Neutrosophic Image Segmentation: An Approach for the Treatment of Uncertainty in Multimodal Information Systems

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Abstract

Information explosion in this era has led to the proliferation of digital data in form of images, text, video, and audio. Uncertainty is a major issue in information access and retrieval models, and incomplete information needs to be treated in information systems because imprecision indicates the existence of a value that cannot be measured. There is no denial of the fact that uncertainty puts a hindrance in obtaining information in real-time systems, and as per knowledge rarely does any study of information retrieval using image segmentation treat imprecise and inconsistent information inherited in information systems. This work proposes to transform images in the neutrosophic domain for the treatment of uncertainty that persists in information recovery. Later, the image is segmented using the neutrosophic segmentation algorithm and its results are compared with the Modified Fuzzy c-Means segmentation algorithm, which is the earlier used segmentation algorithm in information systems. The experiment is conducted on a variety of multimodal images from the Berkeley Segmentation Dataset and Benchmark, showing the effectiveness of the proposed method for information systems. The proposed image segmentation using neutrosophy seems to yield a smaller error of 0.011, but the error obtained using the fuzzy c-means (MFCM) method is 0.13, which is larger than the proposed approach. The work also demonstrates how well neutrosophic segmentation can segment images having different noise levels as well as clean images. The results show that the proposed algorithm yields the most accurate segmented image for feature extraction which can be utilized while designing effective information systems.

Keywords: Image Processing; Image Segmentation; Soft Computing; Fuzzy Logic; Uncertainty; Neutrosophic Logic; Neutrosophic Sets; Multimodal Information Systems.

1. Introduction

Information access and retrieval is a way of collecting, representing, and matching the data. This data is composed of video-audio, audio-text, text-image, etc. In information systems, we acquire information from various sources, aggregate it and again interact with it in a well-defined manner. This data could be in various forms (modalities) like images, text, video, etc. Multi-modal information access empowers us to retrieve information that is formulated using data of different modalities. As reported in [1][2][3] multimodal systems have enabled us to integrate various modalities like visual and text which is proved to be helpful to a particular user. Though there are existing works to design and implement a perfect system, still there are some loopholes that need to be addressed [4][3]. The data being collected for modeling these systems is represented in various forms; and these are, in no way free from imprecision and inconsistency [5][4]. There is no denying the fact that machine learning is not connected with uncertainty since data that is fetched to these algorithms is always incomplete, imprecise, or inconsistent. When the uncertainty is not treated at the initial stage it becomes afflicted

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to generalization. Imperfection in other forms is most of the time regarded as the incompleteness of data. There exist many state-of-the-art approaches not dealing with uncertainty and imperfection in data (image), which in reality indicate an important aspect of information in information systems. These imperfections are thoroughly studied and are defined as: **Uncertainty** basically deals with the truth of the information provided and how adequate is the provided information with respect to reality [6]. **Imprecision** deals with the content of provided information. It also explains the defect of knowledge in quantitative terms [6] together with the absence of precision in quantity. **Incompleteness** on the other hand deals with lack of information or its partial availability. This is the incompleteness of information that has led to the concept of fusion [7]. Though Fuzzy proves to be advantageous in dealing with uncertainty with the use of FCM it lags on certain points in computer vision tasks like image segmentation. The task of image segmentation has been regarded as one of the strenuous tasks in pattern recognition and image processing. Most real-life applications like object recognition, information retrieval medical imaging, computer vision, etc. are in no way free from image segmentation. Till now image segmentation has been carried out using Fuzzy techniques like the Fuzzy c-means algorithm (MFCM) but the problem of uncertainty and indeterminacy was not handled using fuzzy techniques. The uncertainty in images puts a hindrance to generating proper features for image segmentation tasks [8]. Therefore, there is a need to address this issue.

With the introduction of neutrosophy [9], its applications are setting its root in various fields like computer vision and pattern recognition, etc. [10][11][12][13]. This theory is applied on many occasions in image representational, enhancement, and retrieval tasks [14][15]. Imprecision and uncertainty play vital roles while processing the data. The uncertainties present in images are the result of the presence of noise in an image. For performing image segmentation tasks, the location of the segmentation boundary is required to identify the regions accurately and to carry out image segmentation effectively. For this reason, the process of segmentation must handle uncertainties in data efficiently [16]. But the popular MFCM technique does deal with the uncertainties in image data. Figure 1 shows the importance of neutrosophic logic over fuzzy logic.

