Modified Texture, Intensity and Orientation Constraint Based Region Growing Segmentation of 2D MR Brain Tumor Images

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Abstract: *Image segmentation is a process of dividing an image into different regions such that each region is nearly homogeneous. Magnetic Resonance (MR) images always contain a significant amount of noise caused by operator performance, equipment and the environment which can lead to serious inaccuracies with segmentation. Radiologists perform diagnosis manually at early stage. It is a very challenging and difficult task for radiologists to correctly classify the abnormal regions in the brain tissue, because Magnetic Resonance Images (MRI) images are noisy images. Because the tumors are inhomogeneous, un-sharp and faint, but show an intensity pattern that is different from the adjacent healthy tissue, a segmentation based on intensity, orientation and texture properties is proposed here. With this approach the image segmentation problem can be formulated and solved in a principled way based on well-established mathematical theories. The image clustering using texture also reduces the sensitivity to noise and results in enhanced image segmentation performance. The ground truth of the tumor boundaries is manually extracted from publicly available sources. Experimental results show that our method is robust and more accurate than other well known models. The superiority of the proposed method is examined and demonstrated through a large number of experiments using MR images.*

Keywords: *Segmentation, MRI images, texture, region growing.*

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1. Introduction

The image segmentation process can be considered as one of the basic, yet very important, steps in digital image processing and computer vision applications. Segmentation involves partitioning an image into a set of homogeneous and meaningful regions so that the pixels in each partitioned region possess an identical set of properties or attributes. Viji and Kumari [22] concluded that segmentation methods produce better segmentation results than clustering methods. All automatic seed finding methods may suffer with the problem if there is no growth of Tumor and any small white part is there. But, when the edges of tumor are not sharper the segmentation results are not accurate i.e., segmentation may be over or under. According to Kumar and Mehta [11] this process is too much time consuming and if the initial segmentation result is not correct then other consequent results like volume calculation also produces incorrect measurement results. Medical image segmentation methods most probably have limitations because medical images have much similar gray level and texture among the region of interest [2].

Tao *et al*. [21] reported that existing image segmentation algorithms can be generally classified into three major categories, i.e., feature-space-based clustering, spatial segmentation, and graph-based approaches.

Image segmentation may be considerably difficult for images with intensity in-homogeneities due to the overlaps between the ranges of the intensities in the regions to segment. Intensity is an important feature in segmenting tumor from other tissues in the brain. However, using intensity alone for segmentation has proved to be insufficient. However, for patients with poor MRI quality, intensity features may prove inadequate for tumor segmentation. For these patients, another feature such as the texture may be useful for improved tumor segmentation in MRI [1, 10].

The Fluid Vector Flow (FVF) active contour model to address problems of insufficient capture range and poor convergence for concavities [23]. Magnetic Resonance (MR) images always contain a significant amount of noise caused by operator performance, equipment, and the environment, which can lead to serious inaccuracies with segmentation [9].

Region growing is a procedure that groups pixels or sub regions into larger regions. The simplest of these approaches is pixel aggregation, which starts with a set of “seed” points and from these grows regions by appending to each seed points those neighbouring pixels that have similar properties (such as gray level, texture, color, shape). The main problem of watershed algorithm is over segmentation, because all of edge and noise would appear in the image gradient, which make the de- noising process necessary [19].

Lesion volume is often used as an end point in clinical trials of oncology therapy. Two methods, the common method of using orthogonal diameters to estimate lesion volume (the diameter method) is compared with a computer-assisted planimetric technique (the perimeter method) [16]. The perimeter method had a reduced inter-reader and intra-reader variability compared with the diameter method. Region growing is a simple image segmentation method based on the region. It is also classified as a pixel-based image segmentation method since it involves the selection of initial seed points. In a normal region growing technique, the neighbour pixels are examined by only the "intensity" constrain. The normal region growing has the drawback that noise or variation of intensity may result in holes or over segmentation. Another drawback is that the method may not distinguish the shading of the real images. Because these lesions have an irregular shape and inhomogeneous structure, segmentation approaches based on intensity or shape alone may yield imprecise results, characterizing and classifying these un- sharp, faint, inhomogeneous lesions by their textural characteristics appear promising. For improving the normal region growing and effectively tackling the drawbacks of a normal region growing, in the modified region growing, there are two thresholds, one is for the intensity and the other for orientation. Region is grown if only both constrains are met. The inclusion of this additional constrain have yielded in a much better result when compared to the normal region growing. The modified region growing is a three step process which consists of gridding, selection of seed point, applying region growing to the point [8]. The most widely used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the intensity in- homogeneity [13]. Texture has the property of homogeneity. Because the tumors are inhomogeneous, un-sharp, and faint, but show an intensity pattern that is different from the adjacent healthy tissue, a segmentation based on intensity, orientation and texture properties is proposed here. The organization of this paper is as follows: Section 2 explains the methodology. Section 3 describes the segmentation methods and section 4 shows the experimental results. Finally, section 5 concludes the paper.

