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A SOFT-COMPUTING APPROACH TO SEGMENT TUMOUR REGION FROM BRAIN MRI

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Abstract- In recent years, image processing procedures are widely adopted in the medical discipline to evaluate the severity of diseases using the medical images. Magnetic Resonance Image (MRI) is a widely used medical imaging procedure to record the internal brain sections to evaluate its conditions. In the proposed work, a two-step procedure is implemented to extract the tumour section from the brain MRI recorded using the Flair modality. The first stage implements Bat algorithm and Tsallis entropy based tri-level thresholding to enhance the tumour region and the second stage implements the active contour segmentation procedure to extract the tumour. Proposed work is tested using the BRATS 2015 dataset. The merit of the proposed approach is verified by computing the image similarity measures, such as the Jaccard, Dice, false positive rate, false negative rate, sensitivity, specificity, accuracy and precision. The experimental result evident that, proposed approach offers better result on the considered dataset.

Keywords: Brain tumour, Tsallis entropy, Active contour segmentation, BRATS dataset, Image similarity analysis.

1. Introduction

Computer assisted disease assessment is broadly used in medical field to discover anatomical and pathological divisions using the clinical images. Medical imaging procedures will assist the early detection and analysis of a selection of diseases and also helps to diminish the morbidity and mortality rates. In literature, considerable measures are discussed and implemented by the researchers to extract significant information from the conventional and medical images [1-6].

The heuristic approach assisted image processing is widely considered in recent years, due to its simplicity and easiness in implementation [7,8]. Tsallis entropy is one of the procedures, largely adopted by most of the researchers because of its dominance and elasticity [9,10]. From the image processing literature, it can be noted that, Tsallis's entropy based multi-level thresholding was largely adopted by the researchers to extract the important information from the RGB / gray scale test images [11,12] and medical images [5].

The work by Despotovic et al.[13] recommends the segmentation challenges and the available procedures in the brain image processing approaches. This work also notifies that, combination of several techniques is necessary to attain better segmentation result [9].

This work proposes a computer assisted automated technique to segment and analyze the tumor from the well known brain MRI dataset. Initially, multi-level thresholding method[24] based on the Tsallis entropy is implemented to improve the cancerous division of the brain image. Tsallis approach was initially proposed in 1988 [9]. The combination of Tsallis function and various heuristic algorithms has been presented over the past years for image thresholding applications [14].

In this work, recently developed heuristic procedure known as the Social Group Optimization (SGO) [15] assisted work is employed to enhance the tumor of brain MRI and the brain morphological procedure is then applied to group the similar pixels of the thresholded image. Finally, the Localized Active Contour (LAC) [16] based segmentation is implemented to extract the suspicious/enhanced region of brain MRI.

The capability of proposed segmentation task is then confirmed by means of a comparative assessment among the segmented tumor region and the ground truth image offered by the expert member. The experimental results verify that, proposed approach is efficient in obtaining the better image similarity index values [17] and statistical measure values [18].

2. Materials and Methods

This section presents the various pre-processing, post-processing segmentation, and analyzing methodologies considered in this work.

a. Pre-Processing

Pre-processing procedure is implemented by integration of the Bat Algorithm (BA) and the Tsallis function. Usually, entropy is associated to the assessment of chaos within an image. Shannon principle assured that, when a physical system is separated as two statistically free subsystems *A* and *B*, then the entropy value can be expressed as [9,10]:

$$S(A+B)=S(A)+S(B) \tag{1}$$

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

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

where, *T* is the system potentials and *q* is the entropic index .

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

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

$$S_q(A+B)=S_q(A)+S_q(B)+(1-q).S_q(A).S_q(B) \tag{3}$$

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, ..., *L*-1},with probability distributions $p_i = p_0, p_1, ..., p_{L-1}$.

Tsallis multi-level thresholding can then be expressed as:

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

where

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

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

$$S_q^K(T) = \frac{1 - \sum_{i=t_k}^{L-1} \left(\frac{Pi}{P^K} \right)^q}{q-1}, \; P^K = \sum_{i=t_k}^{L2-1} Pi$$

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. In this paper, optimal threshold for the brain MRI image is obtained using the BA assisted Tsallis based multi-level thresholding procedure.

The BA was firstly proposed by imitating the hunting actions of microbats. BA consists of three mathematical equations such as velocity, position and frequency updates as described in the following equations [5]:

$$V_i^{(t+1)} = V_i^{(t)} + (X_i^{(t)} - Gbest).F_i \tag{5}$$

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \tag{6}$$

$$F_i = F_{min} + (F_{max} - F_{min}).\beta^1 \tag{7}$$

where $V_i^{(t+1)}$ and X_i^{t+1} symbolize the velocity and position of the bat, F_{min} is the least frequency and F_{max} is highest frequency.

From Eqn.5, it is noted that, velocity renewal depends predominantly on the frequency renewal. During the heuristic investigation, a new result for every bat is produced based on the subsequent relation:

$$X_{new} = X_{old} + \varepsilon A^t \tag{8}$$

where ε= arbitrary digit of the range [-1,1] and A is the intensity of bats' discharged sound throughout the investigation of a new "area" (set of positions leading to a set of solutions).

