Intuitionistic Fuzzy Segmentation of Brain MRI

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ABSTRACT Intuitionistic fuzzy set (IFS) involves the concept of non-membership degree and hesitation degree. The application of IFS is crucial in medical imaging as the images are poor in illumination as well as the structure is hard to detect. This work is focusing on segmenting brain MRI images by using advanced fuzzy and ordinary fuzzy theory. One of the intentions in image segmentation is to divide the regions in an image so that it is easier to be analyzed as it extracts meaningful information. In addition, the main highlight in this work is to apply IFS concept in focal brain parenchymal lesions image segmentation. The method is known as intuitionistic fuzzy c-mean (IFCM). Furthermore, the output images by using IFCM and fuzzy c-mean (FCM) are compared. Based on the results, IFCM has better outcomes in term of accuracy and performance test compared to FCM. Hence, the IFCM has better results in segmenting the focal brain parenchymal lesions images compared to FCM since it is able to preserve the surrounding structure of the brain.

KEYWORDS: Intuitionistic fuzzy set; Ordinary fuzzy set; Segmentation; c-mean; Medical imaging
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INTRODUCTION

Intuitionistic fuzzy sets (IFS) is a generalization of notion in fuzzy sets. IFS is introduced due to the non-membership degree of an element in fuzzy set might not be equal to one minus degree of membership since there might be some hesitation degree. Thus, IFS is a suitable tool for modelling the hesitancy caused by imprecise details. In medical image processing field, some structures are invisible because they are poor in illumination that caused many of the areas or even boundaries are unclear. This resulting in the segmentation of medical images being hard although the process itself is an essential aspect in image processing analyses. Thus, mathematical tools are needed to deal with such images.

Diverse crisp or classical techniques have been applied to MRI images. However, those methods are lacked in enhancing the image quality since there are uncertainties in pixel interpretation. The classical method is limited in segmenting the regions with unclear boundaries since there is imprecision of information. The fuzzy-based segmentation also produces deficient results in medical image segmentation. Therefore, it is important to figure a way to retrieve information from the brain MRI images to detect the abnormalities or focal brain parenchymal lesions accurately. The IFS is applied in image segmentation to help in handling the unclear boundaries.

This work aims to cluster the medical images into a different appropriate region for medical purposes and this can be done by segmenting the focal brain parenchymal lesions images using IFS. It involves the implementation of IFS in the segmentation of focal brain parenchymal lesions MRI image and evaluation of accuracy and performance by using Dice index and entropy. This study is done to improve the medical images for further processing so that the physicians will be able to diagnose and treat the illness more precisely which consequently, contributes to medical field.

In 2010, Chaira has suggested a method of applying IFS in medical imaging which specifically, implementing the Atanassov's IFS in the blood vessel and blood cell segmentation. Chaira (2010) proposed to apply the IFS by generating the Sugeno type for the sake of building the IFS. Significantly, the results have shown better results in terms of performance as the boundaries of both blood vessels and cells are, evidently, quite obvious since as mentioned before, medical images have poor boundaries and illuminance.

Di Ruberto and Putzu (2015) remarked that the ability of IFS in thresholding is excellent. They demonstrated the effect of IFS in segmenting the blood vessels by thresholding. According to them, the method that was implemented before such as neural network and fuzzy divergence did not produce better result in computational time though the method has better result in terms of performance.

Dubey *et al*. (2016) suggested in segmenting the brain MR images by applying IFS algorithm. Three regions are considered when segmenting the MR image which are grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The fact that application of IFS in image segmentation causes the aftermath of segmenting the brain MR image to be successful. Additionally, Mushrif *et al*. (2017) recommended applying the IFS in kidney MR image segmentation. The results from the image segmentation consist of blood vessels, medulla, and cortex. The method proposed was compared with the classical technique in image segmentation which is K-mean clustering. To conclude, the proposed method has better outcomes compared to the classical technique.

