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New neutrosophic approach to image segmentation

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ABSTRACT

Neutrosophic set (NS), a part of neutrosophy theory, studies the origin, nature and scope of neutralities, as well as their interactions with different ideational spectra. NS is a formal framework that has been recently proposed. However, NS needs to be specified from a technical point of view for a given application or field. We apply NS, after defining some concepts and operations, for image segmentation.
The image is transformed into the NS domain, which is described using three membership sets: *T*, *I* and *F*. The entropy in NS is defined and employed to evaluate the indeterminacy. Two operations, α-mean and β-enhancement operations are proposed to reduce the set indeterminacy. Finally, the proposed method is employed to perform image segmentation using a γ-means clustering. We have conducted experiments on a variety of images. The experimental results demonstrate that the proposed approach can segment the images automatically and effectively. Especially, it can segment the "clean" images and the images having noise with different noise levels.

1. Introduction

Neutrosophy, a branch of philosophy, as a generalization of dialectics, studies the origin, nature and scope of neutralities, as well as their interactions with different ideational spectra [1].

Neutrosophy theory considers proposition, theory, event, concept, or entity, ⟨A⟩ in relation to its opposite ⟨Anti-A⟩ and the neutrality ⟨Neut-A⟩, which is neither ⟨A⟩ nor ⟨Anti-A⟩. The ⟨Neut-A⟩ and ⟨Anti-A⟩ are referred to as ⟨Non-A⟩. According to this theory, every idea ⟨A⟩ tends to be neutralized and balanced by ⟨Anti-A⟩ and ⟨Non-A⟩ ideas [1].

In a classical way ⟨A⟩, ⟨Neut-A⟩ and ⟨Anti-A⟩ are disjoint two by two. In many cases, the borders between notions are vague and imprecise, and it is possible that ⟨A⟩, ⟨Neut-A⟩ and ⟨Anti-A⟩ (and ⟨Non-A⟩ of course) have common parts two by two as well.

Neutrosophy is the basis of neutrosophic logic, neutrosophic probability, neutrosophic set (NS) and neutrosophic statistics [1].

For classical set, the indeterminacy of each element in the set could not be evaluated and described. The fuzzy set [2] has been employed for many real applications to handle the uncertainty. The traditional fuzzy set uses a real number $\mu_A(x) \in [0,1]$ to represent the membership. If $\mu_A(x)$ itself is uncertain, it is hard to be defined by a crisp value [3]. In some applications, such as expert system, belief system and information fusion, we should consider not only the truth-membership supported by the evidence, but also the falsity-membership against the evidence. It is hard for classical fuzzy set to solve these problems as well [3].

In NS, indeterminacy is quantified explicitly and the truth-membership, indeterminacy-membership and falsity-membership can be independent. This assumption is very important in many applications.

For example, when reviewers are invited to review a paper, they need to rank the paper (using μ) and indicate how well (using W) they understand the field related to the paper, required by some journals. Assume that two reviewers A and B review a paper: $\mu_A = \mu_B = 0.8$, and $W_A = 1$ and $W_B = 0.6$. Then, μ_A and μ_B should have different effects on the decision of the paper. This kind of problems can be solved better by using NS. Similar situations happen in many real applications and tasks.

NS had been applied to image thresholding and image denoise applications. Cheng and Guo [4] proposed a thresholding algorithm based on neutrosophy, which could select the thresholds automatically and effectively. Guo and Cheng [5] defined some concepts and operators based on NS and applied them for image denoising. It can process not only noisy images with different levels of noise, but also images with different kinds of noise well.

Image segmentation is one of the most difficult tasks in image processing and pattern recognition, which plays an important role in a variety of applications such as robot vision, object recognition, medical imaging, etc.

Image segmentation is a process of dividing an image into different regions such that each region is, but the union of any two

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adjacent regions is not homogeneous. Segmentation is a partition of the image I into non-overlapping regions S_i [6]:

$$mathop\bigcup S_i = I \quad \text{and} \quad S_i \cap S_j = \phi, \;\; i \neq j$$

Image segmentation is a difficult task due to the complexity and diversity of images. The segmentation results are influenced by many factors such as illuminating, contrast, noise, etc. Numerous approaches have been proposed [7].

Gray image segmentation approaches are based on either discontinuity and/or homogeneity of gray level values in a region. The approach based on discontinuity tends to partition an image by detecting isolated points, lines and edges according to abrupt changes in intensities. Generally, the approaches based on homogeneity can be categorized into thresholding, edge detection, clustering and region growing and merging [6]. Although these methods were successful in many applications, some drawbacks still exist and different algorithms are suitable for particular applications [7]. Thresholding technique is sensitive to noise and ignores the spatial information. Region growing suffers from over-segmentation and time-consuming. For edge detection approaches, noises usually produce wrong edges. Over-segmentation also happens in clustering method.

Since fuzzy set theory shows more advantage than traditional theory in handling uncertainty, it has become a powerful tool to deal with linguistic concepts such as similarity in image processing. Fuzzy C-means (FCM) [5,6] is a clustering method which allows a piece of data to belong to two or more clusters, which is frequently used in computer vision, pattern recognition and image processing. The FCM algorithm obtains segmentation results by fuzzy classification. Unlike hard classification methods which group a pixel to belong exclusively to one class, FCM allows a pixel to belong to multiple classes with varying degree of memberships [7]. FCM approach is quite effective for image segmentation.