The arithmetical illustrations for intensity alteration are shown below:

$$A_i^{(t+1)} = \alpha_1 A_i^{(t)} \tag{9}$$

$$r_i^{(t+1)} = r_i(0)[1 - exp(-\gamma_1 t)] \tag{10}$$

In this work, Chaotic Bat Algorithm (CBA) discussed in [5] is considered with the following parameters:

Number of bats = 25; search dimension = 3; iterations = 500; stopping criteria = $J(t)_{max}$; frequency vector constant β = [0,1];ε is a random value between [-1,1]; A_0 = 10 and A_{min}= 1 (which decays in steps of 0.1); $\alpha^1 = \gamma^1$=0.75.

b. Post-Processing

Image morphology functions are normally adopted to improve the visual appearance. The basic morphology operations, such as line structuring element (*strel*) and image fill (*imfill*) are considered to improve the edges and appearance of multi-threshold retinal image.

c. Segmentation

This section presents the segmentation procedure chosen to extract the cancerous region. Active Contour Segmentation (ACS) proposed in [16] is adopted to extract the image. This procedure has three essential steps such as, boundary detection, initial active contour, and final active contour which offer minimized energy. In this work, variable snake model is considered to track similar pixel groups existing in pre-processed image based on energy minimization concept.

The energy function of the snake can be denoted as;

$$\frac{min}{C}\left\{E_{GAC}(C) = \int_0^{L(C)} g(\left|\nabla I_0 C(s)\right|)\, ds\right\} \tag{11}$$

where *ds* is the Euclidean component of length and *L(C)* is the length of the curve *C* which satisfies $L(C) = \int_0^{L(C)} ds$. The parameter *g* is an edge indicator, which will disappear based on the object boundary defined as;

$$g(\left|\nabla I_0\right|) = \frac{1}{1+\beta\left|\nabla I_0\right|^2} \tag{12}$$

where I_0 represents original image and β is an arbitrary constant. The energy value rapidly decreases based on the edge value, based on gradient descent criterion[12].

This procedure is mathematically represented as;

$$\partial_t C = (kg - \langle \nabla_g, N\rangle)N$$

(10)

where $\partial_t C = \partial C / \partial t$ represents the deformation in the snake model, *t* is the iteration time, and *k* , *N* are the curvature and normal for the snake '*C*'. In this procedure, the snake silhouette is continuously corrected till minimal value of the energy; E_{GAC} is achieved.

d. Analysis

The efficiency of the proposed approach is confirmed in the pre-processing stage and the segmentation stage. During the pre-processing stage, well known image quality measures are computed to find the performance of BA + Tsallis [7,8]. After the segmentation, a comparative analysis between the segmented skin region and the ground truth is performed and the well known statistical image measures [18], such as precision, sensitivity, specificity, and accuracy also the image similarity measures, such as Jaccard, Dice, False Positive Rate (FPR) and False Negative Rate (FNR) are computed to analyze the superiority of the proposed method [17]. Maximized values of these parameters are generally considered to justify the significance of the implemented image segmentation approaches [20,21].

3. Execution

This section provides the details regarding the implementation of the proposed procedure. Fig.1 depicts the block diagram of the proposed brain MRI examination task. Initially, the skull stripped brain MRI test image is pre-processed using the multi-level thresholding. This procedure will enhance the abnormal region of the test image. Later, the image morphological operation is considered to group the similar image pixels in order to get a smooth image. The post-processed image is then treated using the ACS, which extracts the tumor section from the brain MRI. Finally, the extracted tumor is analyzed to confirm the superiority of the proposed brain MRI image processing procedure.

Fig.1 Block diagram of the proposed methodology

4. RESULTS and DISCUSSIONS

This section presents the experimental results of the proposed work. During this study, the well known benchmark brain MRI images are obtained from the MICCAI BRAIN Tumor Segmentation (BRATS) challenge 2012 dataset [23]. This database has a three dimensional (3D) brain MRI images registered using the Flair, T2, T1 and T1c modalities. This dataset also provides the ground truth image offered by the expert member. In this study, the brain MRI image recorded with the Flair modality is considered and the 2D slices of slice numbers 95,105,115 and 125 are extracted from the 3D dataset. The main advantage of this BRATS images are, it does not have the skull section, hence, it is very easy to implement the image processing procedure.

Initially, BA assisted Tsallis entropy based multi-level thresholding process is implemented on the test data in order to enhance the tumor region. After the thresholding, image morphology is applied to group the similar pixels values to obtain an even image. The ACS procedure is then applied to extract the tumor section from the post-processed image. Finally, the extracted tumor core is analyzed with a comparative study against the ground truth existing in the brain MRI dataset. All the simulation works are implemented by means of Matlab 2012 software.

