

Firefly Algorithm Assisted Segmentation of Tumor from Brain MRI using Tsallis Function and Markov Random Field

V. Rajinikanth*, N. Sri Madhava Raja*, K. Kamalanand**

**Department of Electronics and Instrumentation Engineering,
St. Joseph's College of Engineering, Chennai 600 119,
Tamilnadu, India (e-mail: rajinikanthv@stjosephs.ac.in, nsrimadhavaraja@stjosephs.ac.in).*

***Department of Instrumentation Engineering, M.I.T. Campus,
Anna University, Chennai 600 044, Tamilnadu, India (e-mail: kamalanand@mitindia.edu)*

Abstract: Image segmentation plays a vital role in various medical applications for automated disease examination. In this paper, heuristic algorithm assisted approach is proposed to extract the tumor from a two dimensional (2D) magnetic resonance image. The proposed work is segregated into two processing regions, such as pre-processing and post-processing section. In pre-processing, multi-level thresholding is applied for the 2D MR image using the Firefly Algorithm (FA) and Tsallis entropy function to cluster the similar image pixels based on an ideal intensity thresholds. For post-processing section, an image filter is initially considered to eliminate the skull region. The skull stripped image is then segmented into different partitions using Markov Random Field - Expectation Maximization (MRF-EM). This procedure helps to attain three image segments, such as White Matter (WM), Gray Matter (GM) and tumor mass. The proposed method is tested on the MR images acquired using T1, T2 and Flair modalities. Standard image quality measures are considered to analyse the accuracy of pre-processing section. Further, the tumor mass is considered to examine the exactness in post-processing section. The efficacy of the proposed method is applied and validated using the BraTS 2D MRI dataset and achieved better values of Jaccard similarity coefficient and dice similarity co-efficient for all three modalities.

Keywords: Brain MRI; Tumor; Firefly algorithm; Tsallis entropy; Markov random field; Expectation maximization

1. INTRODUCTION

In medical discipline, image segmentation is widely used to divide an image frame into subsets of homogenous sections that reveal various anatomical or pathological sections. This procedure is used in several medical areas, such as cancer diagnosis (Raja et al., 2015), species identification (Manickavasagam et al., 2014), dye concentration analysis (Kamalanand and Ramakrishnan, 2015) and retinal disease modelling (Raja et al., 2012). In general, medical image segmentation is widely adopted to extract an abnormal tissue or lesion from the image frame for disease examination (Abdel-Maksoud et al., 2015; Balafar et al., 2010; Chaddad, 2015; Despotovic et al., 2015; Elazab et al., 2015; Khandani et al., 2009; Larobina et al., 2015; Palani et al., 2016; Rajesh Sharma. and Marikkannu, 2015; Yazdani et al., 2015).

Image multi-thresholding is an initial step in the image processing discipline, which helps in separating an image into non-overlapping, homogenous sections enclosing interrelated objects. Imaging literature provides the information about a number of segmentation practice proposed and implemented by most of the researchers (Agrawal et al., 2013; Sathya and Kayalvizhi, 2010; Tuba, 2015). Image thresholding procedure is categorised as local level threshold and global level threshold. In the local level thresholding, various threshold values are allocated for every

portion of the image. For global level thresholding, a single threshold value is assigned to the whole image. During this process, a probability density function of the grey level histogram is used to find the threshold value based on parametric or a nonparametric approach (Akay, 2013).

Parametric approach in image thresholding is complex and time consuming. The final outcome by this procedure is also affected due to the image quality and initial conditions. Hence, non-parametric approaches are widely adopted by researchers to solve gray and colour image segmentation problem (Raja et al., 2014; Rajinikanth and Couceiro, 2015).

In this paper, image multi-thresholding is proposed using maximal entropy criterion, a non-parametric approach. Recent multi-level thresholding works are performed using heuristic algorithms, due to its reduced computational cost (Kai Chen et al., 2016).

From the literature, it can be observed that, image segmentation work is extensively implemented in medical discipline to extract significant information from medical images. Automated tumor segmentation for 2D and 3D brain MR image is one of the key research field for diagnosis and prognosis of diseases (Chaddad and Tanougast, 2016; Jianjun et al., 2012; Lu et al., 2006). Recent research reveal a number of schemes are available to segment the tumor from the MRI dataset (Christ and Parvathi, 2012).

In this paper, Tsallis entropy based global thresholding scheme is considered to segment 2D MR image database. Tsallis entropy criterion was initially proposed in 1988 and is a non-extensive statistical approach, being typically adopted in image processing applications (Tsallis, 1988). The combination of Tsallis function and various heuristic algorithms have been presented over the past years (Raja et al., 2012). The Firefly Algorithm (FA) assisted Tsallis entropy based global thresholding is employed for segmentation in this work.