Several segmentation algorithms based on fuzzy set theory and FCM were reported. Tobias and Seara [8] proposed an approach to threshold the histogram according to the similarity between gray levels, and the similarity is assessed through a fuzzy measure. Chaira and Ray [9] introduced an image thresholding method using four types of fuzzy thresholding methods and utilizing Gamma membership to determine the membership values of the pixels. The minimization of the indices of fuzziness yields the appropriate value of the threshold. Yang et al. [7] presented a fuzzy clustering approach for image segmentation based on Ant-Tree algorithm. Three features including the gray value, gradient and neighborhood of pixels are extracted for clustering. A three-level tree model makes the clustering structure more adaptive for segmentation. Ma and Staunton [10] modified the recursive FCM algorithm using biased illumination field estimation. New clustering center and fuzzy clustering functions are defined based on the intensity and average intensity of a pixel neighborhood. Cinque et al. [11] presented a modified fuzzy clustering approach for image segmentation. The approach finds a simple model able to instance a prototype for each cluster.

However, traditional fuzzy theory is restricted to some applications. For instance, fuzzy set handles the images without noise effectively, but it is still sensitive to noise and has the disadvantage in handling spatial uncertainty [7].

We employ NS to process the images with noise and propose a novel NS approach for image segmentation. First, the image is transformed into the NS and two new operations, α-mean and β-enhancement, are defined and employed to reduce the indeterminacy of the image, which is measured by the entropy of the indeterminate set. The image becomes more uniform and homogenous, and more suitable for segmentation. Finally, the image in the NS domain is segmented using a γ-means clustering method. The experiments on artificial images with different levels of noise and real images with/without noise demonstrate that the proposed approach can perform segmentation well.

The paper is organized as follows. In Section 2, the proposed method is described. The experiments and comparisons are discussed in Section 3. Finally, the conclusions are given in Section 4.

2. Proposed method

2.1. Neutrosophic set

The NS and its properties are discussed briefly [1].

Definition 1. (*Neutrosophic set*). Let U be a universe of discourse, and a NS A is included in U. An element x in set A is noted as $x(t,i,f)$, where t varies in T, i varies in I and f varies in F. Here, T, I and F are real standard or non-standard sets of $]^{-}0,1^{+}[$ with $sup\,T = t\_sup$, $inf\,T = t\_inf$, $sup\,I = i\_sup$, $inf\,I = i\_inf$, $sup\,F = f\_sup$, $inf\,F = f\_inf$ and $n\_sup = t\_sup + i\_sup + f\_sup$, $n\_inf = t\_inf + i\_inf + f\_inf$ and T, I and F are called neutrosophic components.

The element $x(t,i,f)$ belongs to A in the following way: it is t% true, i% indeterminacy, and f% false, where t varies in T, i varies in I, and f varies in F. Statically, T, I and F are membership sets, but dynamically T, I and F are functions/operators depending on known and/or unknown parameters. The sets T, I and F are not necessarily intervals, and may be any real sub-unitary subsets: discrete or continuous; single-element, finite, or countable or uncountable infinite; union or intersection of various subsets; etc. They may also overlap.

2.2. Neutrosophic image segmentation

2.2.1. Transform the image into NS

A new neutrosophic approach to image processing is discussed.

Definition 2. (*Neutrosophic image*). Let U be a universe of the discourse, and $W \subseteq U$ which is composed by the bright pixels. A neutrosophic image P_{NS} is characterized by three membership sets T, I and F.

A pixel P in the 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.

The pixel $P(i,j)$ in the image domain is transformed into the neutrosophic domain. $P_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\}$. $T(i,j)$, $I(i,j)$ and $F(i,j)$ are the membership values defined as

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

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

$$I(i,j) = \frac{\delta(i,j) - \delta_{\min}}{\delta_{\max} - \delta_{\min}} \tag{3}$$

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

$$F(i,j) = 1 - T(i,j) \tag{5}$$

where $g(i,j)$ is the intensity value of the pixel (i,j), $\overline{g}(i,j)$ is the local mean value of $g(i,j)$, $\delta(i,j)$ is the absolute value of the difference between intensity $g(i,j)$ and its local mean value $\overline{g}(i,j)$.

2.2.2. Neutrosophic image entropy

For a gray level image, the entropy evaluates the distribution of the intensities. If the entropy is maximum, the intensities have equal probability and they distribute uniformly. If the entropy is small, the intensities have different probabilities and their distributions are non-uniform.

Definition 3. (*Neutrosophic image entropy*). The neutrosophic image entropy is defined as the summation of the entropies of three sets T, I and F, which is employed to evaluate the distribution of the elements in the neutrosophic domain:

$$En_{NS} = En_T + En_I + En_F \tag{6}$$

$$En_T = -\sum_{i=\min\{T\}}^{\max\{T\}} p_T(i) \ln p_T(i) \tag{7}$$

$$En_I = -\sum_{i=\min\{I\}}^{\max\{I\}} p_I(i) \ln p_I(i) \tag{8}$$

$$En_F = -\sum_{i=\min\{F\}}^{\max\{F\}} p_F(i) \ln p_F(i) \tag{9}$$

where En_T, En_I and En_F are the entropies of the sets T, I and F, respectively and $p_T(i)$, $p_I(i)$ and $p_F(i)$ are the probabilities of the elements in T, I and F, respectively.

2.2.3. α-mean operation

The value of $I(i,j)$ is employed to measure the indeterminacy of element $P_{NS}(i,j)$. For making T and F correlated with I, the changes in T and F should influence the distribution of the elements and the entropy of I.

