IMAGE MINING USED SEGMENTATION TECHNIQUE MRI SCAN BRAIN TUMOR IMAGES ANALYSIS (IMUSA)

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Abstract: Tumor segmentation from MRI image is important part of medical images experts. This is particularly a challenging task because of the high assorting appearance of tumor tissue among different patients. MRI images are advance of medical imaging because it is give richer information about human soft tissue. There are different segmentation techniques to detect MRI brain tumor. In this paper different procedure segmentation methods are used to segment brain tumors and compare the result of segmentations by sushisen algorithm in datax dataset using correlation and structural similarity List (SSL) to analyses and see the best technique that could be applied to MRI scan image boundaries using different segmentation techniques based and compare the definition of the tumor using MATLAB as technical tool on MR human brain tumor.

Keywords: MR, segmentation, correlation, SSL, Sushisen, MRI scan, MATLAB as technical tool.

1. Introduction

MRI is a non-invasive and good soft tissue contrast imaging modality, which provides invaluable information about shape, size, and localization of brain tumors without exposing the patient to a high ionization radiation. In current clinical routine, the images of different MRI sequences are employed for the diagnosis and delineation of tumor compartments. Due to the large amount of brain tumor images that are currently being generated in the clinics, it is not possible for clinicians to manually annotate and segment these images in a reasonable time. Hence, the automatic segmentation has become inevitable. The requirement for accurate segmentation is very important as the clear location, size and volume of unhealthy tissue is crucial for treatment e.g. radiation treatment.

Image Segmentation is a process of subdividing an image into its constituent’s parts or objects in the image i.e. set of pixels, pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture so as to locate and identify boundaries in an image [1]. Over the last two or three decades, plenty efforts have been focusing on the segmentation process. There are so many image segmentation surveys have been conducted [2, 3]; however, there are very few who have presented how researchers can evaluate one technique against the other on a domain of their segmentation. These show that image segmentation is still a very hot area of research and is still a challenging task for researchers and developers to develop a universal technique for image segmentation. Our driving application in this paper is the segmentation of brain tissue and tumors from two-dimensional magnetic
resonance imaging (MRI). Our goal is a high-quality segmentation of healthy tissue and a precise delineation of tumor boundaries using different segmentation techniques based and compare the definition of the tumor using MATLAB as technical tool on MR human brain tumor.

1.1 Related work

Many techniques for MRI segmentation have been developed over the years based on several techniques. These techniques can be divided into four major classes [4]: threshold-based techniques, region-based techniques, pixel classification techniques, and model-based techniques. There is a large number of tumor types which differ greatly in size, shape, location, tissue composition and tissue homogeneity [5]. Multiple address these difficulties using a soft computing approach based on fuzzy concepts. This fuzzy approach provides several advantages. First, it inherently has the attractive property of the soft classification model, where each point can belong to more than one class. This is consistent with the partial volume effect observed in MR images and thus eliminates the need for explicit modeling of mixed classes (which is required - for example by segmentation methods based on the finite Gaussian mixture [6], the proposed approach to the automatic segmentation of the human brain from two popular benchmark MR datasets: the simulated BrainWeb MR datasets [7], and normal real MR datasets obtained from the Internet Brain Segmentation Repository (IBSR) [8]. We compare these results with those of the standard FCM and several well-known fuzzy and non-fuzzy MRI segmentation techniques found in the literature. We also apply the proposed approach to pathological T1-weighted MRI databases obtained from IBSR and from a local MRI scan center to detect hyper-intense tumors. The uncertainty in this information is also modeled. This information serves to regularize the clusters produced by the FCM algorithm thus boosting its performance under noisy and unexpected data acquisition conditions. In addition, it speeds up the convergence process of the algorithm. To the best of our knowledge, the idea, mathematical formulation, and derivation of incorporating this information have not been reported before in the wide literature of fuzzy clustering and its applications. Region-based segmentation approaches (e.g. [9-12]) examine pixels in an image and form disjoint regions by merging neighborhood pixels with homogeneity properties based on a predefined similarity criterion. One example is the work [13] who presented a comparative analysis of the traditional region growing segmentation and a modified region growing method, addressed to brain tumor segmentation in 3D T1 MR images. Other approaches incorporate the region growing process as a refinement step [14] or in an adaptive fashion [15]. While the advantage of region growing is its capability of correctly segmenting regions that have similar properties and generating connected region, it suffers from the partial volume effect which limits the accuracy of MR brain image segmentation. Partial volume effect blurs the intensity distinction between tissue classes at the border of the two tissues types, because the voxel may represent more than one kind of tissue types [16].
1.1.1 SUSHISEN ALGORITHMS

