Brain Tumour Detection of MR Images using Intuitionistic Fuzzy Sets

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ABSTRACT
This paper proposes segmentation and detection of tumor of MRI brain images using a novel method provided by Attanassov intuitionistic fuzzy set theory. Segmentation of such type can be important in detecting different type of tumor, stroke, paralysis etc which are developed inside brain. This type of segmentation is very important in detecting. Segmentation becomes very difficult in medical images which are not properly illuminated. A image segmentation approach intuitionistic fuzzy set theory and a new membership function called restricted equivalence function from automorphisms, for finding the membership values of the pixels of the image is proposed here. An intuitionistic fuzzy image is constructed using Sugeno type intuitionistic fuzzy generator. A new distance measure Intuitionistic Fuzzy Divergence is used. From this Intuitionistic Fuzzy Divergence edge detection is carried out. The results showed a much better performance on poor illuminated medical images, where the brain tumor is detected properly.

Keywords
Brain MRI, Skull Stripping, Intuitionistic Fuzzy Set, Restricted Equivalence Function, Membership Function, Hesitation degree, Edge Detection , Thresholding, Tumour.

1. INTRODUCTION
Image segmentation is one of the major step in medical image processing. Imaging can be used to visualize different anatomical parts of human body from X-Ray, ultrasound, MRI etc. Brain Imaging is useful in detection of brain tumor, stroke, paralysis etc. Segmentation using edge detection [1] as there are many popular methods such as (Prewitt detector , Edge detector, Gaussian of Laplacian, Canny edge detector etc.) can extract region of interest, boundaries due to changes in brightness level, the edges obtained are not very smooth and correct.

Research has been carried out using Fuzzy set theory [2]. Fuzzy c-means clustering [4] clusters image into several regions. Wu et al [5] used K-means clustering for segmenting brain tumor image. Murugavalli *et al* [6] used neuro fuzzy technique for segmenting brain tumor region. Li *et al* [7] worked on fuzzy clustering on medical images. Xu *et al* [8] suggested an edge detection technique for segmentation using rank ordered filter. Recently, intuitionistic fuzzy set (IFS) theory was used to improve accuracy and uneven illumination in detecting the tumor. K. T. Atanassov [23] primarily introduced the concept of IFS. Chaira T *et al* [9] used IFS technique to detect edges of medical image. M. M. Mushrif *et al* [27] developed A-ifs histon based multithresholding algorithm for color image segmentation. Y.K.Dubey *et al* [28] suggested segmentation of brain MR images using intuitionistic fuzzy clustering algorithm.

Most widely and simpler method for segmentation is thresholding. Threshold can be local or global. In Global thresholding the threshold point is selected for the entire image but this method does not work for uneven illumination, Whereas, In case of local threshold, the threshold points are obtained for each subregions of the image. Kapur *et al.* [10], Sahoo *et al.* [11], and Sankur *et al* [12] used the concept of entropy for thresholding. Otsu [13] is used to select the threshold for maximum seperability of class. Couto *et al* [14] [15] suggested image thresholding methods using IFS for calculating hesitation degree and to find intuitionistic fuzzy entropy to calculate optimum threshold level.

Several researchers segmented brain MRI for tumor detection on medical images. Segmenting brain region is an important in detecting various abnormalities such as Brain tumor, Stroke, paralysis, and breathing difficulty.

This paper provides segmentation and detection of tumor of Magnetic Resonances brain images using intuitionistic fuzzy representation and intuitionistic fuzzy divergence method to find optimum threshold point, skull stripping is carried out which is a major preprocessing step in MRI brain imaging application since it removes the non cerebral and intracranial tissue or non brain region because it does not incorporates any disease related to that part. A Restricted equivalence function from automorphisms is used for calculating membership degree of image. Sugeno type intuitionistic fuzzy generator is used to calculate non-membership and hesitation degree. A distance method intuitionistic fuzzy divergence is used to find the optimum threshold values. This method has better performance and works well when compared with the crisp, fuzzy, and intuitionistic fuzzy methods.