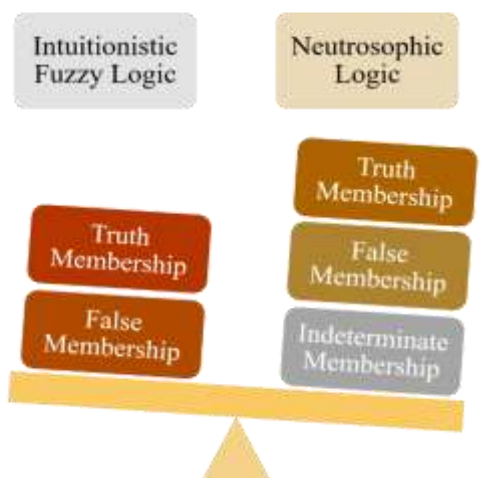

Figure 1: Intuitionistic fuzzy logic vs neutrosophic logic

The present work proposes to use neutrosophy for dealing with the problem of uncertainty while carrying out image segmentation, which is a critical issue for designing information systems. For this purpose, the visual data is represented in the neutrosophic domain and the effectiveness of neutrosophic image segmentation algorithms over modified fuzzy c-means algorithm (MFCM) for image segmentation is demonstrated. This work shows how the image segmentation task is carried out using the concept called neutrosophy. The uncertainty and imprecision are explained both at the decision and representation levels. The proposed work would definitely enhance the accuracy and efficiency of information access and retrieval using neutrosophic sets and theories.

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2. Related work

Soft computing plays a vital role in information access and retrieval tasks. Fuzzy logic has proved to be a boon in representing the information so that it could easily be extracted in the right format. The occasion of the 50th anniversary of the induction of fuzzy clustering [17] has highlighted the importance of fuzzy logic in dealing with uncertainty. In general, the effectiveness of the Fuzzy C-means algorithm for carrying out tasks like image segmentation in pattern recognition is described very well. It is an important tool for image processing. This algorithm allows a pixel to belong to more than one cluster. This application of FCM is utilized in many real-life problems of computer vision, robotics, and pattern recognition. The algorithm helps in segmentation making use of fuzzy classification. The approach seems to be quite effective in carrying out image segmentation tasks. There exists a lot of research work that has employed FCM for image segmentation tasks. [18] have employed this in order to propose an approach to threshold the histogram taking into account similarity at the gray level. [19] have employed Gamma membership in order to determine the membership value of a pixel. They have utilized this in order to propose a fuzzy image thresholding method. An Ant-Tree algorithm-based image segmentation approach has been proposed by [20]. Their approach is based on fuzzy clustering methodology. [21] have used biased illumination field estimation in order to improve the recursive FCM algorithm. They have introduced new fuzzy functions and various clustering centers based on the average pixel intensity of a pixel neighborhood. There have been various other approaches based on deep learning for semantic image segmentation [22] [23]. [24] have proposed an approach to be utilized in pattern recognition which is based on histogram thresholding. This approach is utilized for color image segmentation. These approaches were yielding good results but when it comes to segmenting images with much noise these do not perform well. They could even not handle spatial uncertainty [20]. For fast image segmentation [25] proposed a graph-based approach where based on the partition of the graph the images were segmented. For the segmentation of the regions of an image [26] have proposed a segmentation technique based on a local similarity measure that does not require the preprocessing of the image. In this way, the mentioned approach preserves the structural information of the image. Few of the approaches based on contour and edge-based image segmentation are illustrated in [27]. The approach mentioned in the paper is applicable only for segmenting two-phase images. The image segmentation based on multilevel thresholding is mentioned in [28] [29]. An approach for segmentation based on algebraic topology has been proposed in [30]. Authors in [8] have taken the task to carry out the segmentation of multi-class images using fuzzy sets. The use of fuzzy sets is incorporated into their methodology in an effort to mitigate the problems caused by the inherent unpredictability of the segmentation procedure. In addition, the authors [31] proposed a strategy for image segmentation that was based on the use of multilayer image thresholding. They used Otsu and fuzzy entropy as their objective functions. To justify the present work Table 1 presents an overview of the importance of the image segmentation task in various fields of research [32].