2. Methodology

The total process is as follows:

1. Input a MRI head data.
2. Perform pre-processing and enhancement.
3. Perform texture based region growing segmentation.
   a. The decision of growing the region into next pixel is based on pixel intensity and texture image (texture image is obtained by doing the Local Binary Pattern (LBP) operator over the image).
   b. The decision about assigning segment label is based on pixel intensity, orientation (which is obtained by applying gradient operator to the image) and texture image.
4. Repeat step 1 to 4 for many patients.
5. Feature extraction and classification (using ANN).
6. Tumour detection process.
7. Evaluate performance.

2.1. Image Acquisition

To access the real medical images like MRI, Positron Emission Tomography (PET) or Computerized Tomography (CT) scan and to take up a research is a very complex because of privacy issues and heavy technical hurdles [16]. The first stage in any vision system is the image acquisition stage. In this stage, images can be acquired from cameras and frame grabbers.

2.2. Preprocessing

In medical images, due to diagnostic and therapeutic applications the removal of noise, labels and artifacts is critical. Specially, in MRI, inhomogeneous magnetic field, patient motion in imaging duration and external noise, are some sources of artifacts and other undesired effects. These form the main causes of computational errors in automatic image analysis and brain tumor detection. Therefore, it is necessary to remove them in the preprocessing procedure before any image analyzes can be performed [7].

The enhancement method consists of three processing steps: First, the MRI image is acquired. Second, removal of film artifacts such as labels and marks on the MRI image and finally, the high frequency components are removed. After this stage the medical image is converted into standard image without noise, film artifacts and labels [16].

As Gaussian filters have minimum possible group delay and as they reduce the rise and fall time they are used for pre-processing. Mathematically this filter convolutes the input signal using a Gaussian function. This function is a sequence of integral transforms. This is a continuous function but not discrete. The ratio between sample rate f_s and and standard deviation σ is called the cut-off frequency (f_c) and is defined as:

$$f_c = \frac{f_s}{\sigma} \quad (1)$$

During pre-processing by passing the input image through Gaussian filter, reduces the noise present in the input image and also makes the image fit for further processing. Image quality is also increased using Gaussian filter [8]. The per processed image is shown in Figure 1.

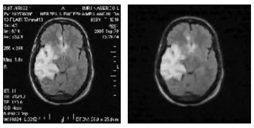


Figure 1. Preprocessed image.

3. Segmentation

Image segmentation is often the precursor to patient diagnosis and treatment evaluation, which is facilitated through a thorough statistical analysis and quantification aided by a variety of visual tools [17]. Different methods are presented for image segmentation. Watershed segmentation entirely relay on the image contrast. Image contrast may be degraded during image acquisition. Watershed algorithm can generate over segmentation or under segmentation on badly contrast images. The normalized cut criterion measures both the total dissimilarity between the different groups as well as the total similarity within the groups [20]. Images with GBM usually have complex and inhomogeneous imaging patterns, which cannot be appropriately simulated using the simple segmentation model [6] .To achieve improved classification performance, it is beneficial to use a segmentation step and form groups of pixels that represent homogeneous regions. [4].

Medical image analysis typically involves heterogeneous data that has been sampled from different underlying anatomic and pathologic physical processes. A key problem in medical imaging is automatically segmenting an image into its constituent heterogeneous processes. Automatic segmentation has the potential to positively impact clinical medicine by freeing physicians from the burden of manual labeling and by providing robust, quantitative measurements to aid in diagnosis and disease modeling. One such problem in clinical medicine is the automatic segmentation and quantification of brain tumors [3]. The basic watershed algorithm is well recognized, as an efficient morphological segmentation tool which has been used in a variety of gray scale image processes and video processing applications. However, a major problem with the watershed transformation is that it produces a large number of segmented regions in the image around each local minima embedded in that image. A solution to sort out this problem is to introduce markers and flood the gradient image starting from these markers instead of regional minima.

