HYBRID SEGMENTATION TECHNIQUE FOR MENINGIOMA TUMOUR DETECTION IN MRI BRAIN IMAGES

C. KIRUBAKARAN*, N. SENTHILKUMARAN

Department of Computer Science and Applications, the Gandhigram Rural Institute
Dindigul, TamilNadu, India - 624302
*Corresponding Author: chakirubakaran@gmail.com

Abstract

To ameliorate the measure of segmentation methods, a contrastive strategy of the hybrid segmentation is suggested in this report. A medical image is complex and difficult to diagnose for the disease identification, surgical preparation, and treatment. Magnetic Resonance Imaging (MRI) of the brain is useful for evaluating problems in the presence of an abnormality in the brain. Two different segmentation approaches are presented in this formulation which uses medical images to produce a hybrid approach. The single-seeded region based segmentation is the disunion of an image into homogenous parts of linked pixels. It develops the region, according to an iterated process and examines the neighboring pixels, whether they should be summarized within the region or not. Another method employed in this work is the thresholding image segmentation using the Differential Evolution (DE) based on entropy parameters. DE is a population-based, effectual and direct search method. It was designated because of its propensity to offer fast convergence rate and capacity of traveling straight away with real numbers (gray scale levels). In this study, the MRI image goes look over a proper pre-processing, like skull stripping and enhancement. After the aforementioned methods are enforced along these images and combine together, the resultant images are analyzed using Structure Similarity Index Measure (SSIM) to obtain a better value, when compared with the ground truth image.

Keywords: Differential evaluation, Entropy, Image segmentation, Magnetic resonance imaging (MRI), Single-seeded region-based segmentation.
1. Introduction

Image segmentation is a literal process which is always rehearsed in most of the image analysis patterns [1]. The simple purpose of the segmentation is to separate an image into a number of non-overlapping reasonably alike components since the manual segmentation is very complex [2]. The segmentation is comfortable to determine by visual but not with a defined system [3]. The precise purpose of brain tumor detection is to procure the important information of the abnormality of the brain. Diagnosis and treatment are highly based on this information. MRI brain image is very complicated to retrieve correct information. Here the problem has to be resolved to state the degree of the segmentation [4, 5].

Parts of the MRI image are Skull, Cerebro-spinal Fluid (CSF), Gray matter, White matter and Tumor parts. These parts are linked through homogenous pixels called regions [6]. If any abnormality is present in the MRI, the same can be determined from the shape, volume and the region of the abnormal brain tissue. A substantial variety of segmentation methods and techniques have been proposed in the past decades. Many works are published using region growing methods [2, 7-10]. Among the variety of segmentation, one suitable segmentation is the seeded region growing, a hybrid method in MRI brain images, and it is relevant to the regional parts of the image [7].

The region is fully grown based only on the intensity value of pixel [4]. It considers the pixels for the intensity and connects to a neighborhood for seed growing. In Single Seeded Region Growing (SSRG) method, the origination of the region selects a start seed point and exact location of the seed point [3, 6]. Seeds for different regions must be disconnected. Region growing methods forever furnish splendid segmentations that correspond well to the edges. This method can appropriately divide the parts that bear set the identical properties. The seed point is for all to see, come under the scheduled criteria and it can take the multiple measures at the same time. The fundamental formulation of region growing methods is, it can provide the original images which have clear edges with good segmentation results [11]. It just requires a humble bit of source points to map the property expected and then develop the area. Single seed region growing is a primitive part of this paper.

Another enormous segmentation method is the Gray level global thresholding. There are many other techniques available for thresholding [12] amidst them, entropy-based global thresholding is a finer proposal [13, 14]. DE is a potent metaheuristic used for less computational time and fast convergence. Shannon - entropy based image segmentation process, boosted by DE is proposed in this work. A hybrid method is introduced in this work. The region growing procedure provides the region with edge image and the thresholding techniques produce the binary image based on gray level intensity.