Table 1: Papers using image segmentation

Fields using Image Segmentation	Related Papers (%)
Medicine, Health	22.4
Object detection/identification	13.5
Agriculture	12.2
Navigation	8.3
Remote sensing/ GIS	8.3
Video processing	8.3
Surveillance & Security	7.1
Human Identification	7.1
Image compression	5.8
Text extraction, Texture, Food identification, Understanding of scenes	6.63

Despite widespread applications of neutrosophy in information retrieval tasks; as per our knowledge it is still not applied in designing multimodal information systems for carrying out image segmentation tasks. The application of neutrosophy is set at its root in various fields[7] [10]. This theory is applied on many occasions in image representational, enhancement, and retrieval tasks [15]. These days' neutrosophic sets have been extensively

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used for image denoising and image thresholding. The results which are obtained by the authors are exceptional since authors have not only taken data into account but have also addressed the notion of uncertainty and indeterminacy within data. [16] in their recent work have employed a neutrosophic set as an uncertainty handling tool for carrying out accurate text region segmentation of complex documents using digital shearlet transform. [33] have proposed an approach based on neutrosophic sets for enhancing the performance of the fuzzy c- means algorithm which was later employed as a color image segmentation algorithm. This has been done to reduce the set indeterminacy. For better classification accuracy [34] their recent work has employed a scheme for effectively detecting cervical cancer. A graph cut-based neutrosophic segmentation scheme has been proposed in their work. The approach seems to minimize indeterminacy associated with spatial uncertainty and also which is associated with each intensity of the image. The authors have claimed that their approach seems to be gaining the best results on average of 13% in contrast to the conventional graph-based approaches for cervical cancer detection based on segmentation. If these issues of uncertainty and indeterminacy are addressed while dealing with image data, that is used while designing information systems; the expected results would not let down the target audience.

3. Limitations of previous approaches

A few algorithms have been proposed in the last twenty years for image segmentation which were employed in earlier multimodal systems. These algorithms when employed could not extract correct regions especially when the image contains too much noise due to indeterminacy. Image modality is not free of uncertainties and indeterminacy. Segmentation of images is much affected by noise and the level of indeterminacy present in images. The various approaches mentioned above are less attentive to managing uncertainties that arise during the segmentation process. Thus the methods have little tolerance for ambiguities due to complex image structure and patterns [35] [7]. Most of the image segmentation techniques are based on Gray image segmentation which totally depends on homogeneity and discontinuity of values in the gray region. The gray level values of an image are much affected by uncertainties in the image. Methods such as clustering and region growth, thresholding, edge detection, and region merging are examples of procedures that are based on homogeneity. Those which are based on discontinuity are based on lines, isolated points, and edges that are used to partition an image. Though these mentioned methods are successful; there remains a loophole in each. The thresholding technique ignores spatial information and is very much affected by noise in the image. The problem of over-segmentation happens in region growing and clustering techniques. This is also very time-consuming. Edge detection faces the problem of wrong edges due to the presence of noise in the images. Fuzzy image segmentation approaches partition space in the meaningful region by extracting its features. These regions are not crisply defined due to incomplete, imprecise, and uncertain information. Thus uncertainty seems to be a major problem when it comes to image segmentation using fuzzy sets.

4. Proposed work

The neutrosophic theory is an emerging field of image processing and linguistic modeling for the treatment of imperfections, according to recent breakthroughs in the field. The important step towards achieving a perfect multimodal system is extracting the features which could represent image content or textual content in the best possible way. These features could be color, texture, shape, and faces which are grouped as visual features, or text-based features (keywords and annotation). Among them, the visual features are grouped into high-level features, middle-level features, and low-level features. These features can be represented in the neutrosophic domain as explained by [36] based on neutrosophic entropy, contrast, energy, and homogeneity. Since these features are a way to represent the semantic content of a modality it is necessary for multimodal systems to represent different modalities like image, text, audio, and video in the neutrosophic domain. Now let us understand some preliminaries which are needed to understand the semantic meaning of an image using neutrosophy so that the above-mentioned work could be carried out more efficiently and effectively.