For a gray level image Im, the mean operation is

$$\overline{Im}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} Im(m,n) \tag{10}$$

Definition 4. (*α-mean operation*). The α-mean operation for P_{NS}, $\overline{P}_{NS}(\alpha)$ is defined as

$$\overline{P}_{NS}(\alpha) = P(\overline{T}(\alpha), \overline{I}(\alpha), \overline{F}(\alpha)) \tag{11}$$

$$\overline{T}(\alpha) = \begin{cases} T, & I < \alpha \\ \overline{T}_\alpha, & I \geqslant \alpha \end{cases} \tag{12}$$

$$\overline{T}_\alpha(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} T(m,n) \tag{13}$$

$$\overline{F}(\alpha) = \begin{cases} F, & I < \alpha \\ \overline{F}, & I \geq \alpha \end{cases} \tag{14}$$

$$\overline{F}_\alpha(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} F(m,n) \tag{15}$$

$$\overline{I}_\alpha(i,j) = \frac{\overline{\delta}_T(i,j) - \overline{\delta}_{T\min}}{\overline{\delta}_{T\max} - \overline{\delta}_{T\min}} \tag{16}$$

$$\overline{\delta}_T(i,j) = abs(\overline{T}(i,j) - \overline{\overline{T}}(i,j)) \tag{17}$$

$$\overline{\overline{T}}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} \overline{T}(m,n) \tag{18}$$

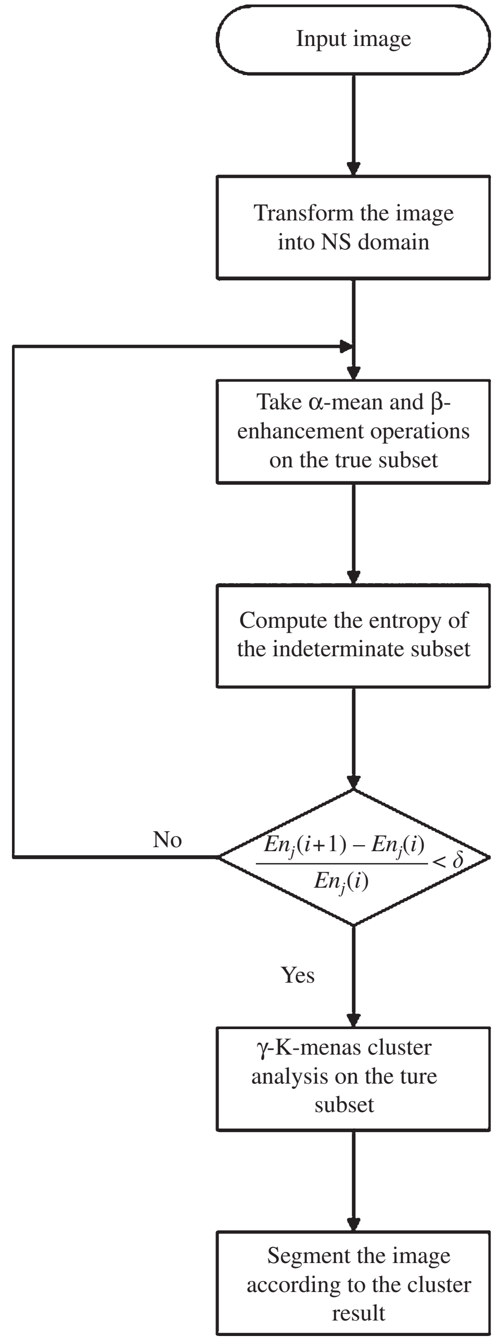

Fig. 1. The flowchart of the segmentation algorithm.

where $\overline{\delta}_T(i,j)$ is the absolute value of the difference between the mean intensity $\overline{T}(i,j)$ and its mean value $\overline{\overline{T}}(i,j)$ after the α-mean operation.

After the α-mean operation, the entropy of the indeterminate subset I is increased and the distribution of the elements in I becomes more uniform. Here, $\alpha = 0.85$ is determined by experiments.

2.2.4. β-enhancement operation

In fuzzy set, the intensification operation [12,13] for the membership μ is defined as

$$\mu'(i,j) = \begin{cases} 2\mu^2(i,j), & \mu(i,j) \leqslant 0.5 \\ 1 - 2(1-\mu(i,j))^2, & \mu(i,j) > 0.5 \end{cases} \tag{19}$$

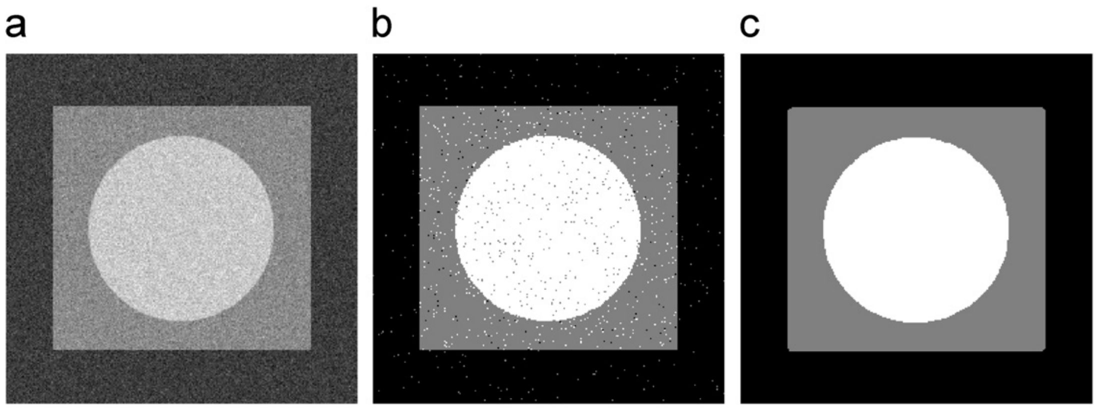

Fig. 2. (a) Original image with Gaussian noise. (b) Result by the MFCM method. (c) Result by the proposed method.