The above two techniques are providing non-homogeneous image Results. Combining the results from the SSRG segmentation algorithm and thresholding using DE method produces a meticulous result than their individual results. Results from the SSRG and thresholding boost up by DE are intersected together to get an accurate tumor brain tissue. The proposed hybrid method is evaluated implementing on MRI meningiomas images. Quality metric results show that the proposed method performs is better than region growing and thresholding using DE-based Shannon entropy.
The organization of this paper is as follows. Section 2 concisely discuss the background of the study, pre-processing of medical images and proposed works are discussed in Section 3. Section 4 is entirely focused on the results and analysis. Finally, the conclusion is placed in Section 5.

2. Background of the Study

Couprie et al. [2] presented an image segmentation method employ the seeded region growing. The work purported the attributes of the seeded region growing method and its merits. Geng-Cheng [7] acknowledged seeded or interactive segmentation is gainful in medical imaging when Compared with model-based segmentation, seeded segmentation is more robust in current image analysis. Rahnamayan et al. [14], Burman [13], and Sarkar [15] suggest DE for least number of control parameters used, quick convergence, determines the true global minimum in any instance of the initial parameter value [16]. Moreover, DE is producing the optimized thresholding values using the entropy as a fitness value, subsequently, thresholding is applied to segment the image. Charutha et al. [1] presented a work associated with various image segmentation techniques. This study holds out an improved and accurate result of segmentation. The obtained results are better are compared with the individual methods.

2.1. Meningioma

Meningiomas are considered as a primary type of a brain tumor; they do not come forth from brain tissue itself, but instead moves up from the meninges, the three thin layers of tissue covering the head and spinal cord. The challenge is difficult to distinguish whether it is meningioma or other neoplasms. These tumors are most oftentimes grew internal, making pressure on the brain or spinal cord, but they may also grow away from the skull, inducing it to thicken [17]. Some of the meningiomas contain cysts (sacks of fluid), calcifications (mineral deposits), or tightly packed clusters of blood vessels. Most meningiomas are benign, slow-developing tumors. A neurological exam observed by an MRI may be helpful in distinguishing meningitis from other neoplasms. A surgical procedure is the main treatment for meningiomas located in an accessible area of the brain or spinal cord. Radiation therapy (external beam) may be used for inoperable tumors.

2.2. Region growing

Region growing is a simple region-based image segmentation method. It is also termed as a pixel-based image segmentation method since it implies the selection of initial seed points. The initial step in the region growing is to select a seed point. The seed point is based on pixels in a certain gray scale intensity range (region-based method). The Region of Interest (ROI) is selected, and the mean of image intensity is calculated for the corresponding ROI. In the case of the pixel-wise method, it can avoid the unwanted pixels from the selected region [9]. The seed is in the exact location of the beginning point of the region [3, 18]. The neighbors of this seed point will be selected under the below conditions as follows:

- If only one neighbor is labeled, then the picture element is labeled as the same region as the labeled neighbor.
If more than one neighbor is labeled and the labels are the same, then the pixel is labeled as the same region as its neighbors are labeled.

If more than one neighbor is labeled and the labels differ, then the pixel is labeled in the region that has the smallest distance to the pixel [7, 10].

The problem is in the basic selection of the seed. The region segmentation becomes more effective if the seed point is selected from the center of the desired region. The three criteria for automatic seed selection are explained in the following way [3, 11]. The seed pixel must have high similarity to its neighbor. For the desired region, a minimum of one seed must be generated to produce this region. Seeds for different regions must be disconnected as it processes the selection of starting seed points; this is also classified as the image with respect to the pixel-based partitioning method.

An initial set of small areas are recursively merged according to its similarity. Start by choosing a seed pixel for the region and check it with its neighboring pixels, by adding in neighboring pixels the region is grown from the seed point and similar to increasing the length of the region [3]. When one region stops its region developing process, simply it chooses another seed pixel [2]. This whole procedure is repeated until all the pixels settle to some region. The primary goal of this operation is to divide an image into parts. Some segmentation methods achieve it by researching the boundaries between regions based on discontinuities in gray levels [19]. The basic formulation for Region-Based Segmentation is given below

\[ \bigcup_{i=1}^{n} R_i = R \]  

\[ R_i \cap R_j = \emptyset \]

\[ P(R_i) = \text{True for } i = 1, 2, 3, \ldots, n \]

\[ P(R_i \cup R_j) = \text{False for any adjacent region } R_i \]

and \( R_i \cdot P(R_i) \) is a logical predicate defined over the points set \( P(R_i) \) and \( \emptyset \) is the null set.