The rest of the paper is organized as follows. In section 2, algorithm for Skull stripping is explained. Section 3 introduces preliminaries on IFSs. Section 4 provides the details of Restricted equivalence function for calculating the membership function. Section 5 introduces the concept of Sugeno type intuitionistic fuzzy generator. Section 6 introduces Intuitionistic fuzzy divergence.

2. SKULL STRIPPING OF BRAIN MR IMAGES
Skull Stripping is used as a preprocessing step for the removal of non-cerebral tissues such as skull, scalp, vein or meninges [16]. Numerous techniques have been applied in skull

stripping studies including region-based segmentation techniques such as watershed techniques [16] [17] [18], region growing techniques [19] [20] and mathematical morphology [1] [21]. Skull stripping using mathematical morphology experimenting on using the double and Otsu threshold values in order to address the drawback of choosing the incorrect threshold values. As morphology requires prior binarization of the image, a mathematical morphology segmentation using double and Otsu's thresholding. **Fig 1** illustrates the non-cerebral tissues (skull, cerebrospinal fluid, meninges) to be extracted.

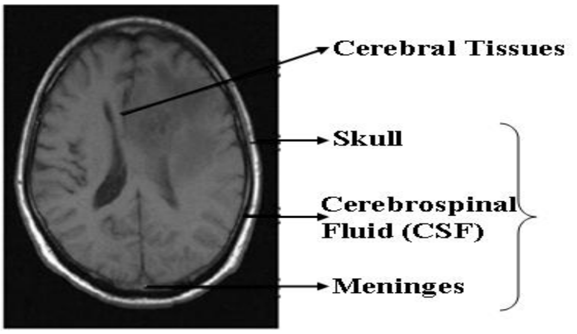

Fig 1: Anatomical of Cerebral & Non-Cerebral Tissues

Algorithm for Skull Stripping: Fig 2 shows the process flow of the Skull Stripped algorithms.

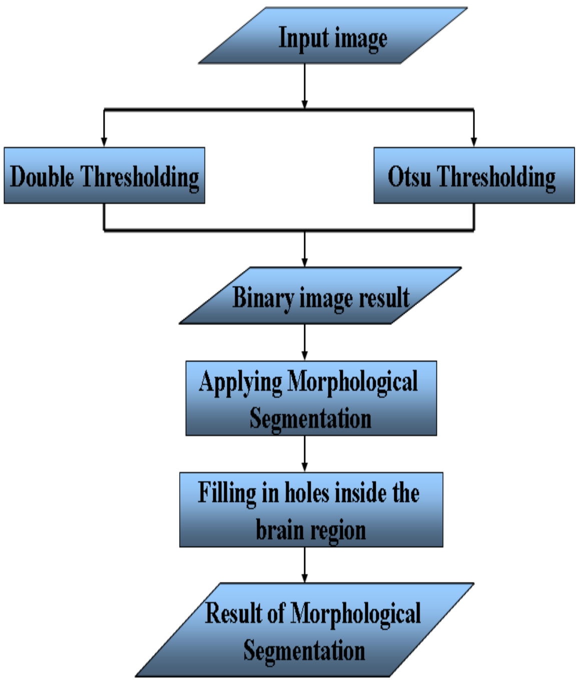

Fig 2: Process flow of the mathematical morphology operations algorithm

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2.1 Methodology:

2.1.1 Input Image: Two-dimensional axial view brain MRI data sets are collected from Lata Mangeshkar & N.K.P Salve institute, nagpur.

2.1.2 Thresholding: Two Thresholding methods are used that is Double Thresholding and Otsu's Method.

Double Threshold: The selection of the double threshold values means choosing on the dual threshold values which defines the intensities of the non-cerebral tissues as shown in Table 1 below.