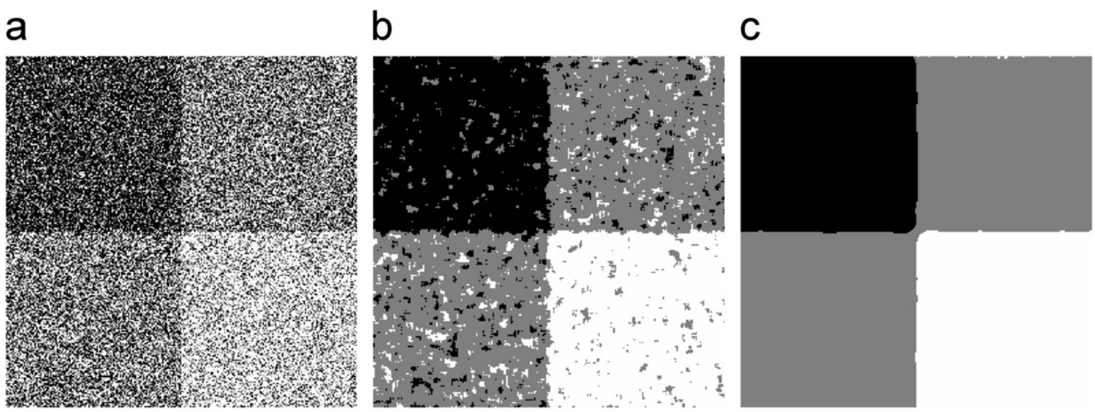

Fig. 3. (a) Original image with Gaussian noise. (b) Segmentation result by the MFCM method. (c) Segmentation result by the proposed approach.

Definition 5. (β-*enhancement operation*). A β-enhancement operation for P_{NS}, $P'_{NS}(\beta)$, is defined as

$$P'_{NS}(\beta) = P(T'(\beta), I'(\beta), F'(\beta)) \tag{20}$$

$$T'(\beta) = \begin{cases} T, & I < \beta \\ T'_{\lambda}, & I \geqslant \beta \end{cases} \tag{21}$$

$$T'_{\beta}(i,j) = \begin{cases} 2T^2(i,j), & T(i,j) \leqslant 0.5 \\ 1 - 2(1 - T(i,j))^2, & T(i,j) > 0.5 \end{cases} \tag{22}$$

$$F'(\beta) = \begin{cases} F, & I < \beta \\ F'_{\lambda}, & I \geqslant \beta \end{cases} \tag{23}$$

$$F'_{\beta}(i,j) = \begin{cases} 2F^2(i,j), & F(i,j) \leqslant 0.5 \\ 1 - 2(1 - F(i,j))^2, & F(i,j) > 0.5 \end{cases} \tag{24}$$

$$I'_{\beta}(i,j) = \frac{\delta'_T(i,j) - \delta'_{T\min}}{\delta'_{T\max} - \delta'_{T\min}} \tag{25}$$

$$\delta'_T(i,j) = abs(T'(i,j) - \overline{T}'(i,j)) \tag{26}$$

$$\overline{T'}(i,j) = \frac{1}{w \times w} \sum_{m=i-w/2}^{i+w/2} \sum_{n=j-w/2}^{j+w/2} T'(m,n) \tag{27}$$

where $\delta'_T(i,j)$ is the absolute value of difference between intensity $T'(i,j)$ and its local mean value $\overline{T}'(i,j)$ after the β-enhancement operation.

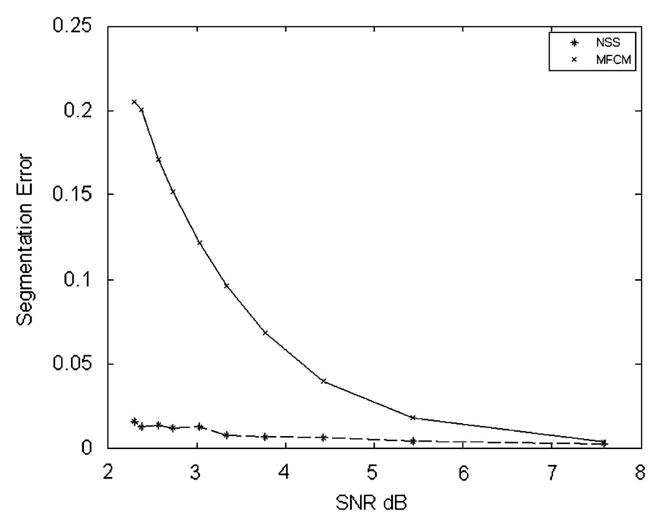

Fig. 4. The relation between SNR and e. *: proposed method; ×: MFCM method.

After the β-enhancement operation, the membership set T becomes more distinct, which is suitable for segmentation. Here, $\beta = 0.85$ is determined by experiments.

2.2.5. γ-means clustering analysis on NS

Clustering can classify similar sample points into the same group [14,15]. Let $X = \{X_i, i = 1, 2, \ldots, n\}$ be a data set, and x_i be a sample in a