METHODOLOGY

The following steps are required in contributing to the algorithm structure in IFCM. Firstly, apply the Yager-type intuitionistic fuzzy generator in terms of construction of IFS, and followed by modifying the objective criterion function along with updating the cluster centre and integrating an objective function which is intuitionistic fuzzy entropy (IFE), in the criterion function. The formula for hesitation degree is shown in Equation (1).

$$\pi_A(x) = 1 - \mu_A(x) - (1 - \mu_A(x)^a)^{1/a} \tag{1}$$

where

$$\mu_A(x) + \nu_A(x) + \pi_A(x) = 1$$

The intuitionistic fuzzy membership can be obtained using Equation (2) which is

$$\mu^*_{ik} = \mu_{ik} + \pi_{ik} \tag{2}$$

as $\mu^*_{ik}(\mu_{ik})$ implies the intuitionistic fuzzy membership matrix of i-th data in class k. The modified cluster center can be attained as shown in Equation (3).

$$\nu^*_k = \frac{\sum_{i=1}^{n} \mu^*_{ij} x_i}{\sum_{i=1}^{n} \mu^*_{ik}} \tag{3}$$

The formula for grey image segmentation is as shown in Equation (4) as

$$\mu_{ik} = \frac{1}{\sum_j^c [d^2(x_k, gray_i)/d^2(x_k, gray_j)]^{\frac{2}{m-1}}} \tag{4}$$

where

$$gray_i = \frac{\sum_{k=1}^{n} \mu_{ik}^m x_k}{\sum_{k=1}^{n} \mu_{ik}^m},$$
$$\forall\, i, k, i = 1,2,3,..,c \text{ and } k = 1,2,3,..n$$

This proposed method consists of several steps as shown in the following algorithm:

1. Number of cluster c=4, constant m=2, iteration number, t=0,1,2, …,100 and the stopping criteria ε<0.0001.
2. Randomly generate membership matrix and normalize the membership matrix.
3. Insert uncertainty value, α and calculate the uncertainty using Equation (1).
4. Change the membership matrix to intuitionistic fuzzy membership matrix using Equation (2).

5. Calculate the cluster center and distance from sample to cluster center using the membership using Equation (3).
6. If the number iterations are less than 1, calculate the new membership matrix using Equation (4).
7. Repeat step 3-6 until the criterion function is at minimum, reaches a specified threshold or reaches the stopping criteria.
8. Find the maximum membership of each element and store the coordinates of each cluster centre.
9. Display the generated segmented image.

Moreover, in order to validate the proposed methods, two tests are conducted to analyze the similarity and the performance of the output image. The tests are listed in Table 1.

Table 1. Type of tests and benchmarking

Type of Tests	Formula	Benchmarking
Dice Index (Albashah *et al*., 2019)	$\text{Dice} = \frac{2\|A \cap B\|}{\|A\|+\|B\|}$ where A is the binary reference image and B is the binary segmented image.	• Count the percentage of segmentation region and to check whether it is same as the ground truth. • If the similarity is 1 or close to one, then the segmentations in the two images mostly perfect match.
Entropy evaluation (Prabha & Kumar, 2016)	$Entropy = -\sum_{i=1}^{a} e_i log e_i$ where e is the frequency of pixels and i is the pixel intensity value	• Calculate the randomness or the content information. • If the entropy value is low, then there is less randomness the in information of the image.

RESULT AND DISCUSSION

Figure 1 shows the input images that are used in this study. There are nine input images with dimension of 343 x 365 pixels for each image. This input images represent focal brain parenchymal lesions.