Non-Cerebral Tissue	Average Intensities
Skull	0.70-1.00
CSF	0.00-0.20
Meninges	0.15-0.50
Cerebral Tissues	0.2-1.0

Table 1: Average Intensities

The binary image g(x,y) of the original image, f(x,y) using double threshold values is given by: --1

$$g(x,y)=\begin{cases}1; 0.1\le f(x,y)\le 0.7\\ 0\end{cases}$$

Otsu Threshold: It is used to obtain only single thresholding. The binary image g(x,y) of the original image, f(x,y) using Otsu threshold values is given by:

$$g(x,y)=\begin{cases}1;\ f(x,y)\ge 0.4\\ 0; otherwise\end{cases} \quad \text{--2}$$

2.1.3 Mathematical Morphology Segmentation:

Mathematical morphology operations [1] (i.e. erosion, dilation and region filling) are applied to the binary image to remove the non-cerebral tissue. The concept is to convolve the binary image with a structuring element to produce the skull stripped image. Since the brain is an oval-shape image, a disk shape structuring element.

1) Erosion: Erosion is used to remove the pixels on the MRI brain image's boundaries, thus removing the non-brain regions such as skull, cerebrospinal fluid and meninges. As defined in [9], erosion of binary image, *A* using structuring element, *B* can be denoted as:

This equation indicates that the erosion of A by B is the set of all points z such that B, translated by z, is contained in A.

2) Dilation : The morphological dilation is applied in order to enhance and connect all the intracranial tissues within the image. Mathematical morphology dilation [9] of binary image, *A* using the structuring element, *B* but with different size can be denoted as:

$$A \oplus B = \left\{ z \mid (\hat{B})_z \cap A \neq \phi \right\} \quad \text{--4}$$

3) Region Filling: It is used to fill in holes inside the brain region to enhance the appearance of the skull-stripped brain image.

2.3 Result of Skull Stripping:

Normal Brain Image:

Original Image Skull Stripped Image

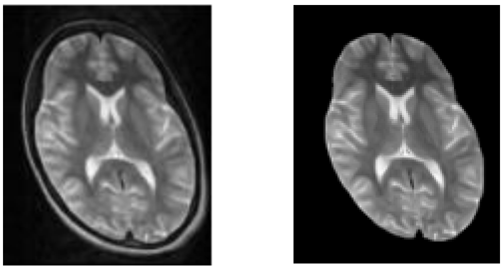


Fig 3: Skull Stripping result of a Normal brain Image

Abnormal Brain Image:

Original Image Skull Stripped Image

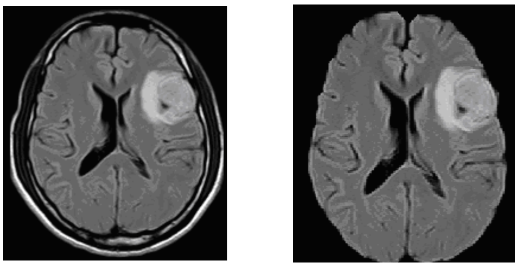


Fig 4: Skull Stripping of an Abnormal brain Image

3. INTUITIONISTIC FUZZY SET

In IFS Membership degree is a measure of belongingness and Non-Membership degree is equal to 1 minus degree of membership. Intuitionistic fuzzy set (IFS) was introduced by Atanassov [22] [23] and Atanassov *et al* [24]. It states that the degree of non-membership is not always equal to 1 minus degree of membership, but there may be some hesitation degree. "Intuitionistic fuzzy index or hesitation degree" arises due to the lack of knowledge or "personal error" Attanassov *et al* [24] in calculating the distances between two fuzzy sets.

An IFS *A* in *X* may be represented as:

$$A = \{(x, \mu_A(x), v_A(x), \pi_A(x)) \mid x \in X\} \quad \text{--5}$$

With the condition

$$\pi_A(x) + \mu_A(x) + v_A(x) = 1 \quad \text{--6}$$

Where,

Such that: $0 \leq \mu_A(x) + v_A(x) \leq 1$ for each $x \in X$

$\mu_A(x)$ - Membership degree

$v_A(x)$ - Non-Membership degree

$\pi_A(x)$ - Hesitation degree

of an element *x* in a finite set *X* with the necessary condition.