Input: $E((i_1, t_1), \ldots, (i_n, t_n))$, $s_{\text{min}}$ + METHODS($K$, $C$, $M$, $TH$)
Output: $F(E, s_{\text{min}})$ + MRI SCAN REPORTS

1: for all $i_j$ occurring in $E$ do
2: $P \leftarrow P \cup i_j$ // add $i_j$ to create a new prefix
3: $\text{init}(E')$ // initialize a new equivalence class with the new prefix $P$
4: for all $i_k$ occurring in $E$ such that $k + C > j$ do
5: $t_{\text{tmp}} = t_j \cap t_k$
6: if $|t_{\text{tmp}}| \geq s_{\text{min}}$ then
7: $E' \leftarrow E \cup (i_k, t_{\text{tmp}}) + Dm$
8: $F = F \cup (i_k \cup P)$
9: end if
10: end for
11: if $E' \neq \emptyset$ then
12: $\text{Eclat}(E', s_{\text{min}+\text{corr}})$
13: end if
14: end for
15: $f(Pi_n) = I > 0$;
16: For $k := n - 1$ down to 1
17: $f(Pi_k) = 2 * f(Pi_{k+1}) + TW$
18: $\text{load}(Pi_k) = f(Pi_k) * \text{sizeOf}(d(Pi_k))$
19: End for
20: isStop = false;
21: for all $i_j$ occurring in $E$ do
22: If(isStop)
23: Break;
24: End if
25: if($\text{load}(Pi_j) \geq \text{threshold}$)

F-Final result; $i_j$ – MR Images
E-Brain Images
E’- k clusters
f-first image scan
U-Union; $s_{\text{min}}$ - MRI Scan
P-Predicted image
Ecat-All methods
Min-Minimum
n-Number of images
isStop – Continues Processing Stop
I-images processing
tmp- threshold
k- fuzzy c means
n-1 Watershed; $f(Pi_k)$ – morphology
C-fuzzy c means
K- unsupervised K means
M-means; $t_j \cap t_k$ – similarity
Re- Region growing
TW-twist; $d(Pi_k)$ – segmentation
Corr- Correlation
Dm- Deformable model
26: \texttt{MRI\_Send(myRank,1,\textit{MRI\_Int},\textit{Master\_node},OVERRIDE,\textit{COMM\_WORLD});}

27: \texttt{MRI\_Recv(&\textit{freeNode},1,\textit{MRI\_Int},\textit{Master\_Node},SEQ\_JOB,\textit{COMM\_WORLD},\textit{status});}

28: \texttt{If (\textit{freeNode} \geq 0)}

29: \texttt{isStop = true;}

30: \texttt{End if}

31: \texttt{End if}

32: \texttt{P := P \cup i_j // add i_j to create a new prefix}

33: \texttt{init}(E') // initialize a new equivalence class with the new prefix P