The thresholded image is then divided into various regions using the Markov Random Field (MRF) approach (Jung and Lee, 2015; Zhang et al., 2001). MRF is a probabilistic method considered in several segmentation works. It makes use of the spatial information of the image based on Markov process. This process is based on stochastic modeling approach and works well on images with various uncertainties, such as noise, degradation, imprecise information, partial data (Palani et al., 2016). In this paper, the segmentation process is implemented and validated using the 2D MRI existing in BRAINIX and BraTS dataset.

2. METHODOLOGY AND IMPLEMENTATION

This paper mainly focuses on developing a heuristic algorithm based tool to segment the tumor from the two dimensional (2D) Magnetic Resonance (MR) images recorded using the T1, T2 and Flair (F) modalities (from BRAINIX and BraTS dataset).

The proposed work is segregated into two processing sections, such as pre-processing section and post-processing section. Implementation of the proposed methodology is depicted in Figure 1. The pre-processing work involves the following operations: optimal multi-thresholding, quality measure computation and skull stripping. In post-processing section, MRF – MAP generation, tumor segmentation and analysis is executed.

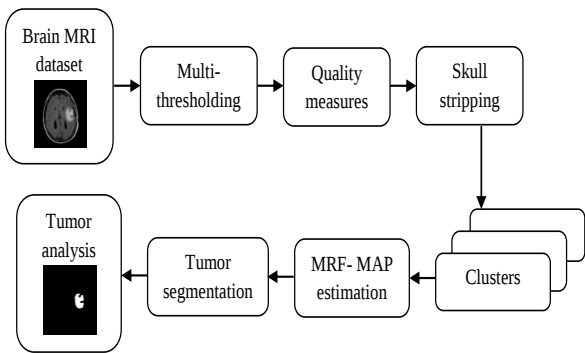


Fig. 1 Structure of the proposed segmentation process

2.1 Tsallis entropy

In general, the entropy is related with the measure of chaos within a system. Shannon primarily considered the entropy to compute the uncertainty regarding the information content of the system (Bhandari et al., 2015). Shannon also assured that, when a physical system is separated as two statistically free

subsystems A and B , then the entropy value can be expressed as:

$$S(A+B) = S(A) + S(B) \quad (1)$$

Based on Shannon's theory, a non-extensive entropy concept was proposed by Tsallis and defined as:

$$S_q = \frac{1 - \sum_{i=1}^T (p_i)^q}{q-1} \quad (2)$$

where, T is the system potentials and q is the entropic index (Agrawal et al., 2013; Sathya and Kayalvizhi, 2010).

Eq. (2) will meet the Shannon's entropy when $q \rightarrow 1$.

The entropy value can be expressed with a pseudo additivity rule as:

$$S_q(A+B) = S_q(A) + S_q(B) + (1-q)S_q(A)S_q(B) \quad (3)$$

Tsallis entropy can be considered to find the optimal thresholds of an image. Consider a given image with L gray levels in the range $\{0, 1, \dots, L-1\}$, with probability distributions $p_i = p_0, p_1, \dots, p_{L-1}$.

Tsallis multi-level thresholding can then be expressed as:

$$f(T) = [T_1, T_2, \dots, T_k] = \text{argmax} [S_q^A(T) + S_q^B(T) + \dots + S_q^K(T) + (1-q)S_q^A(T)S_q^B(T) \dots S_q^K(T)] \quad (4)$$

where

$$S_q^A(T) = \frac{1 - \sum_{i=0}^{t_1-1} \left(\frac{P_i}{P^A}\right)^q}{q-1}, \quad P^A = \sum_{i=0}^{t_1-1} P_i$$

$$S_q^B(T) = \frac{1 - \sum_{i=t_1}^{t_2-1} \left(\frac{P_i}{P^B}\right)^q}{q-1}, \quad P^B = \sum_{i=t_1}^{t_2-1} P_i$$

$$S_q^K(T) = \frac{1 - \sum_{i=t_k}^{L-1} \left(\frac{P_i}{P^K}\right)^q}{q-1}, \quad P^K = \sum_{i=t_k}^{L-1} P_i$$

are subject to the following constraints:

$$|P^A + P^B| - 1 < S < 1 - |P^A - P^B|$$

$$|P^B + P^C| - 1 < S < 1 - |P^B - P^C|$$

$$|P^K + P^{L-1}| - 1 < S < 1 - |P^K - P^{L-1}|$$

During the multi-level thresholding process, the aim is to find the optimal threshold value T which maximizes the objective function $f(T)$. In the proposed work, the threshold value is chosen as $T=3$ thus the required probability values are P^A , P^B , and P^C . In this work, the maximization of function $f(T)$, which deals with the segmentation of a given image, is carried using the heuristic algorithm.

