Middle-East Journal of Scientific Research 24 (9): 2850-2858, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.24.09.23938

Enhanced Fuzzy C-Means Based Segmentation Technique for Brain Magnetic Resonance Images

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Abstract: Brain tumor is most vital disease which commonly penetrates in the human beings. Studies based on brain tumor confirm that people affected by brain tumors die due to their erroneous detection. In this paper, an enhanced Fuzzy C- Means segmentation (FCM) technique is proposed for detecting brain tumor. To justify the performance of the proposed method, a comparative analysis is being carried out with conventional methods. This technique is an Enhanced version of FCM (EFCM) which incorporates neutrosophic (Ns) set, which is applied in image domain and define some concepts and operations. The input image (G) is transformed into Ns domain, which is described using three subsets namely, True,Intermediate and False (T, I and F). The entropy in neutrosophic set is defined and employed to evaluate the indetermination. FCM clustering is applied to the transformed Ns domain set (Advanced than Fuzzy set). The experimental results demonstrate that the proposed approach detects the tumor region in automatic and effective manner compared to the conventional methods. This EFCM method improves the accuracy rate and reduces error rate of MRI brain tumor.

Key words: Neutrosophic set · Image segmentation · MR image · Enhanced Fuzzy C-Means

INTRODUCTION

MR Image is a highly developed medical imaging technique providing rich information on the human soft-tissue anatomy. To predict the structure and function of the human body, this technique is referred in radiology. MRI is different from CT, it does not use ionizing radiation, but uses an effective magnetic field to line up the nuclear magnetization of hydrogen atoms in water in the body [1].

Researchers have revealed that the death rate of people affected by brain tumor has increased over the past three decades [2]. A tumour is a mass of tissue that grows out of control of the normal forces that regulates growth [3]. Tumours can directly destroy all healthy brain cells. It can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull [4].

Brain tumours are of different sizes, locations and positions. They also have overlapping intensities with normal tissues [5]. Several authors analyzed the tumors in benign or malignant etc.. [6] and segmented by different techniques [7], D. Bhattacharyya and Tai-hoon Kim [8].

Several existing thresholding techniques [9] have produced different result in each image. To produce a satisfactory result on brain tumor images, they have proposed a modified k-means technique, where the detection of tumor was done in an exuberant manner. Koley, S. and A. Majumder, [10] have presented a cohesion based self merging (CSM) algorithm for the segmentation of brain MRI in order to find the exact region of brain tumor. Here, the effect of noise has been reduced greatly and found that the chance of obtaining the exact region of tumor was more and the computation time was very less. More than a few, an optimization, intelligent techniques are also [11,12] proposed in the medical image processing. Wen-Feng Kuo *et al*. [13] have proposed a robust medical image segmentation technique, which combines watershed segmentation and Competitive Hopfield clustering network (CHCN) algorithm to minimize undesirable over-segmentation.

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However, due to the uncertainty and complexity of images encountered in actual applications, it is one of the most difficult tasks that affect directly the results of subsequent tasks such as feature extraction and pattern recognition. Since fuzzy logic is an effective way of researching and processing uncertainty, it used to be a powerful tool to deal with the ambiguity images. Different aspects of fuzzy logic theory have been successfully used in image processing problems. For example, fuzzy c-means (FCM) algorithm is a famous method that can obtain segmentation results by fuzzy classification [6]. However, fuzzy logic methods usually do not generate satisfactory results when they are applied to the images with higher degree of uncertainty.

In this paper, Enhanced Fuzzy C-Means (EFCM) of MRI brain image segmentation is proposed and results are compared with conventional watershed segmentation and FCM. The performances of the segmentation methods were compared to highlight the proposed method. In this paper, section 2 describes about the proposed EFCM method. Section 3 details the results and discussion of the segmentation methods. Finally, conclusion is described in section 4.

Neutrosophic Set and Neutrosophic Image

Definition 1: Let *U* be a universe of discourse, a neutrosophic set *A* is included in *U*. An element *x* in the set *A* is noted as *x*(*T*,*I*,*F*). *T*, *I* and *F* are real standard or nonstandard subsets of], $^-$, 0,1 $^+$[. *T*, *I* and *F* are called neutrosophic components [14]. According to this definition, the element *x*(*T*,*I*,*F*) belongs to *A* in the following way: it is *t* true (*t* _*T*), *i* indeterminate (*i*_*I*) and *f* false (*f* _ *F*), where *t*, *i*, *f* are real numbers in the subsets *T*, *I*, *F*. The subsets *T*, *I* and *F* are not necessarily intervals, but 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 [15]. They may also overlap. Following this definition, we apply the neutrosophic logic into image processing. First, we'll give the definition of the new represent-neutrosophic image as follows:

Neutrosophic Image

Definition 2 (Neutrosophic Image): Let *U* be a universe of the discourse and *W*?*U* which is composed by the bright pixels. A neutrosophic image *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 in the bright pixel set, *i*% indeterminate and *f* % false, where *t* varies in *T*, *i* varies in *I* and *f* varies in *F* [16]. 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 value belonging to white set, indeterminate set and non-white set, respectively, which are defined as:

$$T(I,J) = \frac{g'(i,j)-g'min}{g'_{max}-g'_{min}} \quad (1)$$

$$g'(I,J) = \frac{1}{wxw}\sum_{m=i-\frac{w}{2}}^{i+\frac{w}{2}}\sum_{n=j-\frac{w}{2}}^{j+\frac{w}{2}} g(m,n) \quad (2)$$

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

$$\delta(i,j) = abs\left(g(i,j) - g'(i,j)\right) \quad (4)$$

$$F(i,j) = 1-T(i,j) \quad (5)$$

where *g'* (*i*, *j*) is the local mean value of the image. ä (*i*, *j*) is the absolute value of the difference

Cluster Decision in *T*,*F*: Given an image *G*, *P*(*x*,*y*) is a pixel in the image and (*x*, *y*) is the position of this pixel. First, we use a mean filter to remove noise and make the image uniform.

Neutrosophic Image Entropy:

Definition 3 (Neutrosophic Image Entropy): The neutrosphic 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 neutrosphic domain:

$$En_{NS} = En_r + En_I + En_F \quad (6)$$

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

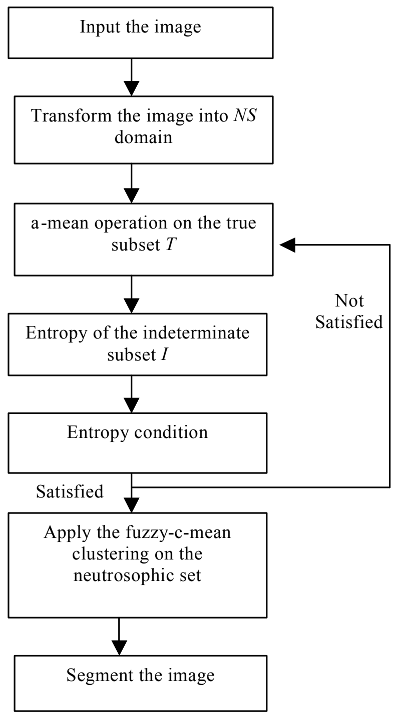
$$En_I = -\sum_{i=min(I)}^{max(I)} p_I(i) \ln p_I(i) \quad (8)$$

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

Where En_T, En_I and En_F are the entropies of the sets *T*, *I* and *F*, respectively. $P_T(i)$,. $P_I(i\ )$and. $P_F(i)$ are the probabilities of elements in *T*, *I* and *F*, respectively, whose values equal to *i*.

EFCM: Enhanced version of FCM is proposed, which incorporates Ns domain set.

EFCM SEGMENTATION ALGORITHM FLOWCHART:



RESULTS AND DISCUSSIONS

In this paper, the proposed approach is applied to a brain tumor of real images and compared with a fuzzy C-means segmentation algorithm and conventional watershed segmentation technique. The segmentation methods have been tested for more than 50 images (a combination of normal and abnormal images). In this paper, for simplicity two images are taken common for analysis (one normal and other of tumor). First the results of watershed algorithm is given, followed by FCM results, finally proposed EFCM results were given.

Figure 1.a and Figure 2.a refers to brain image converted to RGB form. A high pass filter is the basis for most sharpening methods which sharpens the image. A high pass filter tends to retain the high frequency information within an image while reducing the low frequency information. The kernel of the high pass filter is designed to increase the brightness of the center pixel relative to neighboring pixels. The high pass filter is applied to the RGB image the corresponding output is shown in Fig 1.b and Fig2.b.

The filtered image is then passed through threshold segmentation. The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to select the threshold value (or values when multiple-levels are selected). Fig 1.c and Fig 2.c shows the threshold image of normal and tumor MRI. The threshold image is then segmented by conventional watershed method. Watershed segmentation is a gradient-based segmentation technique. It considers the gradient map of the image as a relief map. It segments the image as a dam. The segmented regions are called catchment basins. Watershed segmentation solves a variety of image segmentation problem. It is suitable for the images that have higher intensity value. Fig 1.d and Fig 2.d represents the watershed segmented outputs of normal and abnormal MRI images respectively. Morphological image processing is a collection of nonlinear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values and therefore are especially suited to the processing of binary images.