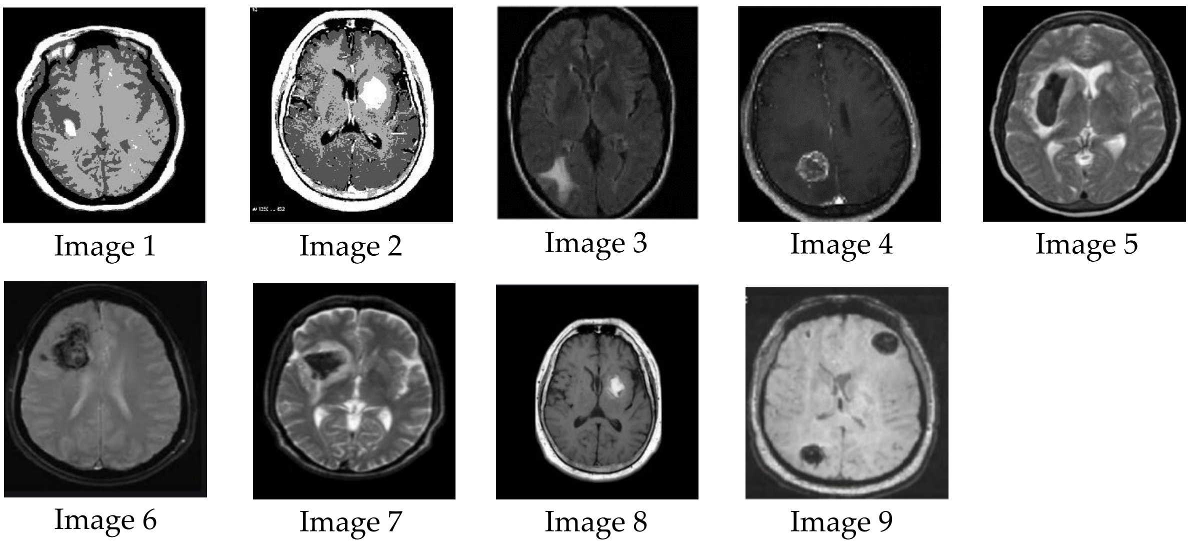

Figure 1. Input Images

(Source: a) Image 1, Image 2, Image 5, Image 7, & Image 8 are retrieved from The Whole Brain Atlas;
b) Image 3 & Image 4 are retrieved from Chaira, 2011;
c) Image 9 is retrieved from Lee, 2018).

Figure 2 shows the output of IFCM on segmentation of brain MRI images with focal brain parenchymal lesions. It shows that the IFCM is able to preserve the surrounding structure of the brain. Figure 3 shows the output of FCM on segmentation of brain MRI images with focal brain parenchymal lesions. Most of the adjacent structures are hard to be seen since it is only targeting the lesions. Table 2 shows the results of Dice index and entropy evaluation after the process of IFCM and FCM segmentation.