2.2 Firefly algorithm

The classical Firefly Algorithm (FA) was initially proposed by Yang (Yang, 2009). FA is a nature inspired meta-heuristic algorithm, in which flashing illumination patterns generated by fireflies are modeled using a suitable mathematical expression.

In the literature, a number of guiding procedures are adopted to enhance the search efficiency of the FA, such as random search, Lévy flight and Brownian walk (Raja et al., 2013). Among the existing methods, it is found that, FA driven by the Brownian walk offers better result in image segmentation application. Hence, in the proposed paper, the recent version of the FA discussed in (Raja et al., 2013; 2014) is considered.

The pseudo code of FA is presented below:

```

START;
  Initialize essential algorithm parameters,  $D$  and  $f(T)$ ;
  Generate initial locations of 'n' fireflies for  $x_i$  ( $i = 1, 2, \dots, n$ )
  Determine the intensity of  $i^{\text{th}}$  firefly based on  $i^{\text{th}}$   $f(T)$  value
For iter <  $M_{\text{iter}}$ ;
For  $i = 1, 2, \dots, n$ ;
For  $j = 1, 2, \dots, n$ ;
  If intensity of firefly  $j > i$ ,
    Calculate the Cartesian distance and move the  $i$  towards  $j$ ;
  End if;
  Repeat the above steps until iter =  $M_{\text{iter}}$ ;
  Estimate light intensity and update firefly positions;
End for j;
End for i;
  Sort the fireflies in descending order based on the rank and
  find the optimal value;
End if;
  Record the  $f(T)$  and optimal threshold values.
STOP;

```

Updated position of a firefly in a D - dimensional search can be expressed as;

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma d_{ij}^2} (X_j^t - X_i^t) + \alpha_1 \cdot \text{sign}(\text{rand} - 1/2) \oplus A |s|^{\alpha/2} \quad (5)$$

where, X_i^{t+1} is updated position of i^{th} firefly, X_i^t is initial position of i^{th} firefly, $\beta_0 e^{-\gamma d_{ij}^2} (X_j^t - X_i^t)$ is the attraction between fireflies, A is a random variable, β is the spatial exponent, α is the temporal exponent, and $\Gamma(\beta)$ is the Gamma function. The details of FA can be found in the literature. The FA parameters are assigned as; dimension of the search $D = T$; population of firefly is chosen as 30, number of iterations are assigned as 500 and the stopping criteria is the $f(T)$.

2.3 Image quality measures

The pre-processing work is the key step in the proposed segmentation work. Hence, the final outcome of the segmentation process mainly depends on the quality of the thresholded image. The multi-thresholding result is assessed

using well known image quality measures, such as the Root Mean Squared Error (RMSE), Normalized Absolute Error (NAE), Peak Signal to Noise Ratio (PSNR), Mean Structural Similarity Index Matrix (MSSIM), Normalized Cross Correlation (NCC) and Structural Content (SC) (Grgic et al., 2004; Wang et al., 2004).

2.4 Skull stripping

Skull stripping is the initial step in the brain image segmentation process. Skull stripping is essential to eliminate the skull and the background area from MRI for quantitative analysis. Skull stripping is normally performed using an image filter which separated the skull and the rest of the image sections by masking the pixels having similar intensity levels. In MR image, generally the skull/bone will have the maximum threshold value (threshold > 200) compared to other brain regions. Hence, the image filter is used to separate the brain regions based on a chosen threshold value. Then by employing the solidity property, the skull is stripped from the brain MRI (Chaddad and Tanougast, 2016).

2.5 Markov random field – Expectation maximization segmentation

Markov Random Field - Expectation Maximization (MRF-EM) is a widely considered methodology for gray scale image segmentation problems.

The MRF-EM can be expressed as follows;

Consider a gray scale test image $I = \{y(m,n) \mid 0 \leq y \leq L-1\}$.

Where y represents the intensity of the image at the pixel location (m, n) and L represents the number of threshold levels. During the segmentation process, MRF will approximate the formation of each pixel by mapping into a group of random labels defined as; $X = \{x_1, \dots, x_N\} \mid x_i \in 1$.