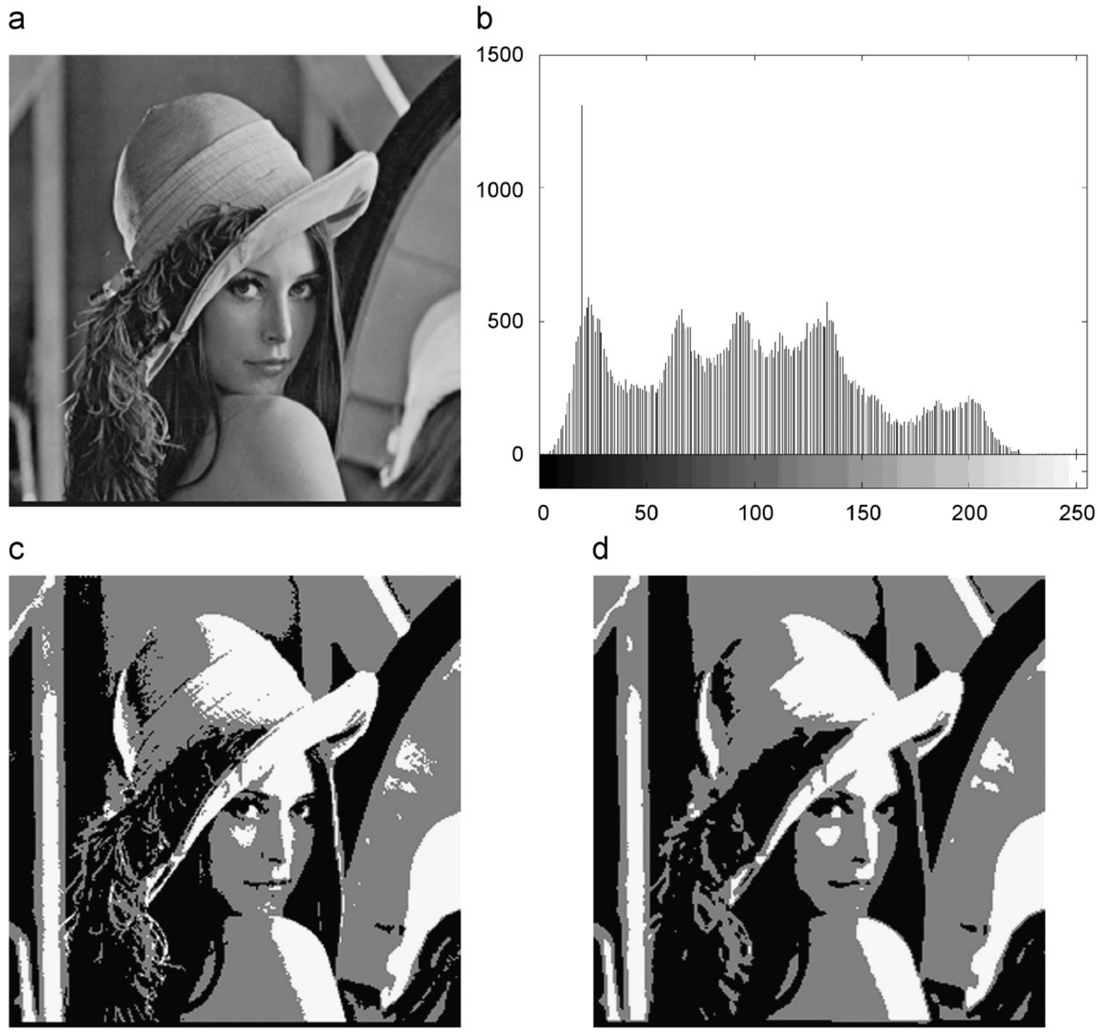

Fig. 5. (a) Lena image. (b) Histogram of (a). (c) Segmentation result by the MFCM method. (d) Segmentation result of the proposed method.

d-dimensional space. The problem of clustering is to find a partition $C=\{C_1,C_2,\ldots,C_m\}$, which satisfies

$$X=\bigcup_{i=1}^{m} C_i$$

$$C_i \neq \Phi \quad \text{for} \quad i=1,2,\ldots,m$$

$$C_i \cap C_j = \Phi \quad \text{for} \quad i,j=1,2,\ldots,m, \quad i \neq j$$

Among clustering methods, the K-means algorithm is widely used. It is important to define an objective function for a clustering analysis method. Each cluster should be as compact as possible. The objective function of K-means is defined as

$$J_C=\sum_{j=1}^{m}\sum_{i=1}^{n_j}\|X_i-Z_j\| \tag{28}$$

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

The necessary condition of the minimum J_c is

$$Z_j=\frac{1}{n_j}\sum_{X_i\in C_j} X_i \tag{29}$$

where n_j is the number of the elements of cluster C_j.

A new clustering method is defined for the NS and it deals with $\overline{P}_{NS}(\alpha,\beta)$, the NS after the α-mean and β-mean operations.

Considering the effect of indeterminacy, we composed the two set, T and I into a new value for clustering:

$$X(i,j)=\begin{cases} T(i,j), & I(i,j)\leqslant\gamma \\ \overline{T}_{\gamma}(i,j), & I(i,j)>\gamma \end{cases} \tag{30}$$

The new clustering algorithm for the NS, γ-means clustering, is applied to the subset T. The new objective function of γ-means is defined as

$$J_{TC}=\sum_{l=1}^{K}\sum_{i=1}^{H}\sum_{j=1}^{W}\|X(i,j)-Z_l\|^2 \tag{31}$$

$$Z_l=\frac{1}{n_l}\sum_{X(i,j)\in C_l} X(i,j) \tag{32}$$

2.2.6. Neutrosophic image segmentation

In the first step, the image is transformed into the NS. The pixel $P(i,j)$ in the image domain is transformed into the neutrosophic domain using Eqs. (1)–(5). Then the indeterminacy of the NS P_{NS} is decreased using the α-mean and β-enhancement operations on subset T using Eqs. (20)–(27) until the entropy of the indeterminate subset