Table 1 presents the chosen image slices and its corresponding outcomes. The quality of the pre-processed image is verified using the well known image quality measures existing in the literature [20-22] and its values are tabulated in Table 2. From this table, it is clear that, proposed approach is efficient in offering better values of RMSE, PSNR, SSIM, NCC, AD, SC and NAE. Details regarding the adopted image quality measures can be found in the literatures [7,8].

Table 1. Image processing results for the chosen image dataset

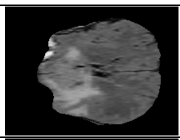
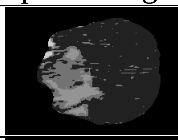
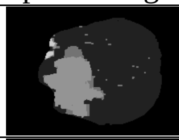
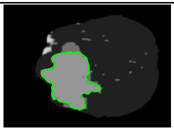
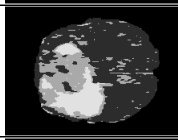
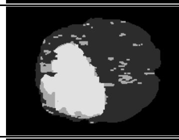
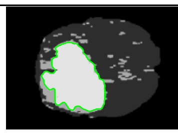
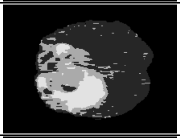
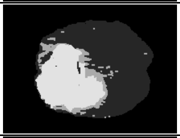
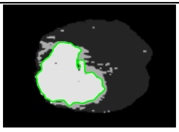
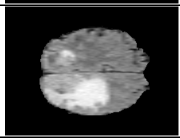
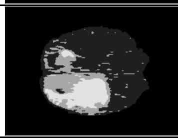
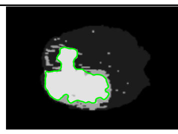
	Test image	Pre-processing	Post-processing	Segmentation
Slice$_{95}$				
Slice$_{105}$				
Slice$_{115}$				
Slice$_{125}$				

Table 2. Image quality measures between original and tri-level threshed image

Flair	RMSE	PSNR	SSIM	NCC	AD	SC	NAE
Slice$_{95}$	30.6995	18.3445	0.7325	0.6622	17.1099	1.8986	0.4226
Slice$_{105}$	43.8925	15.3009	0.6775	0.7249	22.8143	1.5337	0.3714
Slice$_{115}$	44.6004	15.2154	0.7007	0.7275	21.7746	1.5786	0.3833
Slice$_{125}$	43.1006	15.5644	0.7573	0.6882	19.5353	1.6522	0.4046

Table 3. Comparison of the ground truth and the extracted tumor

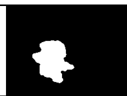
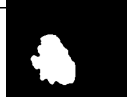
	Ground truth	Tumor section
Slice$_{95}$		
Slice$_{105}$		
Slice$_{115}$		
Slice$_{125}$		

Table 4. Similarity measures between GT and segmented tumor

Flair	**Jaccard**	**Dice**	**FPR**	**FNR**
Slice$_{95}$	0.8340	0.9095	0.1526	0.0387
Slice$_{105}$	0.8291	0.9066	0.1674	0.0321
Slice$_{115}$	0.8397	0.9129	0.1368	0.0454
Slice$_{125}$	0.8221	0.9024	0.1147	0.0836

Table 5. Statistical measures between GT and segmented tumor

Flair	Precision	Sensitivity	Specificity	Accuracy
$Slice_{95}$	0.9963	0.9857	0.9612	0.9734
$Slice_{105}$	0.9955	0.9768	0.9679	0.9723
$Slice_{115}$	0.9937	0.9812	0.9546	0.9678
$Slice_{125}$	0.9910	0.9877	0.9554	0.9514

Table 3 presents the comparison between the ground truth image and the extracted tumor and its results such as the image similarity measures and the statistical measures are presented in Table 4 and 5 respectively. From Table 4, one can observe that, the Jaccard and Dice values are greater than 0.81 (ie. 81%) and also a negligible values for the FPR and FNR. This confirms that, the extracted tumor structure is approximately similar compared to the ground truth image. The pattern of the tumor and the ground truth are identical. From Table 5, it can be noted that, the Precision, Sensitivity, Specificity and Accuracy are greater that 0.95 (ie,95%), which confirms the superiority of the proposed approach in processing the benchmark Flair modality based brain MRI dataset. In future, the proposed approach can be validated on the brain MRI images recorded using the modalities, such as T2, T1 and T1c.

5. CONCLUSIONS

This work proposes a computer assisted scheme to mine and analyze the abnormal region of the BRATS 2012 brain MRI dataset. The work implements the Social Group Optimization (SGO) and Tsallis entropy based procedure to enhance the tumor section and the Active Contour based approach to segment the tumor from the post-processed test image. To exhibit the superiority of the proposed procedure, Flair modality registered various 2D slices of the brain MRI are considered. The experimental result demonstrates that, proposed approach is very efficient in extracting the tumor section from the Flair based MRI slices. This result also confirms that, the proposed SGO assisted approach offers superior image similarity measures and the statistical measures compared to the ground truth. Hence, in future, this procedure can be used to analyse the real time clinical images recorded using various modalities, such as T2, T1 and T1c.

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