In this paper, the number of labels are assigned as three (since, during the multi-thresholding, T value is chosen as three as discussed in section 2.1). Hence, the MRF based segmentation will provide three labels such as white matter, gray matter and tumor. More details regarding the MRF based brain image segmentation are available in (Palani et al., 2016; Zhang et al., 2001)

Implementation of MRF algorithm is defined below:

Step 1: Set the number of labels (l) based on number of threshold values (T)

Step 2: Formation of cluster classes based on the chosen l

$$k_1 = \{y(m,n) = x_1 \mid 0 \leq y \leq t_1\}$$

$$k_2 = \{y(m,n) = x_2 \mid t_1 \leq y \leq t_2\}$$

$$k_3 = \{y(m,n) = x_3 \mid t_2 \leq y \leq L-1\}$$

Step 3: Determine the initial parameter set $\Theta^{(0)}_l$ and likelihood probability function $p^{(0)}(f_l | x_l)$.

Step 4: Update the MRF model $x^{(l)}$ such that, the energy function U is minimised.

$$X^* = \arg \min_x \left\{ \sum_i \left[\frac{(y_i - \mu_{x_i})^2}{2\sigma_{x_i}^2} \ln \sigma_{x_i} \right] + \sum_{N_i} V_c(x) \right\} \quad (6)$$

where, N_i is a four pixel neighbourhood and V_c is the clique potential.

Step 5: Execute the Expectation-Maximization algorithm to update the parameter set $\Theta^{(i)}$ constantly till the log likelihood of $p^{(i)}(f|x)$ is maximized.

Step 6: Display the labels such as white matter, gray matter and tumor.

2.6 Tumor analysis

The major aim of this research work is to extract the tumor region from the 2D brain MR image and to compute the tumor mass associated features for further analysis. In this paper, two types of data, such as brain MRI without the ground truth and brain MRI with the ground truth are considered. For both the cases, the tumor mass is analysed by extracting the key geometric features, such as spread area, major axis length, minor axis length, Equiv. diameter, Solidity and Extent. For the image with the ground truth, the parameters such as normalised are, Jaccard Similarity Coefficient (JSC), Dice Similarity Coefficient (DSC), False Positive Rate (FPR), and False Negative Rate (FNR) are computed (Chaddad and Tanougast, 2016). The mathematical expression is presented below;

$$JSC(I_{gt}, I_t) = I_{gt} \cap I_t / I_{gt} \cup I_t \quad (7)$$

$$DSC(I_{gt}, I_t) = 2(I_{gt} \cap I_t) / (|I_{gt}| + |I_t|) \quad (8)$$

$$FPR(I_{gt}, I_t) = (I_{gt} / I_t) / (I_{gt} \cup I_t) \quad (9)$$

$$FNR(I_{gt}, I_t) = (I_t / I_{gt}) / (I_{gt} \cup I_t) \quad (10)$$

where, I_{gt} represents the ground truth image and I_t stands for the segmented tumor image.

Further, the accuracy measures, such as precision, F-measure, sensitivity, specificity and accuracy are also computed (Lu et al., 2004; Moghaddam and Cheriet, 2010).

3. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed work. All experiments are carried out in a computer with AMD C70 Dual Core 1 GHz CPU, 4GB of RAM and Matlab R2010a software. The thresholding process is repeated 10 times for each image with threshold $T=3$ and the mean value among the trials are recorded as the optimal value. The proposed segmentation procedure is initially implemented on 256×256 sized 2D brain MR images (T1, T2, and Flair) available in BRAINIX dataset. Later, the proposed method is validated using 216×160 sized brain tumor segmentation database (BraTS-MICCAI challenge).

The segmentation process is initially executed on the MR image T1 slice number 8 ($T1_8$) existing in BRAINIX. It is an RGB image with a pixel size of 256×256 and bit depth of 32. The gray version of the RGB image $T1_8$ is considered for the segmentation process. Fig 2 (a) shows the RGB histogram of $T1_8$. Fig. 2 (b) and (c) depicts the histogram of the $T1_8$ gray scale image, before and after the adaptive histogram equalization process. Fig. 3 (a) shows the original $T1_8$ considered in this work. From Fig. 3 (a), one can observe that, the visibility of the T1 modality is poor compared to the T2 and Flair. Hence, the adaptive histogram equalization procedure is applied for all the T1 modality MR images considered in this study ($T1_9$, $T1_{10}$ and $T1_B$). Above said procedure helps to enhance the contrast of the gray test image. The enhanced image is then considered for the multi-thresholding using the FA and Tsallis. The FA based search constantly explores the three dimensional search space ($D=T=3$) till the Objective Function (OF) reaches a maximal value. At the end of the multi-thresholding process, thresholded image is offered by the algorithm (Fig. 3(b)). The quality of the multi-thresholding process is evaluated using the well known image quality measures existing in the literature (Grgic et al., 2004; Wang et al., 2004). Table.2 (a) and (b) shows the image quality measures considered in this work. Fig. 3(c) shows the SSIM map between the original and the thresholded image.