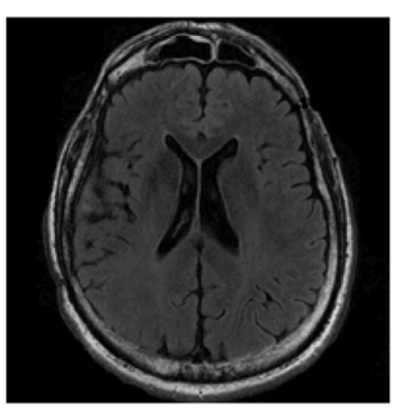


Fig. 1.a: RGB image

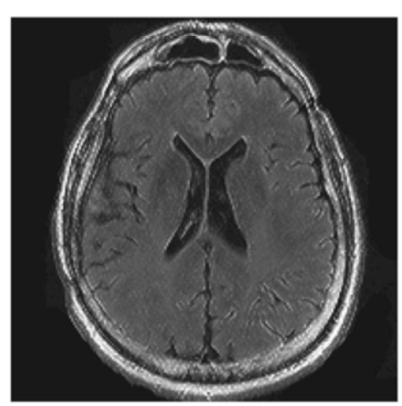


Fig. 1.b: High pass filtered image

Fig. 1.c: Threshold image

Fig. 1.d: Watershed segmented image

Fig. 1.e Morphological output

Fig. 2.a: Original image

Fig. 2.b: High passfiltered image

Fig. 2.c: Threshold image

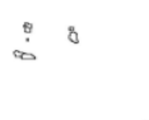


Fig. 2.d: Watershed segmented image

Fig. 2.e: Extracted tumor image

Morphological operations can also be applied to grayscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest. Morphological techniques probe an image with a small shape or template called a structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighborhood of pixels. Fig 1.e and Fig 2.e shows the morphological output images (eroded and dilated image).

The results depicted in Fig 3 and Fig.4 outputs of fuzzy C mean (FCM) for normal and tumor image respectively. Fig 3.a and 4.a shows the RGB image, Fig 3.b and 4.b shows the threshold image. Fig 3.c and 4.c shows the FCM segmented image. Tumor region is exactly located by doing morphological operations, which is displayed in Fig 3.d and 4.d. It is noted that Fig 3.d having full black image, which represents that input image doesn't have tumor, whereas tumor location is displayed in Fig 4.d.

Fig's 5 and Fig's 6 illustrates the EFCM outputs stage by stage for normal and tumor image respectively. First image shows the converted RGB (fig 5.a and 6.a), second and third shows T and F domain image (fig 5.b,5.c and 6.b,6.c). Enhanced image is shown in fig 5.d and fig 6.d. Binarized T and F images are shown in fig 5.e, 5.f and