2.2.1. Single seeded region growing algorithms

Calculating the average pixel intensity values of the region grown so far is checked with a neighboring pixel intensity value. Considering the first seed point as the primary average [6], as the region starts to grow, the average is calculated to control the growing procedures. The Region has been set to ROI average value ± a threshold value \( T \) [3, 8].

\[ \text{region} = \text{Avg}(\text{ROI}) \pm T \]  

Threshold \( T \) is defined by the problem to satisfy image segmentation. Thither is possible to obtain the closest result in the desired segmentation threshold value can be specified by the user. Figure 1 flowchart explains the region growing algorithm.

![Image](image_url)
2.3. Differential evaluation

DE is a population-based search strategy algorithm [16], each mortal in the population is a defined number of chromosomes present (imagine it as a band of human beings and chromosomes or genes in each of them). It is also called an optimized problem-solving algorithm. The Floating - point representations of individuals are defined by DE. Multidimensional global optimization problems are solved by differential evolution [14]. The differential evolution algorithm has some positive merits; they are the least number of control parameters used, fast convergence, determines the true global minimum in any case of the initial parameter value [20].

DE is built with the use of some probability distribution function and does not depend on mutation operator, but it introduces a new arithmetic operator which depends on the differences between randomly chosen pairs of individual parameters [15]. The main procedures of DE are briefly identified as follows and the working flow is given in Fig. 2.

Fig. 1. Seeded region growing algorithm.
2.3.1. Initialization

The DE algorithm starts with a population of initial results, each of dimension $D$, $X_{i,g} = (x_{i,1}, x_{i,2}, \ldots, x_{i,D})$, $i = 1, \ldots, NP$, where the index $i$ denotes the $i^{th}$ solution, or vector of the population, $g$ is the generation, and $NP$ is the population size [13, 21, 22]. The initial population (at $g = 0$) is randomly generated to be within the search space constrained by the minimum and maximum bounds, $X_{min} = \{x_{1,min}, x_{2,min}, \ldots x_{D,min}\}$ and $X_{max} = \{x_{1,max}, x_{2,max}, \ldots, x_{D,max}\}$. The $i^{th}$ vector $x_i$ is initialized as follows the Eq. (3):

$$x_{j,i,0} = x_{j,min} + rndreal_{i,j} (0,1)(x_{j,max} - x_{j,min})$$

2.3.2. Mutation

The differential mutation operator is applied to create the mutant vector $V_i$ for each target vector $x_i$ in the given population [13, 14]. The mutant vector obtained by following Eq. (4):

$$V_{i,g+1} = x_{i,g} + F.(x_{r2,g} - x_{r3,g})$$

Fig. 2. Differential Evolution (DE) algorithm.
whereby randomly chosen for the indexes is called random indexes, \( r_1, r_2, r_3 \in \{1, 2,..., NP\} \). \( F \) is a real and constant factor or mutation constant [22], the value of \( F \in [0, 2] \), and it controls the amplification of the differential variation. Lower values for the \( F \) result in faster convergence and a larger value generates the higher diversity in the population [14]. There are many proposed mutation strategies for DE like “DE/best/1” and “DE/current-to-best/1”. Nevertheless, the strategy used in DE literature is “DE/rand/1/bin” for its slower convergence [20].

### 2.3.3. Crossover

DE performs the crossover operation and generates a new candidate by shuffling current present vectors to increase diversity in the population. Eqs. (5) and (6) denote the crossover process.

\[
u_{i,g+1} = (u_{i_1,g+1}, u_{2i_1,g+1}, \ldots, u_{D_{i,g+1}})
\]

(5)

where \( j = 1 \ldots D \) (\( D = \) problem dimension) and

\[
u_{j,g+1} = \begin{cases} v_{j,g+1} \ldots \text{if} \ (\text{randb}(j) \leq \text{CR}) \text{and} (j = \text{rnbr}(i)) \\ x_{j,g} \ldots \text{if} \ (\text{randb}(j) > \text{CR}) \text{and} (j \neq \text{rnbr}(i)) \end{cases}
\]

(6)

where \( \text{randb}(j) \) is the \( j \)th evaluation of a uniform random number generator with the outcome \( \in [0, 1] \), CR is the crossover rate or crossover constant, its values \( \in [0, 1] \), and \( \text{rnbr}(i) \) is a randomly chosen index \( \in 1, 2, \ldots, D \).