From this expectation maximization map, it can be observed that, the thresholding process enhances the tumor region by grouping the similar pixels. Thresholded image is then applied to an image filter, which separates the skull and soft brain tissue region as shown in Fig. 3(d) and Fig. 3(e). This brain region is then considered for the post-processing work.

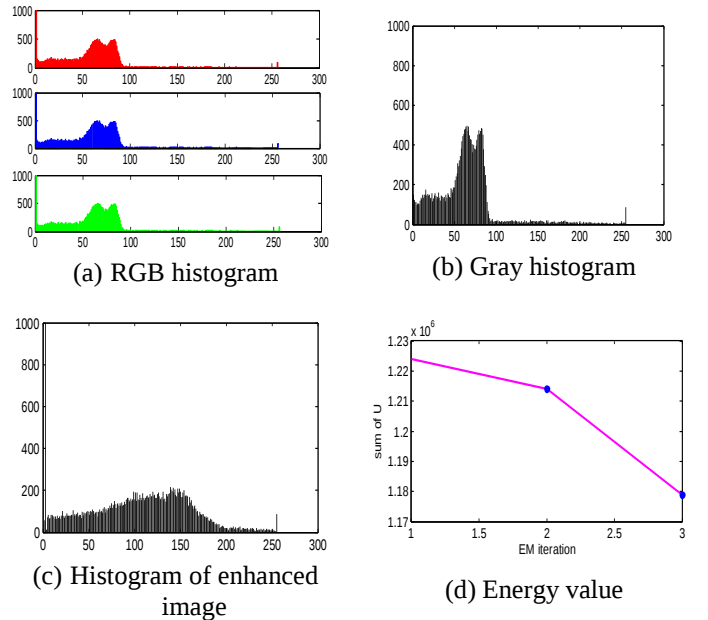


Fig. 2 Histogram and the energy value for $T1_8$ MR image

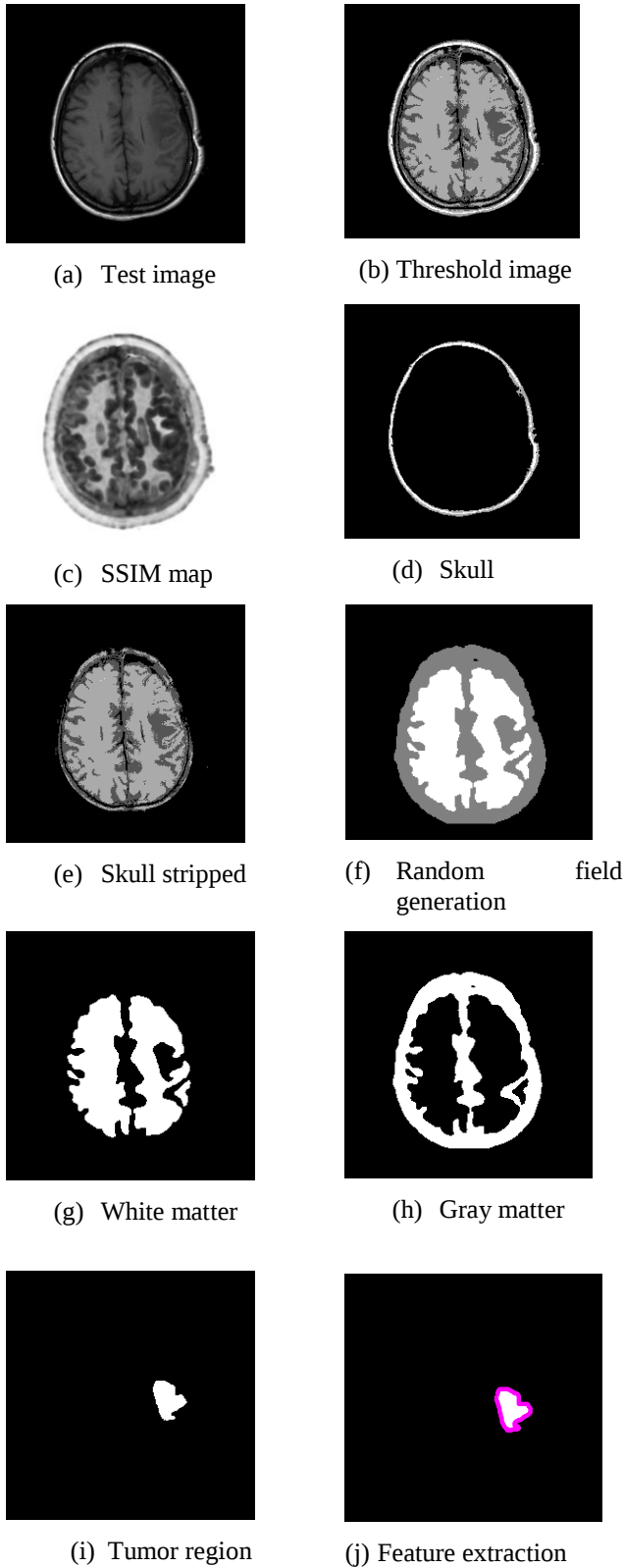


Fig. 3 Various stage results for T1₈ brain MR image segmentation process

In the post-processing work, the skull stripped image is considered for the Markov random field generation process for a preferred number of labels (l). In this work, the l is chosen as three and the MRF model is generated

by minimizing the energy function U as presented in Fig. 2(d). After the MRF-MAP generation, the image is separated into various labels, such as white matter (Fig.3 (g)), gray matter (Fig.3 (h)), and the tumor region (Fig.3 (i)). Geometric feature extraction procedure is then applied for the extracted tumor, which offers the tumor mass dimensions in terms of image pixels (Fig.3 (j)).

Table 1. Segmentation results for the MR image dataset for T1, T2 and Flair modalities

	Test image	FA+Tsallis segmentation (T=3)	Skull Stripped brain	Random field generation (l=3)	Extracted region
T1 ₉					
T1 ₁₀					
T2 ₈					
T2 ₁₀					
F ₈					
F ₁₀					

Table 2 (a). Quality measure values for thresholded image

Test image	OF	Optimal thresholds	RMSE	NAE
T1 ₈	1.1064	29, 132, 186	20.2663	0.2805
T1 ₉	1.0737	34, 118, 177	24.2829	0.3341
T1 ₁₀	1.0835	26, 140, 182	16.9535	0.2368
T2 ₈	1.3820	30, 125, 160	31.3819	0.5777
T2 ₁₀	1.2248	34, 138, 171	31.1028	0.5427
F ₈	1.3004	26, 111, 192	43.0175	0.7736
F ₁₀	1.3275	42, 127, 188	41.7133	0.7480
T1 _B	1.1038	23, 152, 170	33.4952	0.3500