4.1 Image in neutrosophic domain

Image modality when represented in neutrosophic terms; is assumed as an array of neutrosophic singletons [15]. To better understand how image modality could be represented in the neutrosophic domain let us take an example. Consider U to be a universe of discourse and let us take a set Min U. This set M consists of pixels that

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are considered bright for image modality. A modality of PNS in neutrosophic terms is represented by three tuples or subsets T (truth), I (indeterminate), and F (false) where membership degree is represented by T, indeterminacy degree is represented by I, and non-membership is represented by F. In image modality let P be a pixel then it is represented as P (T, I, F). This pixel is supposed to belong to a set M such that in bright pixel it is considered as f% false, i% indeterminate, and t% true. All these t, i, and f vary in T, I, and F respectively. In the image domain as represented by [36] [8] let P(i,j) be a pixel that is being converted to:

$$NDP_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\}.$$

Each of $F(i,j)$ $I(i,j)$, and $T(i,j)$, belongs to the non-white set, indeterminate set, and white set. These can be defined as in [37] using Eq. [1-5].

$$P_{NS}(i,j) = T(i,j), I(i,j), F(i,j) \tag{1}$$

$$T(i,j) = \frac{\overline{g(i,j)} - \overline{g}_{min}}{\overline{g}_{max} - \overline{g}_{min}} \tag{2}$$

$$I(i,j) = 1 - \frac{\overline{H_0(i,j)} - \overline{H}_0}{\overline{H}_{max} - \overline{H}_{0_{min}}} \tag{3}$$

$$F(i,j) = 1 - T(i,j) \tag{4}$$

$$H_0(i,j) = abs(g(i,j) - \overline{g(i,j)} \tag{5}$$

Where the local mean value of the pixel is represented by $\overline{g(i,j)}$. The homogeneity of Tat(i,j) is defined by $H_0(i,j)$.

4.2 Image enhancement in the neutrosophic domain

When images are transformed from one domain to another the transformed image gets distorted as a result of which we need image enhancement. There are various image enhancement techniques that provide a better appearance to the images. [14] have proposed a neutrosophic image enhancement filter that could be employed in multimodal information systems for effective modality (image) enhancement. For this reason, an image G in the neutrosophic domain is represented by using four functions T, I, F, and Π. Applying Gaussian distribution, logarithmic transform, gamma transform, and power-law transform the obtained results are in the form of image $\overline{\mathrm{G}}$ with $\overline{\mathrm{T}}$, $\overline{\mathrm{I}}$, $\overline{\mathrm{F}}$, and $\overline{\Pi}$ represented by Eq. [6-9].

$$\overline{\mathrm{T}}(\mathrm{i,j}) = \mathrm{CT}^{\Upsilon} \tag*{6)}$$

$$\overline{\mathrm{I}}(\mathrm{i,j}) = \frac{1}{\sigma\sqrt{2\Pi}} exp^{\left[\frac{(I(i,j)-\mu)^2}{2\sigma^2}\right]} \tag*{7)}$$

$$\overline{\mathrm{F}}(\mathrm{i,j}) = \mathrm{C}\ln(1 + \mathrm{F}(\mathrm{i,j}) \tag*{8)}$$

$$\overline{\Pi} = 3 - (\overline{\mathrm{F}}(\mathrm{i,j}) + \overline{\mathrm{T}}(\mathrm{i,j}) + \overline{\mathrm{I}}(\mathrm{i,j}) \tag*{9)}$$

The above-mentioned two-fold technique removes unwanted noise from the images. This improves the image contrast which is a need in multimodal systems. Now using the above definitions let us represent an image in the neutrosophic domain. First, we have converted the famous Lena image in grayscale 0-255 using the neutrosophic grayscale image transformation method. Figure (a) (b) (c) shows the original Lena image, the grayscale Lena image, and the corresponding histogram of the image respectively.