4. RESTRICTED EQUIVALENCE FUNCTION

Restricted equivalence function is used to find the membership function. If $\varphi_1 and \varphi_2$ are two automorphisms in a unit interval, then

$$REF(x, y) = \varphi_1^{-1}(1 - |\varphi_2(x) - \varphi_2(x)|)$$
$$c(x) = \varphi_2^{-1}(1 - \varphi_2(x)) \quad \text{--7}$$

is a restricted equivalence function where "*c*" is a strong negation.

Calculating the membership function:

Let us consider $\varphi_2(x) = x$ & $\varphi_2(y) = y$

Then, Restricted equivalence function becomes:

$$REF(x, y) = \varphi_1^{-1}(1 - |\varphi_2(x) - \varphi_2(y)|)$$
$$REF(x, y) = \varphi_1^{-1}(1 - |x - y|) \quad \text{--8}$$

Let,

$$\varphi_1(x) = \ln[x(e^1 - 1) + 1] \quad \text{--9}$$

Taking inverse we have,

$$\varphi_1^{-1}(x) = \frac{(e^x - 1)}{(e^1 - 1)} \qquad \text{--10}$$

So,

$$REF(x, y) = \frac{(e^{1-|x-y|} - 1)}{(e^1 - 1)} \qquad \text{--11}$$

$$REF(x, y) = \frac{1}{(e^1 - 1)}(e^{1-|x-y|} - 1) \qquad \text{--12}$$

Above equation satisfies the conditions for **Restricted equivalence function.**

Let us define the membership function μ : [0, 1] such that

$$\mu_A(x) = REF(x, y) \qquad \text{--13}$$

Hence, the **membership function** becomes:

$$\mu_A(x) = 0.582(e^{1-|x-y|} - 1) \qquad \text{--14}$$

Where, x and *y* relate to the image pixel and the mean for a certain threshold "*t*," respectively

5. CONSTRUCTION OF IFS

IFS are constructed using Sugeno type intuitionistic fuzzy generator [25]. **Sugeno type intuitionistic fuzzy generator** is written as:

$$N(\mu_A(x)) = (1 - \mu_A(x))/(1 + \lambda.\mu_A(x)) \qquad \text{--15}$$

where $N(1) = 0$ and $N(0) = 1$ for $\lambda > 0$.

Intuitionistic fuzzy set may be written as

$$A_{IFS} = \left\{ \left(x, \mu_A(x), \frac{1 - \mu_A(x)}{1 + \lambda\mu_A(x)} \right) | \, x \in X \right\} \qquad \text{--16}$$

The hesitation degree from (2),

$$\pi_A(x) = 1 - \mu_A(x) - \frac{1 - \mu_A(x)}{1 + \lambda\mu_A(x)} \qquad \text{--17}$$

Since the denominator $1 + \lambda\mu_A(x)$ is greater than 1, so,

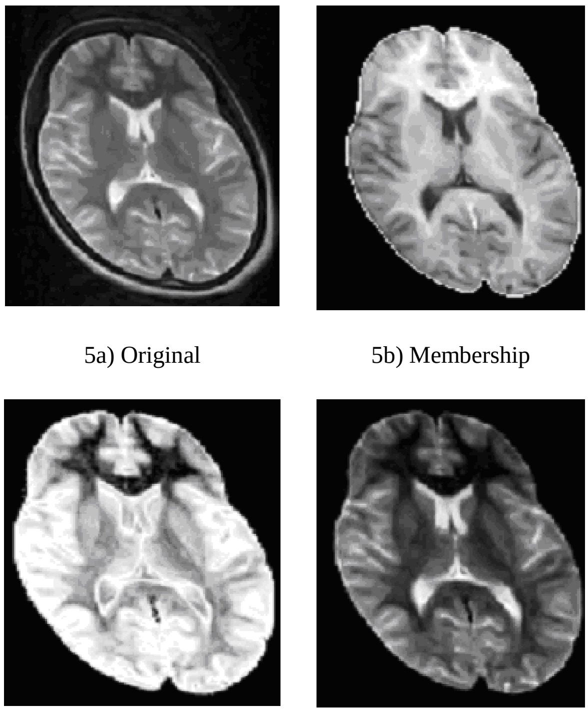
$\dfrac{1 - \mu_A(x)}{1 + \lambda\mu_A(x)}$ is less than 1.