T2 _B	1.1846	34, 144, 185	39.9465	0.5116
F _B	1.2273	22, 128, 193	26.9228	0.2561

Table 2(b). Quality measure values for multi-thresholded image

Test image	PSNR (dB)	MSSIM	NCC	SC
T1 ₈	20.2663	0.5324	1.1622	0.7146
T1 ₉	20.4248	0.5299	1.2278	0.6393
T1 ₁₀	23.5456	0.5514	1.0855	0.8202
T2 ₈	18.1972	0.7098	0.7254	1.3342
T2 ₁₀	18.2748	0.7038	0.7597	1.2839
F ₈	15.4579	0.6204	0.4056	2.5228
F ₁₀	15.7253	0.6039	0.4645	2.1431
T1 _B	17.6312	0.7755	1.3379	0.5456
T2 _B	16.1012	0.6691	0.6264	1.8459
F _B	19.5284	0.7857	1.2026	0.6734

Above discussed segmentation procedure is then applied for the MRI gray scale image with various modalities, such as T1, T2 and Flair for the BRAINIX dataset and the outcome of the pre-processing and the post-processing work is presented in Table 1. The pre-processing operation is used to group the pixels based on the chosen threshold ($T=3$) and the final outcome of the post-processing work offers the tumor existing in the considered test image.

The geometric features (size of tumor) are then extracted and the values are tabulated in Table 3. In this table, the geometric features are recorded based on tumor pixels. In future, these extracted features can be used in the automated classification of tumor, such as benign and malignant.

Table 3. Geometric feature values for the segmented tumor

Test image	Area	Major axis length	Minor axis length	Equiv diameter	Solidity	Extent
T1 ₈	869	41.72	29.16	33.26	0.8876	0.6056
T1 ₉	818	46.25	23.45	32.27	0.8872	0.6716
T1 ₁₀	1529	63.61	40.59	44.12	0.7281	0.5560
T2 ₈	1077	45.38	35.40	37.03	0.8134	0.5635
T2 ₁₀	1325	50.23	37.92	41.07	0.8461	0.6760
F ₈	1036	45.33	32.10	36.32	0.8691	0.6407
F ₁₀	1354	51.41	37.24	41.52	0.8769	0.7319
GT	3880	90.82	64.15	70.29	0.8331	0.5565
T1 _B	3409	84.46	60.39	65.88	0.8628	0.5939
T2 _B	3769	85.20	67.09	69.27	0.8000	0.5472
F _B	3865	93.82	63.91	70.15	0.7823	0.5349

