS algorithm. Similar results can be seen in the "Woman" image in Fig. 6. The face, hair, background regions are segmented correctly by the NSC method for the first and second noise levels. In addition, the proposed NSC method can obtain reasonable segmentations even for the third noise level. For the second and third noise levels the NS based method yields many misclassifications in the face and background of the "Woman" image. The segmentation results of the "Lena" image are given in the second and the third columns of the Fig. 7. It is obvious that the results obtained under the first and second noise variance are better than the NS method. The shoulder, face and the

hair regions are segmented correctly. The NS based method obtains several wrong segmentations in the hair and the face regions. Both NSC and NS have several wrong segmentations for the third noise level. However, by visual inspection, the NSC method has better segmentation than the NS method when we consider the overall results.

From the experiments on the artificial and real world images, we can draw a conclusion that the NSC method is feasible to segment both the clear images without noise and the noisy images with different noise levels.

#### 4. Conclusions

This paper presents a new image segmentation algorithm using neutrosophic similarity clustering algorithm. The image is depicted in neutrosophic set. A neutrosophic similarity function is defined to measure the membership to the object pixels on the image, and used in the clustering algorithm. Finally, an optimized clustering partition is obtained using the NSC algorithm. The experimental results show that the NSC method can segment the images properly and effectively. It is able to process both images without noise and noisy images with different levels of noises. This advantage will bring the proposed method into more applications in the research areas such as image processing and computer vision.

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