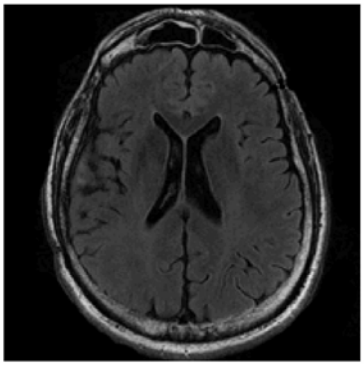


Fig. 3.a: RGB MRI image

Fig. 3.b: Threshold image

Fig. 3.c: FCM segmented image

Fig. 3.d: Morphological output

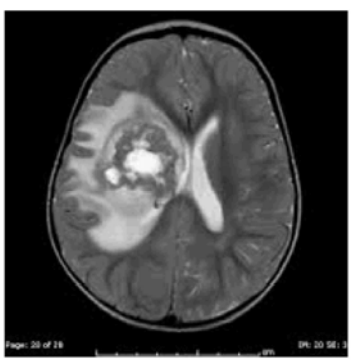


Fig. 4.a: RGB tumor image

Fig. 4.b: Threshold image

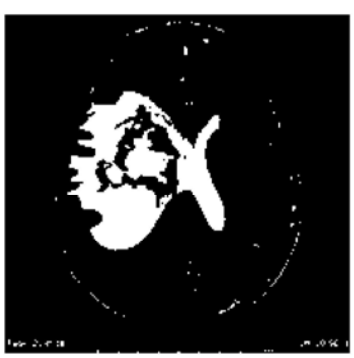


Fig. 4.c: FCM segmented image

Fig. 4.d: Morphological output

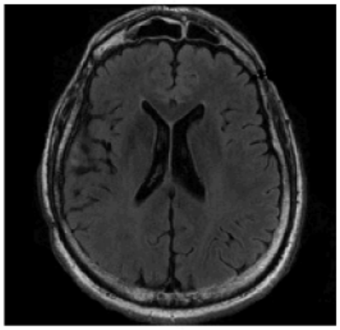


Fig. 5: a Original

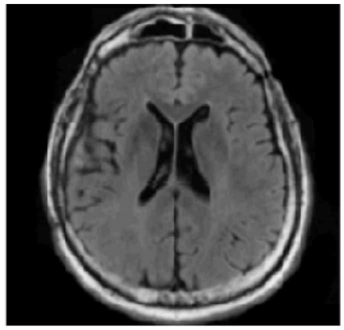


Fig. 5.b: T-domain

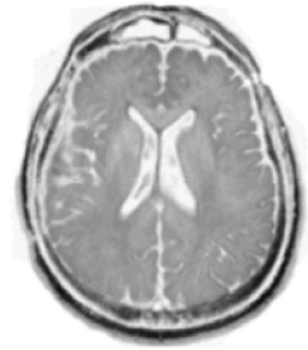


Fig. 5.c: F domain

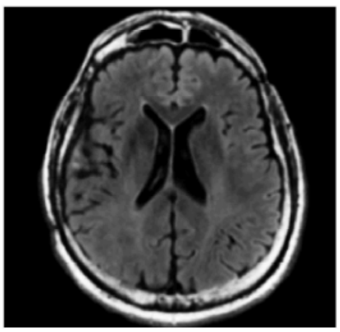


Fig. 5.d: Enhanced

Fig. 5.e: Binarized T-image

Fig. 5.f: Binarized F-image

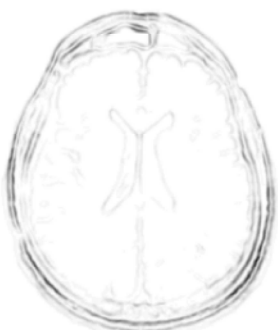


Fig. 5.g: Homogeneity image

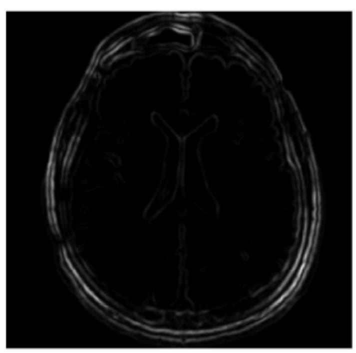


Fig. 5.h: Indeterminate image

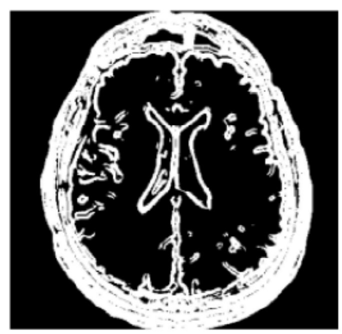


Fig. 5.i: Binary image of T,I,F

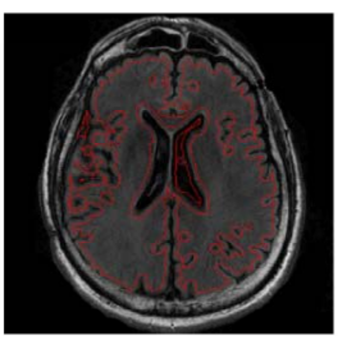


Fig. 5.J: Segmented area

Fig. 5.k: EFCM output

Fig. 5.l: Morphological output

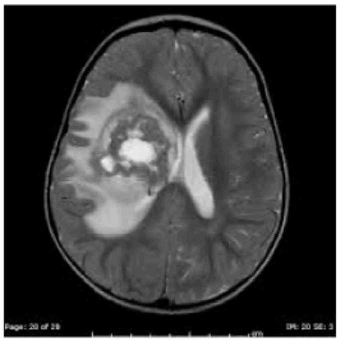


Fig. 6.a: original RGB image

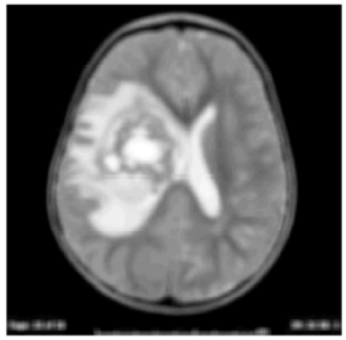


Fig. 6.b: T-domain

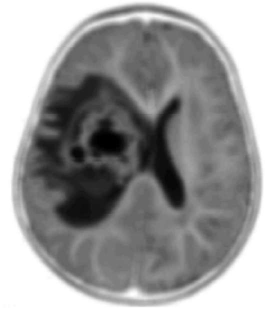


Fig 6.c: F domain

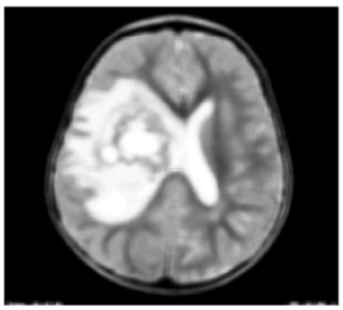


Fig. 6.d: Enhanced

Fig. 6.e: Binarized T-image

Fig. 6.f: Binarized F-image

Fig. 6.g: Homogeneity

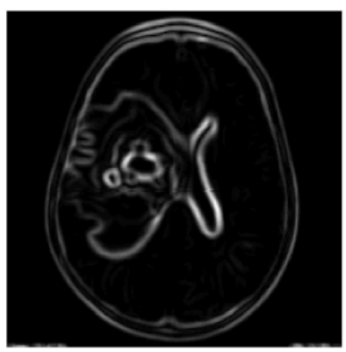


Fig. 6.h: Indeterminate image

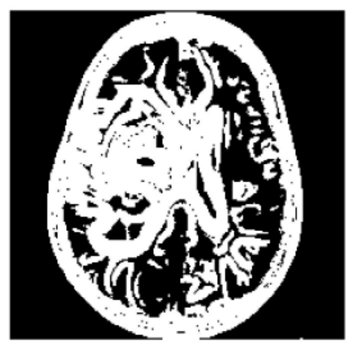


Fig. 6.i: Binary image of T,I,F

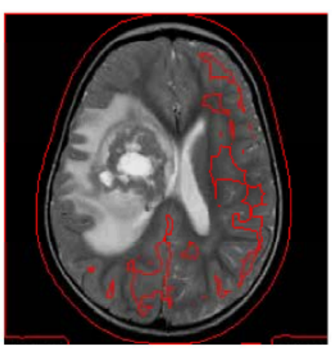


Fig. 6.J: Segmented area

Fig. 6.k: EFCM output

Fig. 6.l: Morphological output

fig 6.e,6.f. Fig 5.h and 6.h shows the intermediate images of normal and tumor image. Binary image of T, I, F is shown in Fig 5.i and 6.i. The segmented area and EFCM output are shown in fig 5.j, 5.k and Fig 6s.j, 6.k respectively. Fig 5.l and Fig 6.l shows the morphological output which highlights the tumor images.