Table 4. Segmentation results for the BraTS dataset

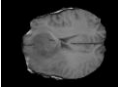
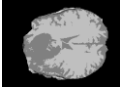
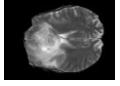
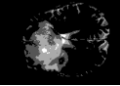
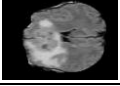
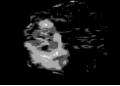
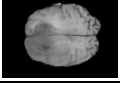
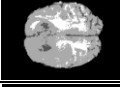
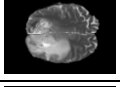
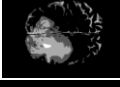
Test image		FA+Tsallis segmentation (T=3)	Ground truth	Segmented tumor
T1 ₁₀₀				
T2 ₁₀₀				
F ₁₀₀				
T1 ₁₂₀				
T2 ₁₂₀				
F ₁₂₀				

Table 5. Relative result between ground truth and segmented tumor

Test image	Area (normalized)	JSC	DSC	FPR	FNR
T1 ₁₀₀	0.9916	0.9260	0.9616	0.0694	0.0098
T2 ₁₀₀	0.9928	0.9233	0.9601	0.0542	0.0267
F ₁₀₀	0.9936	0.9343	0.9660	0.0473	0.0215
T1 ₁₂₀	0.8823	0.8186	0.9003	0.0330	0.1544
T2 ₁₂₀	0.9773	0.8725	0.9319	0.0528	0.0814
F ₁₂₀	0.9538	0.8625	0.9262	0.0776	0.0706

Table 6. Segmentation accuracy measure

Test image	Precision	F-measure	Sensitivity	Specificity	Accuracy
T1 ₁₀₀	0.9989	0.9955	0.9922	0.9902	0.9912
T2 ₁₀₀	0.9970	0.9954	0.9939	0.9733	0.9836
F ₁₀₀	0.9975	0.9961	0.9947	0.9785	0.9865
T1 ₁₂₀	0.9807	0.9874	0.9943	0.8435	0.9158
T2 ₁₂₀	0.9897	0.9907	0.9918	0.9173	0.9538
F ₁₂₀	0.9910	0.9898	0.9887	0.9285	0.9581

In order to assess the accuracy and clinical significance of the proposed methodology, widely used MRI dataset, BraTS 2012 from multimodal brain tumor segmentation challenge is considered (Kistler et al., 2013; Menze et al., 2015). In this database, the 2D brain MR image doesnot have the skull section, hence it doesnot require the image filtering algorithm to segment the skull. This dataset also has the ground truth (tumor region offered by a radiologist). Hence, the efficiency of the proposed segmentation process is to be validated against the MR images with ground truth. This dataset has the 2D brain MR images recorded with T1, T2 and Flair modalities. A comparative study between the segmented image and the expert's ground truth will help to evaluate the accuracy and clinical significance of proposed segmentation approach.

Proposed pre-processing and post-processing works are then implemented on the BraTS MRI dataset and the corresponding results are depicted in table 4. In this study, the slice numbers, 100 and 120 are chosen for the analysis. This table presents the considered image dataset, tri-level thresholded image, ground truth and the extracted tumor from the proposed methodology. From these results, it can be noted that, the shape of extracted tumor from the T1, T2 and Flair modality based MRI are approximately similar with the corresponding ground truth.

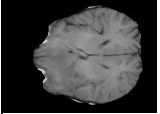
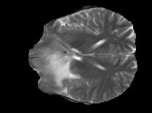
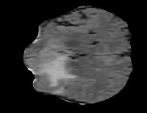
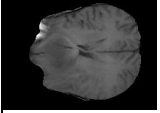
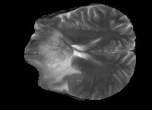
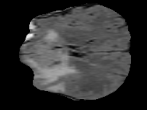
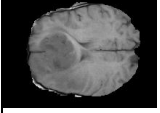
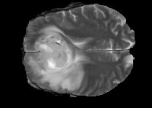
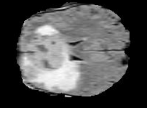
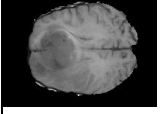
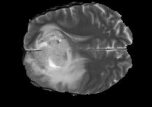
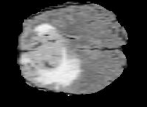
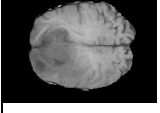
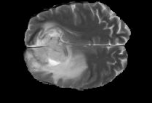
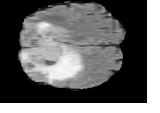
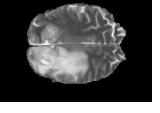
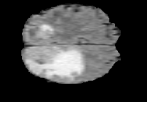
In image segmentation literature, a usual practice is that, the efficiency of proposed segmentation procedure is analyzed using the well known image quantitative measures namely the normalized segmented area, mean error rate, JSC, DSC, FPR and FNR. The statistical measures, such as precision, F-measure, sensitivity, specificity and accuracy are also to be measured to justify the eminence of the proposed