### 2.3.4. Selection

Selection process performs, whether the target vector or the trial vector sustain the new next generation of new candidate population [13, 14, 23]. The selection processed is based on the following Eq. (7).

\[
x_{i,g+1} = \begin{cases} u_{i,g} \ldots \text{if} \ -f(u_{i,g}) \leq f(x_{i,g}) \\ x_{i,g} \ldots \text{if} \ -f(u_{i,g}) > f(x_{i,g}) \end{cases}
\]

(7)

### 2.4. Shannon entropy

Shannon entropy is defined for a given discrete probability distribution; it evaluates how much information is required, on average, to identify random samples from that distribution. \( P \) denotes probability distributions [21]. Then the entropy of the entire image can be described as followed Eq. (8):

\[
H(P) = -\sum_{i=1}^{n} p_i \log_2 p_i
\]

(8)

There are \((n-1)\) thresholds (\( \tau \)), then dividing the normalized histogram into \( n \) classes, a histogram for an image with \( L = 255 \) gray levels and the dimension of a gray level digital image is \( M \times N \). The Eq. (9) provides the threshold for each class of gray level.
\[ H_n(t) = - \sum_{i=1}^{n-1} \frac{p_i}{p_n} \ln \frac{p_i}{p_n} \]  
\hspace{1cm} (9)

Calculating some dummy threshold values \( t_0 < t_1 < \ldots < t_{n-1} < t_n \) and the optimum thresholding value can get from Eq. (10) using the dummy thresholding values.

\[ \varphi(t_1, t_2, \ldots, t_n) = \text{Arg } \max \{ H_1(t) + H_2(t) + \ldots + H_n(t) \} \]  
\hspace{1cm} (10)

3. Methodology

3.1. Pre-processing

Pre-processing is an essential step in digital image processing. It is because the MRI images are generating some impulsive noise due to the movement of the patient during the imaging process. The images should be enhanced for efficient brain tumor detection by the following.

- **Image Conversion** - The image used in this research is in *.jpg format. It is essential to first convert the image from RGB model to gray-level image.
- **Resizing of Images** - The converted gray-level image is resized to 400×400 for supplying uniform time consuming throughout the whole work.
- **Median filtering** - Median filter \( 3 \times 3 \) is used to remove the impulsive noise present in the image and reduces the edge blurring effects.
- **Skull Removing** - The skull stripping process removes the non-brain tissues. The non-brain tissues of the skull, CSF, fat, and skin are also named as cortical tissue [1, 6, 19]. In MRI image the skull part is like a ring around the brain tissues. The skull is removed because the intensity values of the skull and tumor are the same. The skull stripping process results from the brain portion alone using mathematical morphological operation [24] and watershed transform.

3.2. Proposed work

The MRI Images procured from the online dataset available sources cannot be fed directly for processing because these images contain noises. They have to be taken out and enhanced for efficient brain tumor detection. The proposed work is implemented in MATLAB. The algorithm is described in Fig. 3. The process starts with reading the corresponding input MRI brain image in MATLAB. Pre-processing methods are applied to the input image. Then, it is segmented by SSRG method. As a result, the segmented tumor part is obtained. Furthermore, using morphological operation [24] as post-processing, small areas are removed and filled within the edges.

Finding thresholding boosted by Differential evaluation based on Shannon entropy segmentation is applied to the pre-processed image. The result obtained from seeded region growing and thresholding by DE based on Shannon entropy segmentation is intersected. The intersected portion is overlaid on the original image with tumor identification.
4. Results and Analysis

The proposed method can successfully detect most of the edges in all images. Object boundaries and other details in the images are reflected in the output image of the proposed detector are much better. In a visual analysis, the edges are more detailed in the regions of the input images and are successfully detected, as observed in Fig. 4. The results of the quality metrics are also shown in Table 1 and Fig. 5.