34: \texttt{for all i_k occurring in E such that k > j do}

35: \texttt{\textit{t}_{tmp} = t_j \cap t_k}

36: \texttt{if |\textit{t}_{tmp}| \geq s_{min} then}

37: \texttt{E' := E \cup (i_k, Re, t_{tmp})}

38: \texttt{F = F \cup (i_k \cup P)}

39: \texttt{end if}

40: \texttt{end for}

41: \texttt{if E' \neq \emptyset then}

42: \texttt{Eclat(\textit{E'}, s_{min})}

43: \texttt{end if}

44: \texttt{end for}

2. Segmentation method:

Various segmentation algorithms for the MRI of Brain images by using MATLAB R2015b have been implemented in this paper. These segmentation algorithms assimilate computation, visualization, as well as programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. MATLAB features a family of application specific solutions called toolboxes. The MATLAB toolboxes permit you to learn and apply specialized technology. Toolboxes are inclusive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are accessible include signal processing, control systems, fuzzy logic, neural networks, wavelets, simulation, and numerous others. There are several types of segmentation techniques that are developed to process the medical image.
2.1 Thresholding:

This technique is based on a threshold value to turn a gray-scale image into a binary image [4]. In this technique image is segmented by comparing pixel values with the predefined threshold limit L [5]. The equation to define the threshold level is given by:

\[ G = \frac{p(H + A) + (1-p)\text{One}(1/n)}{2} \]  

\[ (1) \]

Figure 1: Technique image is segmented by comparing pixel values to RGB Images

<table>
<thead>
<tr>
<th>Variables</th>
<th>Actual A</th>
<th>Actual D</th>
<th>Actual E</th>
<th>Actual P</th>
<th>Actual T</th>
<th>Correct</th>
<th>Incorrect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted A</td>
<td>37909000 / 82.25%</td>
<td>1978022 / 4.81%</td>
<td>117330 / 2.86%</td>
<td>324 / 0.01%</td>
<td>37909000 / 32.95%</td>
<td>315642 / 7.68%</td>
<td></td>
</tr>
<tr>
<td>Predicted D</td>
<td>328 / 0.01%</td>
<td>181 / 0.04%</td>
<td>32 / 0.00%</td>
<td>0 / 0.00%</td>
<td>181 / 0.04%</td>
<td>360 / 0.01%</td>
<td></td>
</tr>
<tr>
<td>Predicted E</td>
<td>103 / 0.00%</td>
<td>22 / 0.00%</td>
<td>359 / 0.01%</td>
<td>0 / 0.00%</td>
<td>359 / 0.01%</td>
<td>125 / 0.00%</td>
<td></td>
</tr>
<tr>
<td>Predicted P</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td></td>
</tr>
<tr>
<td>Predicted T</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td>0 / 0.00%</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2: Analysis the Over all methods

There are different type of threshold methods such as ousts threshold, local threshold and global threshold. After the global threshold function is applied to the DICOM image, there is problem in differentiating the tumor from some healthy tissue due to the fact that some of the tissue in the brain appeared to have a similar color to the tumor area. In order to resolve such problems a filtration algorithm for the image has been applied (see figure 1).

2.2 K means clustering:

K-means is one of the simplest unsupervised learning algorithms. This algorithm easy to solve the well-known clustering problem. The procedure follows an easy way to classify a given data set through a different number of clusters k clusters) fixed a priori. [7]

After reading and display the original image by the MATLAB, specify the structural element desk with diameter 20 and reconstruct the image, then again reconstruct the output by and then complement the result, because
the k means cluster depend on data set (randomly) it was needed to remapping the image into vector, after that determined the number of cluster equal 7, reshaping into image, and then create image segment, the last steps extracting the tumor. The steps that are used the k-means clustering are shown in (figure 2).

2.3 Fuzzy c means algorithm:

The aim of a clustering analysis is to divide a given set of data into a cluster, which represents subsets or a group. The partition must have two properties, the first one is homogeneity inside clusters data, which should be as homologous as possible, and the second one is heterogeneity between the clusters data. Which belongs to different clusters, and this should be as different as possible [8].