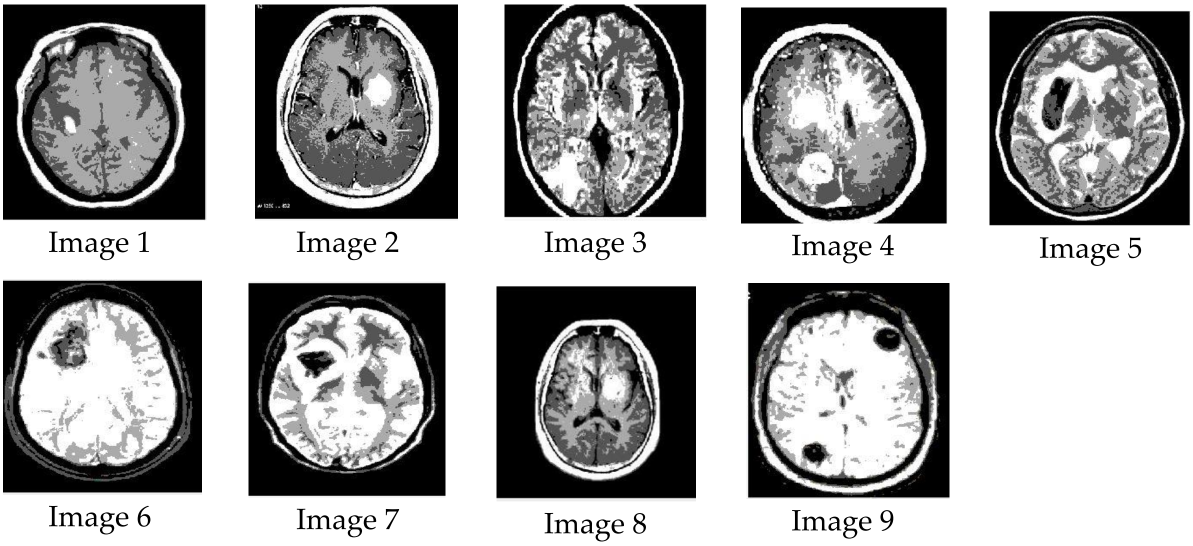

Figure 2. Output Images

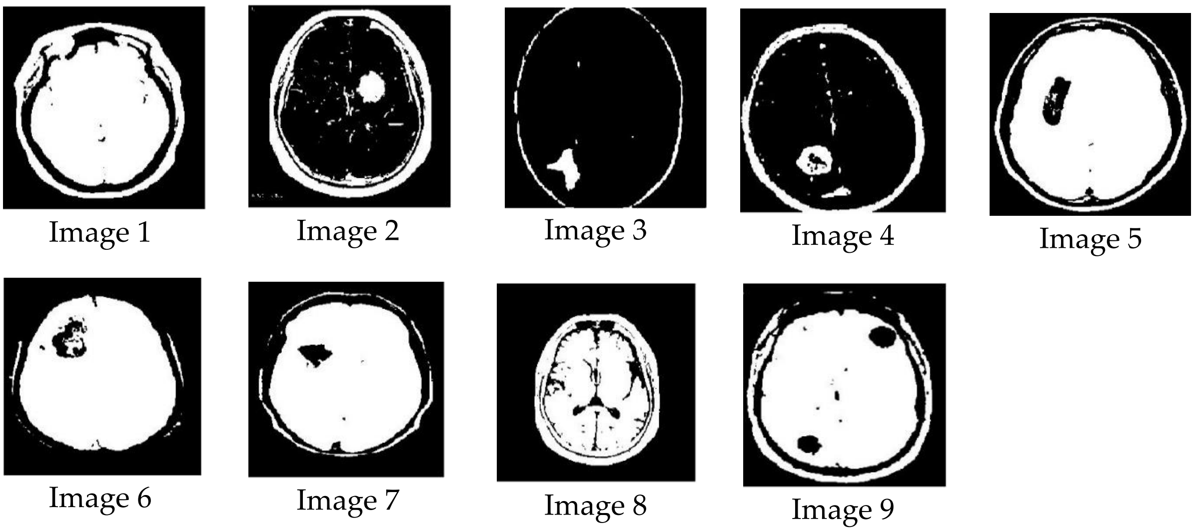

Figure 3. Output Images for FCM

Table 2. Results of Dice index and entropy evaluation

Data	Dice index		Entropy	
	IFCM	FCM	IFCM	FCM
1	0.88726	0.871101	0.392395	0.999383
2	0.729211	0.319187	0.57833	0.690529
3	0.756525	0.142413	0.357239	0.385902
4	0.855091	0.277181	0.474676	0.568232
5	0.88449	0.861094	0.632366	0.988026
6	0.720358	0.643133	0.862484	0.998046
7	0.844112	0.816339	0.617708	0.998965
8	0.776995	0.740779	0.372769	0.922919
9	0.732606	0.727756	0.584326	0.985961

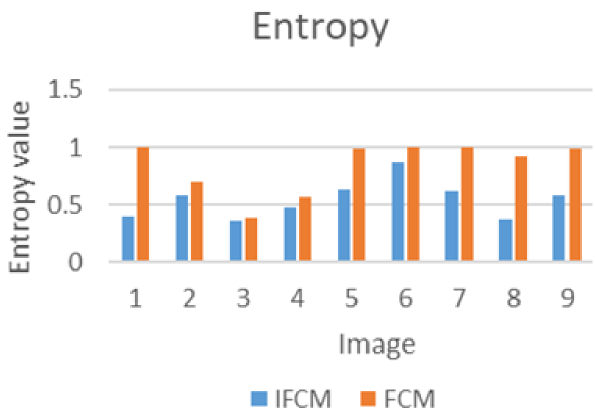

Figure 4. Entropy

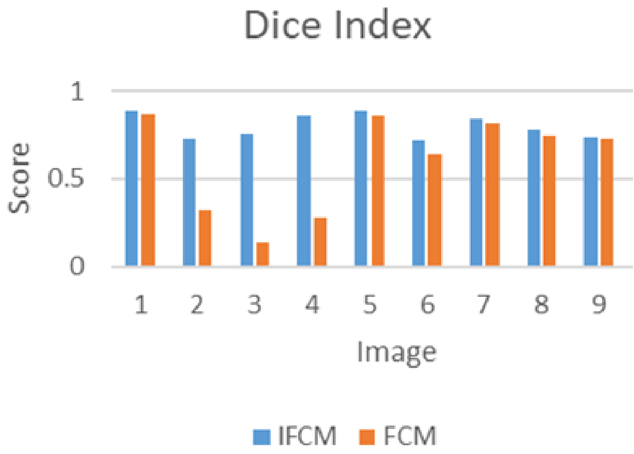

Figure 5. Dice index

Based on Figure 4, it is clearly shown that the IFCM reduces the loss of information in the images. However, in FCM the loss of content of information is more significant. Based on the entropy evaluation concept, if the value is lower, then the performance of image segmentation is better. Figure 5 shows that images segmented by using IFCM are almost similar to the original images. This further demonstrates the Dice index concept where if the result is 1 or near to 1, then the segmentation of the images is a match. However, FCM shows a significantly low accuracy which hence, proves the robust accuracy of IFCM.

CONCLUSION

The IFCM is applied to segment the adjacent structures or specific area in the brain. It shows that the IFCM produces better output images compared to FCM. Although the IFCM and FCM are able to segment the lesions but the jewel lies in the ability of the IFCM to assess and preserve the details or the surrounding structures in the brain. On the other hand, the FCM is unable to preserve the adjacent structures in the brain. The output images by using IFCM is crucial in comparison and reassessment of the lesions.

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