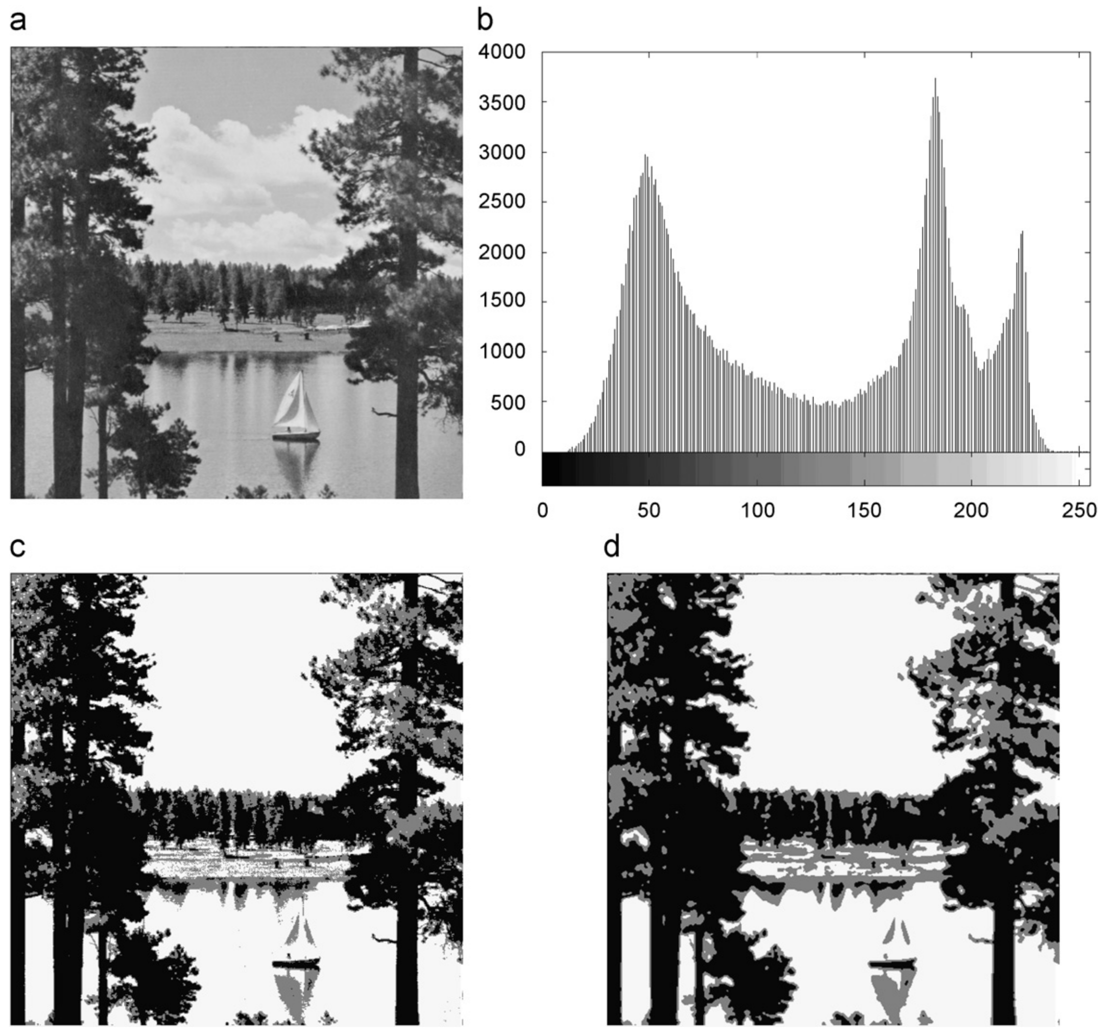

Fig. 6. (a) Lake image. (b) Histogram of (a). (c) Segmentation result by the MFCM method. (c) Segmentation result of the proposed method.

I becomes unchanged. It removes the noise and preserves the useful information. Finally, the image is segmented by using the proposed γ-mean clustering for the NS. The elements in subset *T* are input into the clustering algorithm and the objective function is defined according to Eqs. (31) and (32).

The algorithm is summarized as below:

Step 1: Transform the image into NS domain using Eqs. (1)–(5);
Step 2: Perform the α-mean and β-enhancement operations on the subset *T* using Eqs. (20)–(27);
Step 3: Compute the entropy of the indeterminate subset *I* $En_I(i)$ using Eqs. (6)–(9);
Step 4: If $En_I(i+1) - En_I(i)/En_I(i) < \delta$, go to Step 5;
Else go to Step 2;
Step 5: Apply the γ-means clustering to the subset *T*.
Step 6: Segment the image according to the result in Step 5.

The flowchart of the proposed algorithm is shown in Fig. 1.

3. Experiments and discussions

We have applied the proposed approach to a variety of images and compared the performance with that of some existing methods.

3.1. Performance evaluation

A modified fuzzy *C*-means (MFCM) segmentation algorithm [10] based on the intensity and average intensity of a pixel neighborhood, which claimed that it has significantly reduced the number of segmentation error inherent in the traditional FCM approach [16] and Otsu method [17]. In this method, the recursive FCM algorithm is modified to include biased illumination field estimation. New clustering center and fuzzy clustering functions are defined based on the intensity and average intensity of a pixel neighborhood.

Because the MFCM method [10] is a novel image segmentation approach based on fuzzy set theory and achieves better results on different image, we will compare the performance of the proposed approach with that of the MFCM method [10].

First, we use several synthetic images to compare the performance. Fig. 2(a) is an artificial image with three intensities (0, 127 and 255) added Gaussian noise, whose mean is 0 and variance is 127. Fig. 3(a) is an artificial image with three intensities (0, 127 and 255) added with Gaussian noise, whose mean is 0 and variance is 255.