Hence,

$$\begin{aligned} \mu_A(x) &= 0.582(e^{1-|x-y|} - 1) \\ \pi_A(x) &= 1 - \mu_A(x) - \nu_A(x) \\ \nu_A(x) &= 1 - (\mu_A(x) + \pi_A(x)) \end{aligned} \qquad \text{--18}$$

Hence, $\mu_A(x), \pi_A(x), \nu_A(x)$ are analyzed.

Intuitionistic Fuzzy Set Representation Result: Results in **Fig 5a** below shows Original, **Fig 5b** shows Membership, **Fig 5c** shows non-membership & **Fig 5c** shows Hesitation in deciding the membership of pixel.



5a) Original

5b) Membership

5c) Hesitation

5d) Non-Membership

Fig 5: Intutionistic Representation of membership, Non-membership and Hesitation degree.

6. A NEW DISTANCE MEASURE-INTUITIONISTIC FUZZY DIVERGENCE

In order to find a distance between two objects knowledge of distance between two fuzzy set is necessary. There are some popular distance measures between two fuzzy sets A and B such as Intuitionistic Hamming distance and intuitionistic Euclidean distance. A new distance measure using IFS is Intuitionistic Fuzzy Divergence (IFD) [26] is used where the three parameters membership, non-membership and hesitation degree has been considered.

Let $A = \{(x, \mu_A(x), v_A(x) \mid x \in X\}$ and $B = \{(x, \mu_B(x), v_B(x) \mid x \in X\}$ be the two intuitionistic fuzzy sets with the hesitation degree calculated as $\pi_A = 1 - \mu_A(x) - v_A(x)$ and $\pi_B = 1 - \mu_B(x) - v_B(x)$.

Intuitionistic fuzzy divergence is between the images A and B is given by:

$$IFD(A,B) = \sum_i \sum_j 2 - [1 - \mu_A(a_{ij}) + \mu_B(b_{ij})] e^{\mu_A(a_{ij}) - \mu_B(b_{ij})}$$
$$[1 - \mu_B(b_{ij}) + \mu_A(a_{ij})] e^{\mu_B(b_{ij}) - \mu_A(a_{ij})} + (2 - [1 - (\mu_A(a_{ij}) - \mu_B(b_{ij})) +$$
$$(\pi_B(b_{ij}) - \pi_A(a_{ij}))] e^{\mu_A(a_{ij}) - \mu_B(b_{ij}) - (\pi_B(b_{ij}) - \pi_A(a_{ij}))}$$
$$-[1 - (\pi_B(b_{ij}) - \pi_A(a_{ij})) + (\mu_A(a_{ij}) - \mu_B(b_{ij}))]$$
$$e^{\pi_B(b_{ij}) - \pi_A(a_{ij}) - (\mu_A(a_{ij}) - \mu_B(b_{ij}))}$$

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6.1 Algorithm for Brain tumour Detection

Steps for Brain tumour Detection Algorithm is explained as follows:

Step 1: 16 Edge Detected templates of 3X3 matrix with values a,b,0 represent pixels of edge templates and values of a, b are chosen ranging from 0 to 1.

Step 2: Apply the edge detected templates over the image placing the center of each point (i,j) template over the normalized image.

Step 3: Calculate Intuitionistic Fuzzy Divergence between each element of template and the image and choose the minimum IFD value.

$$IFD(i, j) = \max_N [\min_r (IFD(A, B)]$$

Step 4: Choose the maximum of all 16 the minimum of Intuitionistic Fuzzy Divergence values.

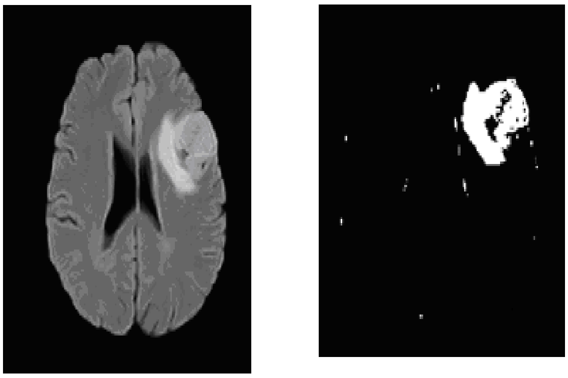
Step 5: Positioned the maximum value at the point where the template is centered over the image.