3.1. Textural based Region Growing Segmentation

Texture is the feature used to characterize the surface of a given object or region and it is one of the main features utilized in image processing and the pattern recognition.

Extraction of good features is thus fundamental to successful image segmentation. Due to the complex structures of different tissues such as White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF) in the brain MR images, extraction of useful features is a demanding task. Intensity is an important feature in discriminating different tissue types in the brain MR images. However, using intensity feature alone to segment complex brain tissues and tumor in a single modality MR image has been proved to be insufficient. Consequently, multi-spectral MR image offers improved image segmentation results compared to that in single modality image [4].

Texture can be many types such as smooth or rough, regular or irregular, coarse or fine [11]. Region growing is a simple image segmentation method based on the region. This approach to segmentation examines the neighboring pixels of initial “seed points” and determines whether the pixel neighbors should be added to the region or not, based on certain conditions. The process is iterated to yield different regions. In a normal region growing technique, the neighbor pixels are examined by only the “intensity” constrain. For this, a threshold level for intensity value is set and those neighbor pixels that satisfy this threshold is selected for region growing. The normal region growing has the drawback that noise or variation of intensity may result in holes or over-segmentation. Another drawback is that the method may not distinguish the shading of the real images. Because lesions typically have an intensity distribution that is different from the surrounding tissue, providing an intensity-based segmentation is often insufficient. For improving the normal region growing and effectively tackling the drawbacks of a normal region growing, an additional constrain of “orientation” is added in extended region growing method. In the modified region growing, there are two thresholds; one is for the intensity and the other for orientation. Region is grown if only both constrains are met. The inclusion of this additional constrain have yielded in a much better result when compared to the normal region growing.

Intensity in-homogeneity often occurs in real-world images, which presents a considerable challenge in image segmentation. The most widely used image segmentation algorithms are region-based and typically rely on the homogeneity of the image intensities in the regions of interest, which often fail to provide accurate segmentation results due to the intensity in-homogeneity. In particular, image segmentation may be considerably difficult for images with intensity in-homogeneities due to the overlaps between the ranges of the intensities in the regions to segment. This makes it impossible to identify these regions based on the pixel intensity [13]. Most of region-based models are based on the assumption of intensity homogeneity.

But the intensity in-homogeneity problem must also be met. Texture has the property of homogeneity. Texture statistics refers to the classification of normal and abnormal brain tissue patterns or texture. Texture perception has a very important aspect in the human visual system of recognition and interpretation [14]. Because these lesions have an irregular shape and inhomogeneous structure, segmentation approaches based on intensity or shape alone may yield imprecise results, characterizing and classifying these un-sharp, faint, inhomogeneous lesions by their textural characteristics appear promising [10].

In recent years, medical image segmentation problems has been approached with several solution methods by different range of applicability such as Particle Swarm Optimization, Genetic Algorithm, Adaptive Network-based Fuzzy Inference System (ANFIS), Region Growing, Active Contour Snake model, Self Organizing Map (SOM) and Fuzzy C-Means (FCM). However, segmenting the brain internal structures remains a challenging task due to their small size, partial volume effects, anatomical variability and the lack of clearly defined edges. Thus, considerable effort is required in order to find reliable and accurate algorithms to solve this difficult problem. So two innovative modifications are performed in the region growing segmentation algorithm. The proposed methods is called as texture based region growing algorithm that had been tested in brain abnormalities which produces satisfactory results.