<table>
<thead>
<tr>
<th>Slice</th>
<th>Single Seeded Region Growing</th>
<th>DE-based Thresholding</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9817</td>
<td>0.9761</td>
<td>0.9853</td>
</tr>
<tr>
<td>2</td>
<td>0.9487</td>
<td>0.8941</td>
<td>0.9630</td>
</tr>
<tr>
<td>3</td>
<td>0.9770</td>
<td>0.9734</td>
<td>0.9805</td>
</tr>
<tr>
<td>4</td>
<td>0.9896</td>
<td>0.9920</td>
<td>0.9942</td>
</tr>
<tr>
<td>5</td>
<td>0.9825</td>
<td>0.9610</td>
<td>0.9851</td>
</tr>
<tr>
<td>6</td>
<td>0.9876</td>
<td>0.9940</td>
<td>0.9948</td>
</tr>
</tbody>
</table>
Fig. 4. (a) Original image, (b) Skull Removed image, (c) Result by Single SSRG, (d) Tumor detection by SSRG, (e) Result by DE-based Shannon entropy, (f) Tumor Detection by DE-based Shannon entropy, (g) Optimal tumor Detection by the proposed method.

Fig. 5. SSIM values.
The Structural Similarity Index metric is a comparison of structural information of two images. Ground truth images are used to compare the results. The SSIM is calculated on X, Y axis of an image. The calculation is made between two windows and of common size $N \times N$ in Eq. (11):

$$SSIM (X, Y) = l(x, y)c(x, y)s(x, y)$$

where $l(x, y)$ luminance changes, $c(x, y)$ contrast change, and $s(x, y)$ structural change.

5. Conclusion

A Brain tumor named meningioma detection, which combines SSRG and thresholding boosted by DE based on Shannon entropy segmentation is executed in this paper. MRI input images are enhanced by pre-processing. The experimental results show that the proposed method is an efficient brain tumor detection technique. Both the algorithms are then employed to isolate the tumor region. A conjunction of both algorithms provides a better result for the detection of a meningioma tumor. It avoids the over-segmentation and under-segmentation and detects the exact area of a tumor. The results are analyzed using SSIM to prove the efficiency of the proposed method. The SSIM values prove the performance of the proposed method.

<table>
<thead>
<tr>
<th><strong>Nomenclatures</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>Crossover rate</td>
</tr>
<tr>
<td>D</td>
<td>Dimension</td>
</tr>
<tr>
<td>F</td>
<td>Constant factor or Mutation factor</td>
</tr>
<tr>
<td>g</td>
<td>Generation of new candidate</td>
</tr>
<tr>
<td>G</td>
<td>Generation</td>
</tr>
<tr>
<td>H</td>
<td>Histogram</td>
</tr>
<tr>
<td>L</td>
<td>Grey levels</td>
</tr>
<tr>
<td>NP</td>
<td>Population Size</td>
</tr>
<tr>
<td>P</td>
<td>Probability Distribution</td>
</tr>
<tr>
<td>R</td>
<td>Region</td>
</tr>
<tr>
<td>T</td>
<td>Threshold</td>
</tr>
<tr>
<td>V</td>
<td>Mutant Vector</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Greek Symbols</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Sigma$</td>
<td>Summation - the sum of all values in a range of series</td>
</tr>
<tr>
<td>$\cap$</td>
<td>A probability of events intersection</td>
</tr>
<tr>
<td>$\cup$</td>
<td>A probability of events union</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Epsilon, represents a very small number, near zero</td>
</tr>
<tr>
<td>$\Phi$</td>
<td>Shannon entropy</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Abbreviations</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CSF</td>
<td>Cerebro-spinal Fluid</td>
</tr>
<tr>
<td>DE</td>
<td>Differential Evolution</td>
</tr>
<tr>
<td>MRI</td>
<td>Magnetic Resonance Imaging</td>
</tr>
<tr>
<td>ROI</td>
<td>Region of interest</td>
</tr>
<tr>
<td>SSIM</td>
<td>Structure Similarity Index Measure</td>
</tr>
<tr>
<td>SSRG</td>
<td>Single Seeded Region Growing</td>
</tr>
</tbody>
</table>
References


Hybrid Segmentation Technique for Meningioma Tumour Detection

Intelligence Research Group, University of Waterloo, Waterloo, Ontario, N2L 3G1, Canada.