Figs. 2(b) and 3(b) are the segmentation results using the MFCM method. Figs. 2(c) and 3(c) are the results using the proposed method. Many pixels are wrongly segmented in Figs. 2(b) and 3(b), while they are segmented correctly in Figs. 2(c) and 3(c). The regions in Figs. 2(c) and 3(c) are more consistent and homogenous, which are

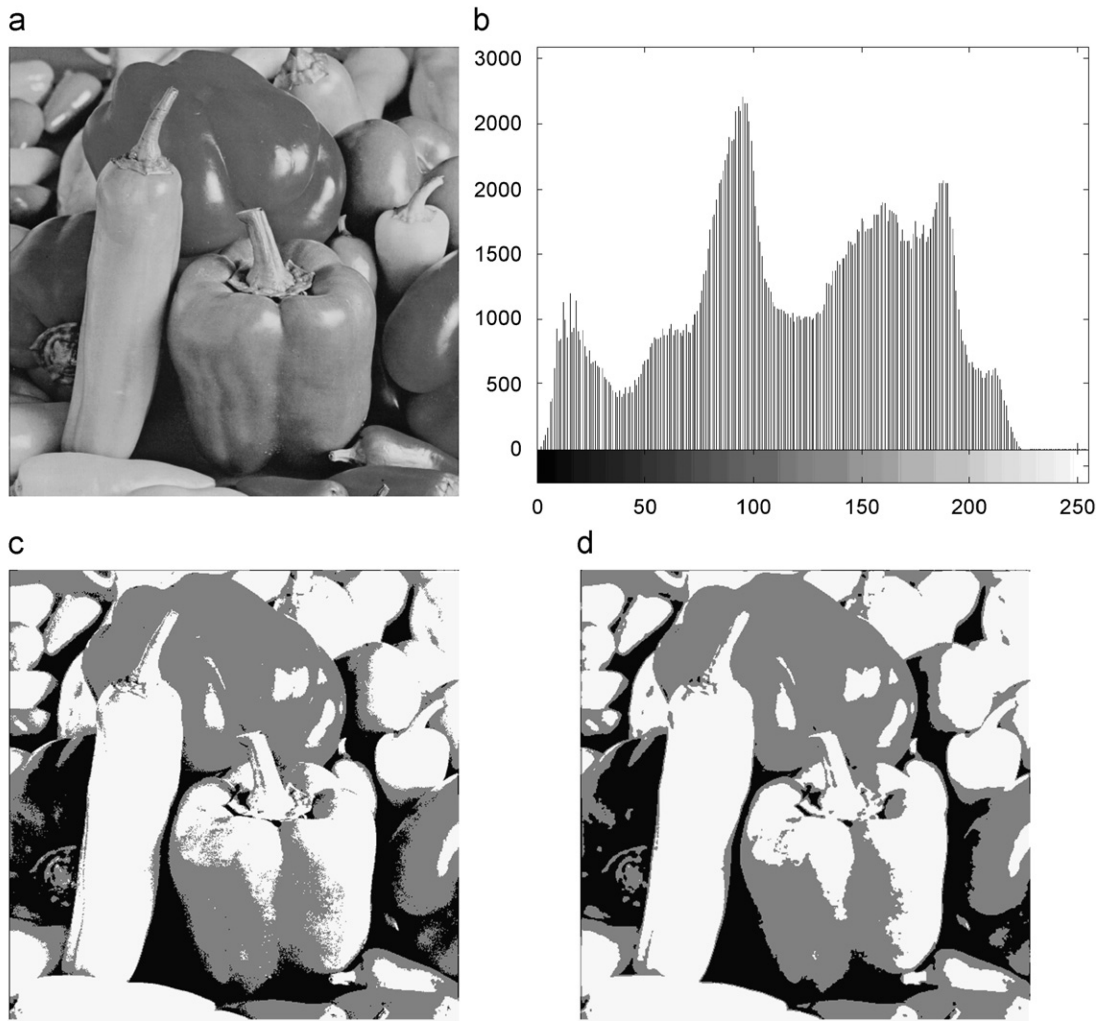

Fig. 7. (a) Pepper image. (b) Histogram of (a). (c) Segmentation result by the MFCM method. (d) Segmentation result of the proposed method.

better for further processing, such as object extraction and classification. It can be seen clearly that the proposed method can perform better than the MFCM method in segmenting artificial images with different gray levels and different noise levels.

There is no a universally accepted objective criterion to evaluate the performance of the segmentation algorithms yet. However, we can know the desired results exactly for the artificial images, and we can use some objective criteria to evaluate the algorithms.

To compare the segmentation results of the artificial images fairly, we utilize the same metric used in the MFCM method, the segmentation error is defined as [10]:

$$e = \frac{ideal\ object\ pixels - real\ object\ pixels}{ideal\ object\ pixels} \tag{33}$$

The segmentation error provides a measure of the misclassified pixels between the measured ideally segmented image and the really segmented image by the proposed algorithm. The quality of an image can be described in term of signal-to-noise ratio (SNR):

$$SNR = 10 \log \left[\frac{\sum_{r=0}^{H-1} \sum_{c=0}^{W-1} I^2(r,c)}{\sum_{r=0}^{H-1} \sum_{c=0}^{W-1} (I(r,c) - I_n(r,c))^2} \right] \tag{34}$$

where $I(r,c)$ and $I_n(r,c)$ represent the intensities of pixel (r,c) in the ideally segmented images and really segmented images, respectively.

The relationship between the segmentation error and SNR is plotted in Fig. 4. From Fig. 4, we can see clearly that the proposed method achieves better performance and lower segmentation error at all Snores. The segmentation errors of the proposed method are all smaller than 0.0155, and the errors of MFCM method are all bigger than that of the proposed method. While the SNR is low, the proposed method performs much better than the MFCM. The proposed approach can obtain the optimum value with error rate 0.0155 which is very low when SNR is 2.2936 dB, while the error of MFCM approach reaches 0.205.

3.2. Experiments on real images

We have applied the proposed approach to a variety of real images. Due to the page limit, only some images are shown here. Figs. 5(a)–7(a) are the original images, Figs. 5(b)–7(b) are the results using the MFCM method, and Figs. 5(c)–7(c) are the results using the proposed method.