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a b c

Figure 2: (a) True Lena Image, (b) Gray Scale Lena Image, (c) Histogram of Lena Image (b)

Later the image is converted into the neutrosophic domain and is represented in Figure. i.e. True image Fig. 3 (a), False Image Fig. 3 (b), and Indeterminate Images Fig. 3 (c). This step holds very much significance in image processing since it aids object detection and edge detection where all pixels of an image are divided into True (T), False (F), and Indeterminate (I) subsets.

a b c

Figure. 3 Lena Image in Neutrosophic Domain (a) True Image (b) False Image (c) Indeterminate Image

4.3 Neutrosophic image entropy

The distribution of intensities of a grayscale image is evaluated using entropy. The maximum of entropy shows that the intensities distribute uniformly and intensities have equal probabilities.

Definition: The sum of three entropy sets i.e. T, I, and F. It is defined as evaluation criteria for the distribution of various elements in the domain of neutrosophy. In the below Eq. [10-13] En_T, En_I and En_F refer to entropies in True (T), Indeterminate (I) and False (F) sets respectively. $p_T(i)$, $p_I(i)$, and $p_F(i)$ are referred to as the probability of mentioned elements in T, I, and F respectively.

$$En_{NS} = En_T + En_F + En_I \tag{10}$$

$$En_T = -\sum_{i=\min\{T\}}^{\max\{T\}} p_T(i) \;\; ln \;\; p_T(i) \tag{11}$$

$$En_I = -\sum_{i=\min\{I\}}^{\max\{I\}} p_I(i) \;\; ln \;\; p_I(i) \tag{12}$$

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$$En_F = -\sum_{i=\min\{F\}}^{\max\{F\}} p_F(i) \;\; ln \;\; p_F(i) \tag{13)}$$

4.3.1 α-mean operation

The indeterminacy of any element $P_{NS}(i,j)$ is measured by the value of $I(i,j)$. The value of T and F must correlate with the indeterminate value I. For this reason, there needs to be a change in the distribution of elements and entropy, once T and F are changed i.e. changes in T and F must influence elements and entropy. The mean operation for any gray level image is given by Eq. 14. This is referred to as the AlphaSmt operation.

$$\overline{Im}(i,j) = \frac{1}{w \times w} \sum_{m=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{n=j-\frac{w}{2}}^{j+\frac{w}{2}} \mathrm{Im}(\mathrm{m},\mathrm{n}) \tag{14)}$$

The α-mean operation for $P_{NS}(i,j)$ and $\bar{P}_{NS}(i,j)$ is defined in Eq. 15 [38]:

$$\bar{P}_{NS}(\alpha) = P(\bar{T}(\alpha), \bar{}\;(\quad)\overline{I\alpha, F}(\alpha)) \tag{15)}$$

4.3.2 β-enhancement operation

When this operation is applied for $P_{NS}(i,j)$, and $\bar{P}_{NS}(i,j)$ then these are defined by Eq. 16 [38]. This is referred to as BetaSmt operation.

$$P'_{NS}(\beta) = P(T'(\beta), I'(\beta), F'(\beta)) \tag{16)}$$

Let's define $\bar{\partial}_T(i,j) = abs(\bar{T}(i,j) - \bar{\bar{T}}(i,j))$ which absolute difference between mean intensity and its mean value after the α-mean operation.

4.4 Image segmentation

Image segmentation is an important step toward analyzing an imaging modality. The neutrosophic image segmentation algorithm being employed in the present work could well be understood by the flowchart given in Fig. 4.