Step 6: A new Intuitionistic Fuzzy Divergence matrix has been formed and threshold value is chosen and then thinning is applied.

Step 7: An tumour detected image is obtained.

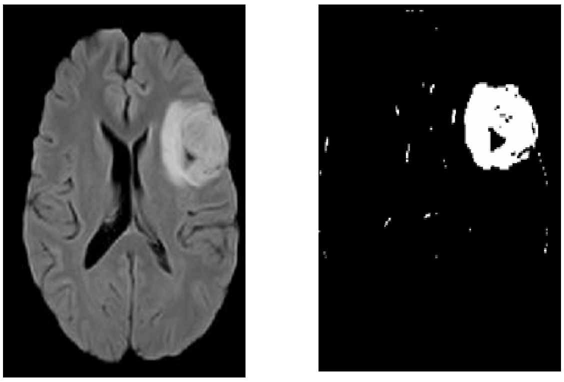
7. EXPERIMENTAL RESULTS

Fig 6a) & 7a) shows the tumour detected abnormal Brain image and Fig 6b) & 7b) shows the Abnormal Brain image with tumor detected by applying Intuitionistic Fuzzy Divergence .



6a) Skull stripped image   6b) IFD image After applying optimum threshold

Fig 6: Abnormal Brain Image showing tumor detection with a=0.63; b=0.48;



7a) Skull stripped image   7b) IFD image After applying optimum threshold

Fig 7: Abnormal Brain Image showing tumor detection with a=0.63; b=0.48;

8. CONCLUSIONS

This paper provides a approach to detect tumor region and thresholding using IFS theory and image results are observed to be better or almost similar to other recent methods and fuzzy methods .A new distance measure Intuitionistic fuzzy divergence (IFD) is used to determine the optimum threshold values used for segmentation. IFS considers more number of uncertainties (membership function and hesitation degree), and as medical images are low contrasted image with vague region/boundaries, IFS give better result. Thus, when membership function is not always accurately defined due to lack of personal error, an IFS may help in solving the problem.

9. REFERENCES

[1] Gonzalez R C & Woods W E, *Digital Image Processing*, **2nd edn** (Prentice Hall, New York) 2002.

[2] Chaira T & Ray A K, Threshold selection using fuzzy set theory, *Pattern Recognition Lett*, **25** (2004) 865-874.

[3] Sankur B & Sezgin M, Survey over image thresholding techniques and quantitative performance evaluation, *J Electron Imaging*, **13** (2004) 146-165.

[4] Bezdek J C, Hall O C & Clark L P, Review of MR segmentation technique in pattern recognition, *Med Phys*, **10** (1993) 33-48.

[5] Wu M N, Lin C C & Chang C C, Brain tumor detection using color- based K- means clustering segmentation, in *Proc IEEE Third Int Conf on Information Hiding & Multimedia Signal Processing* (IHP-MSP) (IEEE Explorer, California) 2007.

[6] Murugavalli S & Rajamani V, An improved implementation of brain tumour detection using segmentation based on neuro fuzzy technique, *J Comput Sci*, **3** (2007) 841-846.

[7] Li C H & Yuen P C, Regularized color clustering of medical image database, *IEEE Trans Med Imaging*, **19** (2000) 150-155.

[8] Xu X, Yang X & Wang Y, A method based on rank-ordered filter to detect edges in cellular image, *Pattern Recogn Lett*, **30** (2009) 634-640.

[9] Chaira T & Ray A K, A new measure using intuitionistic fuzzy set theory and its application to edge detection, *Appl Soft Comput*, **8** (2008) 919-927.