The steps of fuzzy c means are the same steps of k means clustering, but in fuzzy we determinate the initial points. In this paper abbreviation of codes after read and display the image , then double fuzzy c means algorithm was applied and the function (the first time returns a segment which labels the tumor with different color intensity and the second one segment the tumor) by clustering equal 7. Finally, the last steps were enhancement by applying morphological filtration and creating structural element using disk with diameter of 4, the block diagram below was shown the steps fuzzy c mean (figure3):

![Figure 3: Morphological filtration and creating structural element](image)

2.4 Watershed segmentation:

Watershed deals with group of pixels, and it is an algorithm based on integrator. Watershed algorithm is based on morphological process mixed with edge based segmentation to yield a hybrid technique [9].

Figure 4 shows the block diagram which describes the steps in details:

![Figure 4: Watershed deals with group of pixels and algorithm based on integrator](image)
2.5 Morphological based segmentation:

Morphological or morphology image process [10] describes a range of image processing techniques that deal with the shape operation typically applied to remove demerit that introduced during segmentation, and so typically operate on bi-level images [11]. Morphological used operation in boundary extraction, Region filling, extraction of connected components, thinning/thickening, skeletonisation, opening and closing [12]. All morphological processing operations are based on these simple ideas [11]. Structuring elements can be any size and make any shape. Basically morphological image processing is very like spatial filtering and the structuring element is moved across every pixel in the original image to give a pixel in a new processed image [13]. The steps are shown in figure below in details:

![Figure 5: Watershed deals with group of pixels and algorithm based on integrator](image)

2.6 Region seed growing:

This requires a seed point that is selected by the user and removes all pixels connected to the Preliminary seed. It is a used for extracting an image region that is connected based on some predefined criterion. These conditions of selected it is can be based on intensity information or boundaries in the image [14]. The manual selected dealings to obtain the seed point is the great disadvantage for this region growing. the region that needs to be extracted, a seed must be planted but split-and-merge is an algorithm related to region growing, but it does not require a seed point [15, 16]. Region growing has also been restriction to sense to noise that causing extracted regions to have holes. These problems may overcome by using a hemitrrophic region-growing algorithm [16].

After the read and display the DICOM image on the MATLAB. The first step in this process to achieve the region seed growing is to specify the seed starting region including (getting user input and flooring) the X and Y to real numbers. This is followed by processing the image seed with starting point including apply region seed growing segmentation with maximum intensity distance of 0.2. This method of segmentation is described in the (figure 6).

![Figure 6: Region seed growing segmentation with maximum](image)

2.7 Parametric deformable model:

There are two type of deformable model parametric and geometric. In parametric deformable model clearly move predefined Twist points based on an energy minimization scheme [18]. The deformation play climactically role in representation or shape such as balloon force, topology Twist, and distance Twist. In 2-D the Twist can be define by curve the energy usually formed by internal forces and external forces [19] as,
After the read and display DICOM image; the images was shown and at least 4 points are selected manually by the user. The deformable model process was then started by including the following steps: make the external force field under the influence of the Twist in a clockwise and transform the image into external energy. Then apply the external force field, after that make the internal force matrix. Finally, apply the deformable model function. Figure 7 describe the schematic work flow of deformable model process.

\[
\text{Twist} = MRI \text{ Scan} \ast \text{ Data}x(Sushisen) + Eexernal \quad (2)
\]

2.8 System Description

The Toshiba Portege R600 U2530 laptop is powered by Intel Core 2 Duo SU9400, 1400 Mega Hertz (Mhz) processor. This Portege series laptop from Toshiba comes with 3072 Megabytes (MB) of RAM, which is expandable up to Megabytes (MB). Toshiba Portege R600 U2530 laptop or notebook PC has a 128Solid State Drive Gigabytes (GB) hard disk capacity, and HDMI Port. The display of Toshiba Portege R600 U2530 is with 1280 x 800 pixels’ resolution. This Toshiba laptop has a battery life of hours and weighs around 1 kgs. Operation system Windows 10 running the MATLAB Software programming.

3. Result:

The DICOM image of MR brain used to implement the codes were downloaded from the math works website. This image doesn't need to apply preprocess. The results of the image is shown below with steps.