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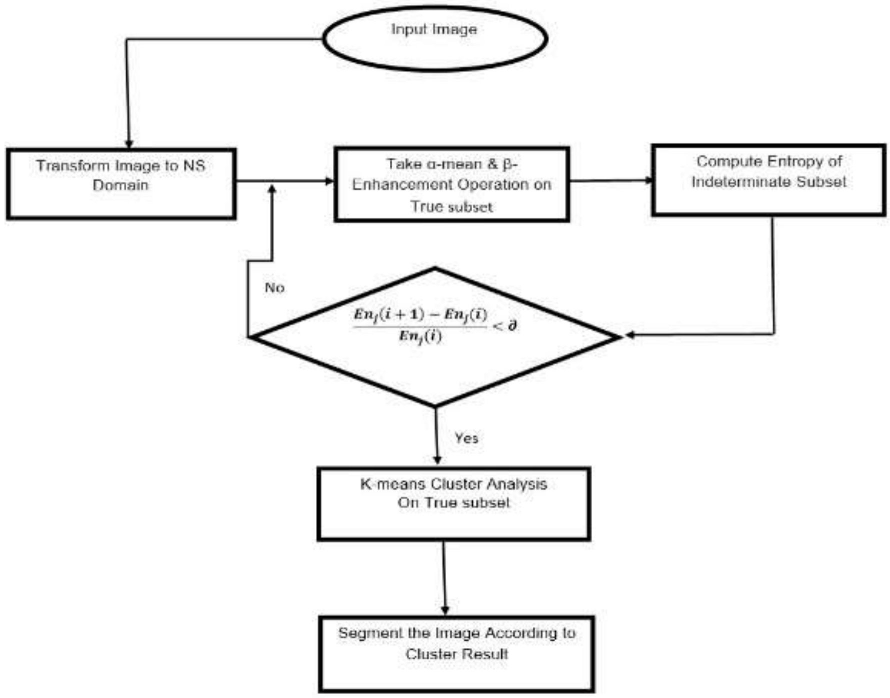

Figure 4: Flow chart of Neutrosophic Segmentation Algorithm

5. Experimental results and discussion

In order to demonstrate that the neutrosophic segmentation method is superior to the other algorithms that were utilized previously; like the fuzzy c-means algorithm, we have used the most famous Berkeley Segmentation Dataset [39] as the test images. This dataset set is most suitable for the current experiment since it provides manually segmented versions of segmented images in their dataset which seems to be a perfect evaluation criterion for any segmentation algorithm. Now let us take images and convert them into their respective gray level image and later to their corresponding histogram to better understand the images. Fig. 4 represents the same. Fig. 5 (a) shows a Swamp deer image with two main regions: the deer and the grassland. Between these two regions, the intensities of the regions are different which could easily be inferred from the histogram. It also shows a Bear Fig. 5 (b) having two main regions. The next image is of a flying bee Fig. 5 (c). The histogram of the image Fig. 5 (f) shows that it has one major region and which is also reflected by its segmented image in Fig. 6 (f) using the neutrosophic algorithm. The results obtained by the fuzzy algorithm are distorted which could easily be inferred from Fig 6 (a) (c) (e).

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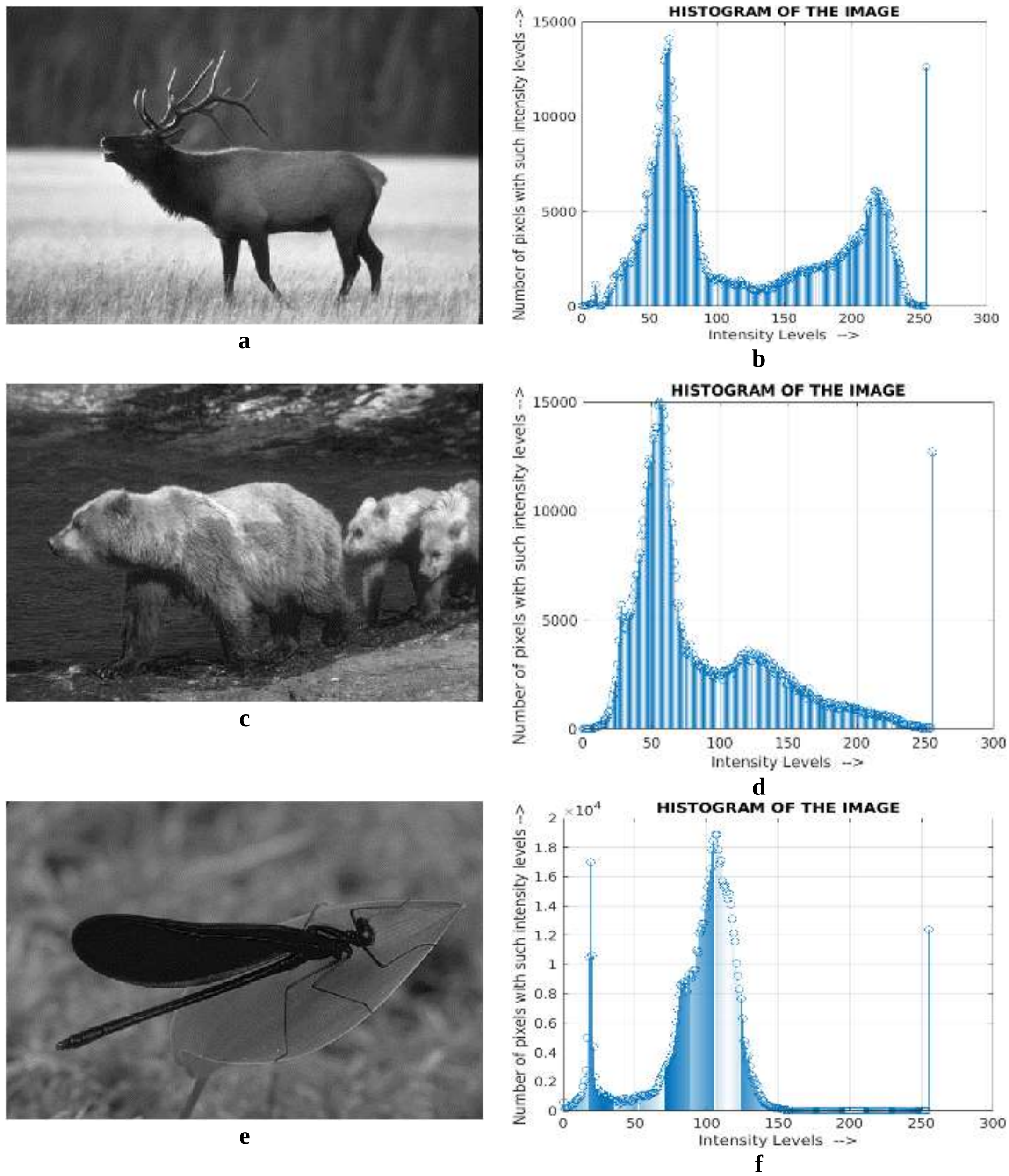