[10] J. N. Kapur, P. K. Sahoo, and A. K. C. Wong, "A new method of gray level picture thresholding using the entropy of the histogram," *Comput Vis., Graph. Image Process.*, vol. 29, pp. 273–285, 1985.

[11] P. K. Sahoo, S. Soltani, A. K. C. Wong, and Y. C. Chen, "A survey of thresholding techniques," *Comput. Vis., Graph. Image Process.*, vol. 41, no. 2, pp. 233–260, 1988.

[12] B. Sankur andM. Sezgin, "Survey over image thresholding techniques and quantitative performance evaluation," *J. Electron. Imag.*, vol. 13, no. 1, pp. 146–165, 2004.

[13] N. Otsu, "A Threshold selection method from gray level histograms," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-9, no. 1, pp. 62–66, Jan. 1979.

[14] P. Couto, M. Pagola, H. Bustince, E. Barranechea, and P. Melo-Pinto, "Image segmentation using A-IFS," in *Proc. Process. IPMU*, Malaga, 2008, pp. 1620–1627.

[15] P. Couto, M. Pagola, H. Bustince, E. Barranechea, and P. Melo-Pinto, "Uncertainty in multilevel thresholding using Atanassov's Intuitionistic fuzzy sets," in *Proc. IEEE World Congr. Comput.*, Hong Kong, China, 2008, pp. 330–335.

[16] H.K. Hahn and H.-O. Peitgen, "The Skull Stripping Problem in MRI Solved by a Single 3D Watershed Transform," *Lecture Notes in Computer Science, Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, Vol. 1935/2000, pp. 134-143, 2000.

[17] F. Segonne, A.M. Dale, E. Busa, M. Glessner, D. Salat, H.K.Hahn and B. Fischl, "A hybrid approach to the skull stripping problem in MRI," *NeuroImage*, 22(3), 1060–1075, 2004.

[18] V. Grau, A.U.J. Mewes, M. Alcaniz, R. Kikinis and S.K.Warfield, "Improved watershed transform for medical image segmentation using prior information," *IEEE Trans. Med. Imag.*, 23(4), 447–458, 2004.

[19] R. Adams and L. Bischof, "Seeded region growing," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 16(6), 641–646, 1994.

[20] S.A. Hojjatoleslami and J. Kittler, "Region Growing: A New Approach," *IEEE Transactions on Image Processing*, Vol. 7, No. 7,1998.

[21] T. Kapur, W.E.L. Grimson, W.M. Wells and R. Kikinis, "Segmentation of Brain Tissue from Magnetic Resonance Images," *Medical Image Analysis*, Volume 1, Number 2, pp 109-127, 1996.

[22] K. T. Atanassov, *Intuitionistic Fuzzy Sets, Theory, and Applications* (Series in Fuzziness and Soft Computing). Heidelberg, Germany: Phisica-Verlag, 1999.

[23] K. T. Atanassov, "Intuitionistic fuzzy set," *Fuzzy Sets Syst.*, vol. 20, pp. 87–97, 1986.

[24] K. T. Atanassov and S. Stoeva, "Intuitionistic fuzzy set," in *Proc. Polish Symp. Interval Fuzzy Math.*, Poznan, Poland, 1993, pp.23–26.

[25] M. Sugeno, "Fuzzy measures and fuzzy integral: A survey," in *Fuzzy Automata and Decision Processes*, M. M. Gupta, G. S. Sergiadis, and B. R. Gaines, Eds. Amsterdam, The Netherlands: North Holland, 1977, pp. 89–102.

[26] T. Chaira and A. K. Ray, "A new measure on intuitionistic fuzzy set and its application to edge detection," *Appl. Soft Comput.*,vol. 8, no. 2, pp. 919–927, 2008.

[27] M. M. Mushrif and A. K. Ray. A-ifs histon based multithresholding algorithm for color image segmentation. IEEE Signal Processing Letters, 16(3), March 2009.

[28] Y.K.Dubey and M.M.Mushrif. "Segmentation of brain MR images using intuitionistic fuzzy clustering algorithm." *Proceedings of the Eighth Indian Conference on Computer Vision, Graphics and Image Processing*. ACM, 2012.