3.1 Thresholding:

After apply the global threshold function in figure (8) b show the some of background have the same of tumor then apply filtration algorithm the figure below show that:
2.3 K means clustering:

The figure below show the result after determination the cluster=7 and shows the segmented that created by cluster.

3.3 Fuzzy c means algorithm:

Figure (b) show the segmented by cluster =7 and apply the double fuzzy c means algorithm , in (c) show the result after enhancement:
3.4 Watershed segmentation:

The figure below shows the steps of resultant segment:

3.5 Morphological based segmentation:

The boundaries of tumor cells were unclear, indicating the infiltration into the surrounding normal brain tissue. We also observed pronounced nuclear and cytoplasmic polymorphism, intra humoral necrosis, and mitotic figures (Fig. 9c, d). The results confirmed the successful establishment of rat glioma model. In figure below show the morphological segmenting result:
Figure 12 (a) original image, (b) description of Twist movement (b1 image with initial counter, b2 the external force, b3 the external force field, b4 Twist movement), (c) colored and imposing to original image, (d) the result.

Then the output results of all techniques were compression after segmented with each other’s by correlation and structural similarity the tables follow shown:

**Table (1) global comparison method**

<table>
<thead>
<tr>
<th>Method</th>
<th>Correlation</th>
<th>Structural similarity</th>
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</thead>
<tbody>
<tr>
<td>K means</td>
<td>0.9408</td>
<td>1.0000</td>
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<tr>
<td>Fuzzy c mean</td>
<td>0.9019</td>
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<tr>
<td>Watershed</td>
<td>0.9485</td>
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<td>Region seed growing</td>
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<tr>
<td>Deformable model</td>
<td>0.7943</td>
<td>0.9999</td>
</tr>
<tr>
<td>Morphological</td>
<td>0.9404</td>
<td>1.0000</td>
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**Table (2) K means comparison method**

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<tr>
<td>Deformable model</td>
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Table (3) Fuzzy c means comparison method

<table>
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Table (4) Watershed comparison method

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Table (5) Morphological comparison method

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Table (6) Region seed growing comparison method

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<td>Fuzzy c means</td>
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<td>1.0000</td>
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<tr>
<td>watershed</td>
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<td>Deformable model</td>
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<tr>
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Table (7) Deformable model comparison method

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<td>Global threshold</td>
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4. Discussion:

We have presented different segmentation techniques of brain tissue in MR image. These techniques were employed to evaluate for their effectiveness as a tool for segmentation based on physical and structural similarities. Our results show that the deformable method was the lowest of all the techniques used in this paper because the image that used in this paper is 2D. In figure 14 (d) show the overshooting that acquiring by Twist movement when the balloon forces movement with clockwise and the structural similarity (SSL) is very evident because the different of masks unable to differentiate the boundaries. Our result show that best methods or algorithms that gives better segmentation with physical and structural similarity is region seed growing. The fuzzy c means also comparable results.

5. Conclusion:

This paper has provided the state of the art MRI-based brain tumor segmentation methods and comprehensive comparison of different segmentation techniques. An MR image size of 512x512 with GBM tumor has been used in this study. Prior to segmentation no pre-processing of the image was required to correct for background as the image had very low noise. The segmentation techniques that are compared in this paper includes: the global threshold, k means clustering, fuzzy c means algorithm, watershed, morphological, region seed growing, and deformable model. The accuracy of localization, shape and size of the input image is compared against the processed output images based on statistical parameters of correlation and structural Similarity List (SSL). The closeness of the region of interest between the original image and the output was compared using the correlation and structural similarity List (SSL). The correlation coefficient value of +1 and −1 in our result indicate that the regions of interest are highly similar and dissimilar respectively. The value of 1 is only achievable if the two sets of data are identical (see tables). Our results show that seed region growing method offers best imaging segmentation technique.

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AUTHOR’S BIOGRAPHIES

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