The performances of segmentation algorithms are compared through the performance indices. The image segmentation parameters are used to compare the segmentation results for the same set of images. (i) Rand Index (RI): It counts the fraction of pairs of pixels whose labeling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception. The Rand index or Rand measure is a measure of the similarity between two data clusters. (ii) Global Consistency Error (GCE): It measures the extent to which the segmentation can be viewed as a refinement of the other. If one segment is a proper subset of the other, then the pixel lies in an area of refinement and the error should be zero. If there is no subset relationship, then the two regions overlap in an inconsistent manner. (iii) Variation of Information (VOI): It defines the distance between two segmentations as the average conditional entropy of the segmentation given the other and thus measures the amount of randomness in the segmentation which cannot be explained by the other.

The Table 1 shows comparison of the proposed EFCM with FCM and conventional watershed technique in terms of VOI, GCE and RI.

Table 1: Performance metrics of segmentation methods

Image type	Method	VOI	GCE	RI
Normal	Watershed	5.4365	0	0.1032
Tumor	Watershed	4.7906	0.0246	0.3206
Normal	FCM	5.4354	0.0076	0.1118
Tumor	FCM	4.7670	0.0239	0.3286
Normal	EFCM	0.0368	0	0.0923
Tumor	EFCM	0. 2733	0	0.9105

In summary, the proposed method not only can segment the clear images, but also can segment noisy images, due to the fact that the proposed approach can handle the indeterminacy of the images well.

CONCLUSIONS

In this paper, an enhanced FCM approach is proposed. The image is detailed by using three subsets. A new ë-mean operation is proposed to reduce the set's indetermination. Finally, the proposed method is employed to brain tumor image. From the table 1 it is observed that the performance of EFCM uplifts than the watershed and FCM method. EFCM is having low VOI, GCE and RI values (it is a well known fact that the performance indices should be low for a good segmentation method). From the segmented outputs and from the observations it is concluded that EFCM is producing better results. The experiment results show that the proposed method performs better than the conventional techniques also with the performance values. The proposed approach can find more applications in image processing and patter recognition.

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