Figure 5: (a) Gray image of Swamp deer, (b) histogram of (a), (c) Gray image of a bear, (d) histogram of (c), (e) Gray image of flying bee, (f) histogram of (e).

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Figure 6: (a), (c), (e) segmented images results using MFCM method and (b), (d), (f) segmented images using neutrosophic segmentation algorithm

For this experiment, there are 196 segmentations. We have performed the experiment over a set of multimodal images to show the effectiveness of the neutrosophic image segmentation algorithm over the earlier used fuzzy algorithms. The image segmentation results obtained using both algorithms i.e. MFCM and neutrosophic segmentation are shown and compared in Fig. 6. It can clearly be seen that the fuzzy algorithm has some misclassified regions which are different from the results obtained by the neutrosophic image segmentation algorithm. The results obtained above show that the neutrosophic way of handling images is very efficient in handling uncertainty and indeterminacy present in image modality. Therefore it achieves better results and can segment images well. These image modalities serve as a major source of data for information systems. Thus, once indeterminacy and uncertainty are handled at this level, they would not be afflicted by machine learning algorithms and also to information systems in general. The values of segmentation error obtained while carrying out segmentation using MFCM and neutrosophic segmentation algorithms are as follows:

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Table 2: Results in terms of segmentation error vs SNR

S.No.	SNR dB	MFCM	NS
1	2.2	0.21	0.021
2	2.3	0.2	0.009
3	2.5	0.15	0.01
4	3.1	0.13	0.011
5	3.8	0.07	0.008
6	4.4	0.05	0.007
7	5.4	0.03	0.003
8	6.1	0.02	0.002

The above table demonstrates that the proposed neutrosophic segmentation method produces a low level of error in comparison to the fuzzy c-means technique that was previously utilized.