In the first modification i.e., Intensity Based Textural Region Growing (IBTRG), the decision of growing the region into next pixel is based on pixel intensity and texture image (texture image is obtained by doing the LBP operator over the image). In the second modification i.e., Intensity and Orientation Based Textural Region Growing (IOBTRG), the decision about assigning segment label is based on pixel intensity, orientation (which is obtained by applying gradient operator to the image) and texture image. In our work, texture feature descriptors are used, which are complementary to intensity features due to their illumination invariant nature. The used feature descriptor is Local Binary Pattern (LBP) which is extracted from a spatial neighbourhood of n x n pixels. To deal with intensity variation, the LBP feature is extracted, which is a very powerful texture feature descriptor. It encodes 256 possible texture patterns at each pixel, providing an efficient representation of texture [15]. It is simple and robust to compute. The proposed approach for detection of Brain Tumour in the MRI involves the following steps, pre-processing, segmentation, feature extraction and tumour detection process. In the pre-processing step, image de-noising is done using the linear smoothing filters, such as Gaussian Filter. The proposed modified region growing algorithms IBTRG and IOBTRG are subsequently applied to the images.

3.2. Proposed Algorithms

Algorithm 1:

Procedure: *IBTRG*
Input: Pre-processed image.
Output: Regions
Step 1. Start
Step 2. Apply LBP operator to the image to get the texture image.
Step 3. Split the image I into grids G_i.
Step 4. Set the intensity threshold T_I and texture threshold T_T.
Step 5. For each grid (*denoted as G_i*) *do*:

a. *Find the histogram* (*denoted as Hist*) *of every pixel P_j in the grid G_i.*
b. *Find the most frequent histogram of the G_i^{th} grid and denote it as $Freq_{Hist}$.*
c. *Select any pixel P_j corresponding to the $Freq_{Hist}$ and assign that pixel as seed point SP having intensity I_P.*
d. *For the neighboring pixel having intensity I_N and texture value T_N, check for intensity constraint $\|I_P-I_N\|\leq T_I$ and texture constraint $\|T_P-T_N\|\leq T_T$.*
e. *If both the constraints are satisfied and met, region is grown to neighboring pixel. The region is not grown to the neighboring pixel in the other case*.

Step 6. *Stop*.

Algorithm 2:

Procedure: IOBTRG.
Input: Pre- processed image.
Output: Regions.
Step 1. Start
Step 2. Find the gradient of the Image I in both x axis (I_X) and y axis (I_Y).
Step 3. Combine the gradient values using the formula to get $g = 1 \big/ 1+(I_x^2+I_y^2)$ *the gradient vector g.*
Step 4. Gradient vector values will be in radians. Convert it to degrees to get the orientation values of the pixels of the image.
Step 5. Apply LBP operator to the image to get the texture image.
Step 6. Split the image I into Grids G_i.
Step 7. Set the intensity threshold T_I , texture threshold T_T and the orientation threshold T_O.
Step 8. For each Grid (denoted as G_i) do

a. *Find the histogram (denoted as Hist) of every pixel P_j in the grid G_i.*
b. *Find the most frequent histogram of the G_i^{th} grid and denote it as $Freq_{Hist}$.*
c. *Select any pixel P_j corresponding to the $Freq_{Hist}$ and assign that pixel as seed point SP having intensity I_P and orientation O_P.*
d. *For the neighboring pixel having intensity I_N, orientation O_N and texture value T_N, check for intensity constraint $\|I_P-I_N\| \leq T_I$, orientation constraint $\|O_P-O_N\|\leq T_O$ and texture constraint $\|T_P-T_N\|\leq T_T$.*
e. *If three constraints are satisfied and met, region is grown to the neighbouring pixel. The region is not grown to the neighbouring pixel in the other case.*

Step 9. Stop.

3.3. Feature Extraction and Classification

Feature extraction is the process by which certain features of interest with in an image are detected and represented for further processing. After segmentation, features are extracted from the segmented regions for each grid. Features are extracted from pixels. The features extracted are area, eccentricity, major axis length, minor axis length and form factor. These features are used to train the classifier. Area is a two dimensional quantity. There are several formulae for finding the area of different shapes. Area of an image is the total number of pixels in that particular region. The maximum number of segmentation pixels along the horizontal axis is the Major Axis Length (MaAL) and the one in vertical axis is the Minor Axis Length (MiAL). The ratio of major axis length and minor axis length is called as eccentricity. After segmentation, the tumor area will be in one gray value and the remaining area will be in the opposite gray scale value i.e., 0 and:

1. If the tumor area is assigned as 1 then:

$$Eccentricity = R_{max} / C_{max} \tag{2}$$

Where R_{max} is the maximum number of 1's along the row and C_{max} is the maximum number of 1's along the column. Total number pixel change from 1 to 0 or 0 to 1 is counted as perimeter in image regions. The form factor is calculated using the following formula:

$$Form\ Factor = 4\pi Area / Perimeter^2 \tag{3}$$

The feature extraction extracts the features of importance for image recognition. The feature extracted gives the property of the text character, which can be used for training in the database. The obtained trained feature is compared with the test sample feature obtained and classified as one of the extracted character. Gray-Level Co-occurrence Matrix (GLCM) introduced by Haralick (1973) is a popular and robust statistical tool for extracting second-order texture information from images. A GLCM indicates the probability of grey-level i occurring in the neighbourhood of grey-level j at a distance d and direction θ. GLCMs can be computed from texture images using different values of d and θ and these probability values create the co-occurrence matrix(i, $j|d$, θ). GLCM is also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image creating a GLCM, and then extracting statistical measures from this matrix. Important steps include

1. Creating a gray-level co-occurrence matrix.
2. Specifying the offsets.
3. Deriving statistics from a GLCM/

After creating GLCM, several statistics can be derived using graycoprops function in MATLAB. The features extracted in our work are contrast, correlation, energy and homogeneity. Contrast returns a measure of intensity between a pixel and its neighbour over the whole image. Contrast is 0 for a constant image. For two neighbouring pixels i and j the contrast is calculated as:

$$C = \sum_{i,j} \left| i, j \right|^2 p(i, j) \tag{4}$$

Correlation returns a measure of how correlated a pixel to its neighbour over the whole image. Correlation is 1 or -1 for perfectly positively or negatively correlated image. Correlation is NaN for constant image. The correlation is given by:

$$Corr = \sum \frac{(i, \mu_i)(j, \mu_j) p(i, j)}{\sigma_i \sigma_j} \tag{5}$$

Where μ and σ are mean and standard deviation respectively. The sum of squared elements in the GLCM is its energy and is computed as:

$$E = \sum_{i,j} p(i, j)^2 \tag{6}$$

Energy is 1 for a contrast image. A value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal is homogeneity. Homogeneity is defined as:

$$H = \sum_{i,j} \frac{p(i, j)}{1 + |i - j|} \tag{7}$$

Neural network is a suitable tool for image classification. We use neural network to model real world relationships because they are non linear models. The three layers of the neural network include:

1. Input layer.
2. Hidden layer.
3. Output layer.

A feed forward neural network classifier is used to classify the input MRI images into tumor or normal. Features are extracted and the neural networks are trained by those features. We took around 28 images of which 23 are tumorous and 5 non tumorous. We have used Feed Forward Neural Network (FFNN) for classification. The input MRI image is fed into the trained neural network after the pre-processing and modified region growing. The classifier compares the trained data with those of the input image feature data and classifies it into tumour or normal.

The input MRI image is fed into the trained neural network after the pre-processing and texture based region growing. The classifier compares the trained data with those of the input image feature data and classifies it into normal or abnormal.

4. Experimental Results

In this section, experimental results are described to compare the segmentation performance of IBTRG and

IOBTRG with that of ordinary region growing and textural segmentation. The area, eccentricity, form factor, perimeter, major axis length and minor axis length of five MRI images are shown in Tables 1, 2, 3, 4 and 5 respectively.

Table 1. Extracted features of sample image 1.

Parameters	Image 1					
	Area	Eccentricity	Form Factor	Perimter	MaAL	MiAL
Texture	3632	0.3451	0.3561	358	39	113
RegionGrowing	42269	0.8618	0.1207	486	187	217
IBTRG	3382	0.4254	0.0057	350	134	315
IOBTRG	3390	0.5590	0.0059	340	109	195

Table 2. Extracted features of sample image 2.

Parameters	Image 2					
	Area	Eccentricity	Form Factor	Perimter	MaAL	MiAL
Texture	2283	0.3451	0.5330	232	46	67
RegionGrowing	1947	0.8618	0.0815	548	186	195
IBTRG	935	0.3514	0.0013	467	175	498
IOBTRG	1004	1.0864	0.0121	654	176	162

Table 3. Extracted features of sample image 3.

Parameters	Image 3					
	Area	Eccentricity	Form Factor	Perimter	MaAL	MiAL
Texture	3557	1.1864	0.5621	282	70	59
RegionGrowing	3580	0.8802	0.0108	646	169	192
IBTRG	2172	1.2662	0.0070	597	195	154
IOBTRG	1567	1.1656	0.0049	467	183	157

Table 4. Extracted features of sample image 4.