Fig. 5(a) is the Lena image with gray levels 0–255, whose histogram is shown in Fig. 5(b). Fig. 5(c) is the segmented image using the MFCM algorithm with three classes. The regions of the hair and hat are not homogenous and separated in the segmentation result using the MFCM approach, which are caused by the noise and the textures of the hair and the hat. However, the proposed approach

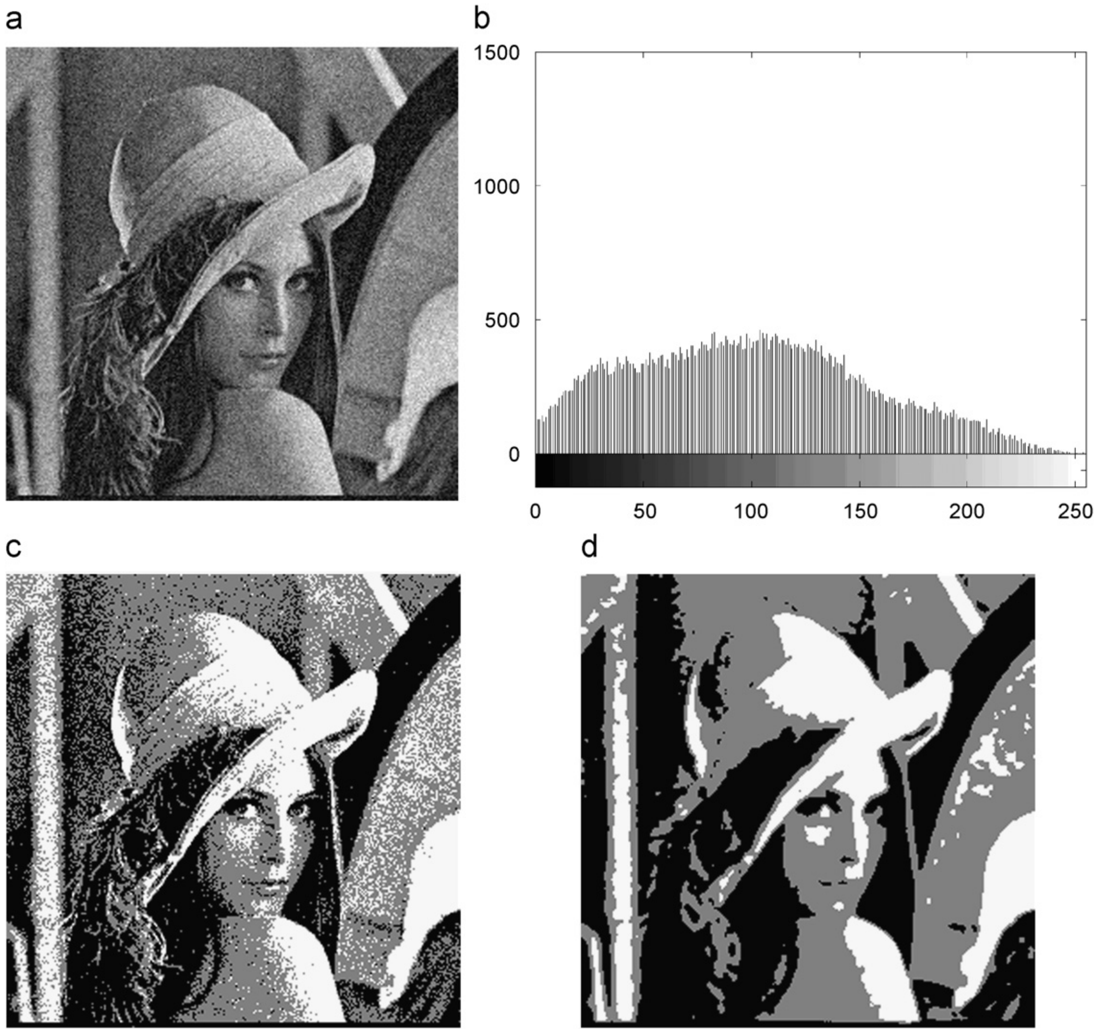

Fig. 8. (a) Lena image with Gaussian noise. (b) Histogram of (a). (c) Result by the MFCM method. (d) Result of the proposed method.

can successfully partition the image well, as shown in the Fig. 5(c). The regions in Fig. 5(c) are more consistent and not affected by the noise of the hair and hat.

Fig. 6(a) is a lake image, which has four main regions: sky, tree, grass, and lake. Among the four regions, the intensities of the sky and the lake could be regarded as the same level. From its histogram in Fig. 6(b), it could show that the lake image has two significant valleys, which divide the image into three groups. Fig. 6(c) is the result of the MFCM algorithm, which contains some misclassified regions, especially, the grass region. In Fig. 6(d), the proposed approach makes the four regions distinct and easy to recognize.

Fig. 7(a) is the original image, whose histogram has three significant peaks. The intensities on the surface of the peppers vary greatly and the boundaries are not distinct. The regions of the bottom pepper in Fig. 7(c) are not consistent and the boundaries are broken by noise. In Fig. 7(d), the regions of the bottom pepper become homogenous and the boundaries are continuous.

Fig. 8(a) is the Lena image with Gaussian noise (mean is 0 and variance is 2.55), whose histogram, Fig. 8(b), has no distinct peaks. Fig. 8(c) is the segmentation result using the MFCM method, which is affected greatly by noise, while the result by the proposed method is much better, as shown in Fig. 8(d), and the hat, hair and woman's face are segmented correctly.

The images are inherently fuzzy and vague. The proposed approach can handle the indeterminacy and uncertainty of the images better, therefore, it can achieve better results and can segment the clean images and noisy images well.

4. Conclusions

In this paper, a novel neutrosophic set approach to image segmentation is proposed. The image is described using three membership sets, T, F and I. The entropy in *NS* domain is defined and employed to evaluate the indeterminacy. Two new operations in the neutrosophic set domain are proposed to reduce the set's indeterminacy. Finally, the proposed method is utilized to perform segmentation. The experimental results show that the proposed method not only can perform better on 'clean' images, but also on noisy images. The proposed approach can find more applications in image processing and pattern recognition.

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