segmentation approach (Lu et al., 2004; Moghaddam and Cheriet, 2010). In this paper, the quantitative measures and the statistical measures are computed for the BraTS MRI dataset and the corresponding results are shown in table 5 and 6 respectively.

Table 5 demonstrate that, in all the image cases, the segmented tumor image is closely correlated with the ground truth image and the JSC and DSC are found to be greater than 0.8. Further, the normalised area is found to be high in all the cases. Also by comparing the segmented area with that of the ground truth, it appears that the adopted method is highly efficient in extracting most of the tumor mass irrespective of the modalities. Table 6 confirms that, proposed approach helps to attain better values of precision, F-measure, sensitivity, specificity and accuracy. These results proves that, the proposed segmentation work offers better results for 2D brain MR images recorded with T1, T2, and Flair modalities.

As in Table 7, BraTS MRI dataset with the slice numbers 90, 95, 105, 110, 115 and 125 are also analysed in the proposed work and better results are obtained similar to the slice number 100 and 120 for all the modality cases.

Table 7. Test images of BraTS dataset

Slice number	T1	T2	Flair
90			
95			
105			
110			
115			
125			

The average values of image similarity measures and the statistical measures obtained for all the considered BraTS MRI dataset are depicted in Fig. 4 and 5 respectively.

From Fig.4, it can be noted that, the proposed segmentation procedure offers better values of normalised tumor area, Jaccard, Dice, false positive rate and true positive rate. The area, JSC and DSC values are approximately unity and the FPR and FNR are nearer to zero. These values confirm the efficiency of the segmentation procedure.

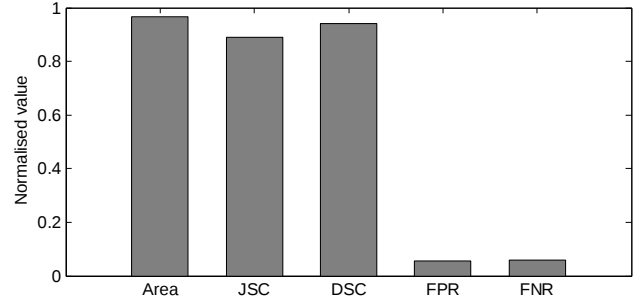


Fig. 4 Average image similarity measures

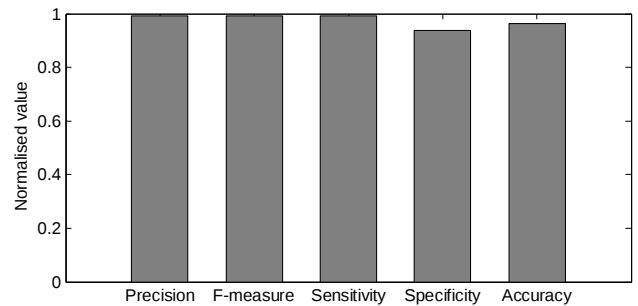


Fig. 5 Average image statistical measures

From Fig.5, it can be observed that, the average statistical measures obtained for the BraTS MRI dataset is superior and the precision, F-measure, sensitivity, specificity and accuracy values are closer to unity (100%). From these results, it is verified that, proposed two-stage segmentation approach tenders enhanced result in extracting the tumor from the brain MRI images registered with T1, T2 and Flair modality.

4. CONCLUSION

In this paper, Firefly Algorithm assisted segmentation and analysis of brain tumor is demonstrated by considering 2D gray scale brain MR images. It is an automated procedure and effectively extracts the tumor mass from the MRI dataset obtained using various modalities, such as T1, T2 and Flair. The proposed approach is grouped in to two sections, namely the pre-processing region and the post-processing region. The simulation result shows that, both the methods offer better result for the considered dataset. The competence of the proposed segmentation procedure is validated using the BraTS dataset. Results of this study exhibit that, the segmented tumor mass is approximately similar to the ground truth image and offers better result in normalized area, JSC, DSC, FPR and FNR for the T1, T2 and Flair MRI dataset. The accuracy measure values, such as precision, F-measure, sensitivity, specificity and accuracy are better. Hence the proposed segmentation approach is clinically significant.

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