5.1 Performance evaluation

Among different evaluation methods for segmentation tasks, the most reliable comes in the form of subjective (supervised) evaluation. In subjective evaluation, the segmentation results are evaluated by human evaluators. The current work is based on the subjective evaluation of segmented images. The dataset used in the present work is a rich source of subjective evaluation since it contains manually segmented images. The evaluation of neutrosophic segmentation employed in this work shows that it achieves better results than the other state-of-the-art approaches. Though there does not exist any universally acceptable objective (unsupervised) method for evaluating segmentation tasks, we can still employ some criteria to evaluate the results. We also employ the objective method of evaluation used to evaluate MFCM algorithm results. The segmentation error is defined as a measure of misclassified pixels among neutrosophic classified pixels and ideally classified pixels. This is denoted as e and is defined by Eq. 17.

$$e = \frac{ideal\ image\ pixel - real\ image\ pixels}{ideal\ image\ pixels} \quad 17)$$

Now we need to know SNR (signal-to-noise ratio) values so that is can be plotted against the segmented error to judge the performance of neutrosophic algorithms. The SNR values are basically used to determine the quality of an imaging modality. The SNR can be well understood by Eq. 18.

$$SNR = 10 \log \left[\frac{\sum_{r=0}^{H-1} \sum_{c=0}^{W-1} I^2(r,c)}{\sum_{r=0}^{H-1} \sum_{c=0}^{W-1} (I(r,c) - I_n(r,c))^2} \right] \quad 18)$$

The $I_n(r,c)$, and $I(r,c)$ in the above equation denote pixels intensity in the neutrosophic segmented image modality and ideally segmented image respectively. Fig. 6 clearly shows that neutrosophic segmentation achieves good segmentation with fewer segmentation errors.

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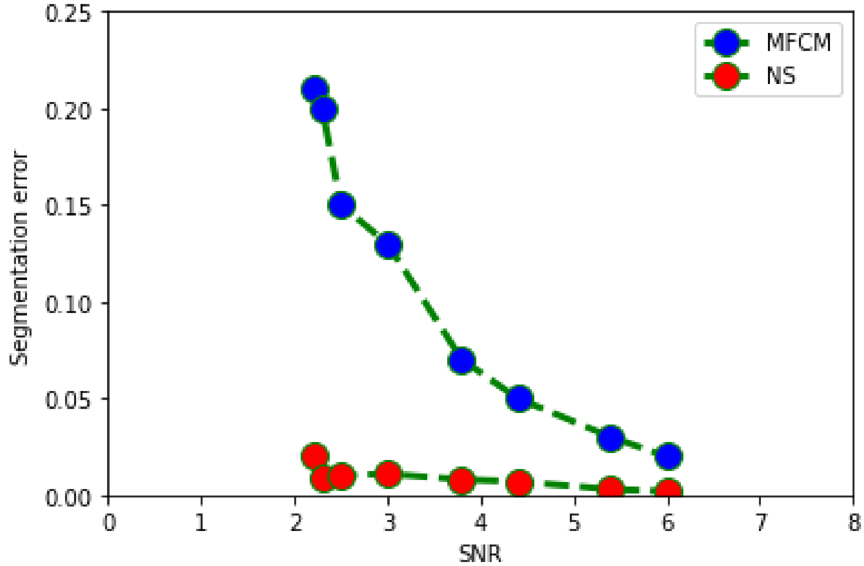

Figure 7: The relation between Segmentation error and SNR

Though segmentation of the image in Fig. 6 clearly shows that the performance of the neutrosophic algorithm is giving good results. The relationship between SNR and e of the neutrosophic segmentation and modified fuzzy c-means segmentation is represented in Fig. 7. The proposed image segmentation using neutrosophy seems to yield a smaller error of 0.011, but the error obtained using fuzzy c-means (MFCM) method is 0.13, which is larger than the proposed approach. It can be noticed that we obtain the least segmentation error at all snores by the proposed method of image segmentation for information systems.

6. Conclusion

We have applied neutrosophy to image processing in this work. The multimodal images are represented in the neutrosophic domain where the image has been described using three memberships, T, F, and I. The concept of entropy is defined using neutrosophy and later employed to evaluate indeterminacy in images. This is done in order to carry out neutrosophic image segmentation while designing information systems so that the uncertain and indeterminate data could be well represented and indeterminacy may not get afflicted by machine learning algorithms. The effectiveness of neutrosophic image segmentation is shown over MFCM using data from the Berkley image segmentation database. In the future, we plan to represent text in the neutrosophic domain in order to combine it with image data to design multimodal information systems. We will also try to demonstrate various applications and implementations of neutrosophic classification algorithms while handling image data.

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