Parameters	Image 4					
	Area	Eccentricity	Form Factor	Perimter	MaAL	MiAL
Texture	9264	0.6712	0.9290	354	98	146
RegionGrowing	7780	0.8844	0.4351	474	176	199
IBTRG	8456	1.5467	0.2018	567	150	187
IOBTRG	8245	0.9634	0.6217	549	159	169

Table 5. Extracted features of sample image 5.

Parameters	Image 5					
	Area	Eccentricity	Form Factor	Perimter	MaAL	MiAL
Texture	2875	0.7429	0.7462	220	52	70
RegionGrowing	1600	0.9900	0.0459	662	198	200
IBTRG	2155	0.9367	1.6735	657	170	175
IOBTRG	2698	1.4532	0.9856	598	173	195

4.1. Performance Evaluation

Completeness (Co) and Correctness (Cor) are statistical measures of the performance of a binary classification test, also known in statistics as classification function. Co measures the proportion of actual positives which are correctly identified as positive. Cor measures the proportion of negatives which are correctly identified. Accuracy (A) determines the success or failure rate of the proposed algorithms. In order to find Co, Cor and accuracy, first we have to compute some of the terms like, True Positive (TP), True Negative (TN), False Negative (FN) and False Positive (FP) from the Ground Truth (GT) and Segmented Image (SI) [5]. The segmentation result is evaluated with the help of quality rate as given below. Ground truth values are obtained from some publicly available databases. Segmented image value is the total number of pixels obtained through the proposed algorithms. TP refers to the number of pixels that are truly tumor in our algorithm but FP is the number of pixels that are non tumor but classified as tumor. TN is the region that is not a tumor and classified as non-tumorand FN is atumor region but classified as non tumor. All studies were reviewed by radiologists with with several years' of experience in neuroradiology. Tumor detection in different images is carried out using the following metrics:

$$Completeness = {TP}/{(TP + FN)} * 100\,\% \tag{8}$$

$$Correctness = {TN}/{TN + FP} * 100\% \tag{9}$$

$$Accuracy = (TN + TP) / (TN + TP + FN + FP) \tag{10}$$

The Relative Error (RE) rate is calculated using the following formula

$$RE = (SI - GT) / GT * 100 \tag{11}$$

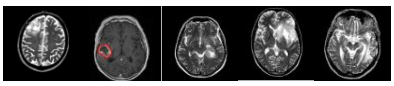
Where SI is the segmented image and GT is the ground truth. Some original images and their ground truth images are shown below in Figure 2. The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmented images are shown below in Figure 3.

A similarity coefficient measures the resemblance between two individuals or objects based on either or both of two logically distinct kinds of information. Consider two objects A and B, a is the number of features (characteristics) present in A and absent in B, b is the number of features absent in A and present in B, c is the number of features common to both objects, and d is the number of features absent from both objects. Thus, c and d measure the present and the absent matches, respectively, i.e., similarity; while a and b measure the corresponding mismatches, i.e., dissimilarity [12]. Coefficient of similarity (ε) is calculated using the formula as:

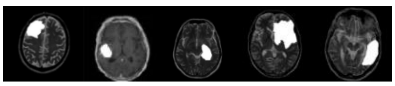
$$\varepsilon = 1 - \frac{|manual - automatic|}{manual} \tag{12}$$

Spatial overlap (£) is calculated as:

$$E = \frac{2 * intersection}{manual + automatic} \tag{13}$$



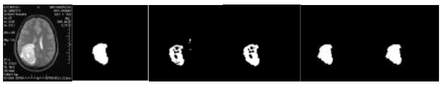
a) Original images.



b) Ground truth images

Figure 2. Original and ground truth images.

a) The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 1.



b) The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 2.

c) he input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 3.

d) The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 4.

e) The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 5.

Figure 3. Segmentation results of images 1, 2, 3, 4 and 5.

The Co, Cor, accuracy, relative error, coefficient of similarity and spatial overlap of five images are shown in Tables 6, 7, 8, 9, 10 respectively. The spatial overlap and coefficient of similarity of two images are shown in Tables 11 and 12.

Table 6. Co, Cor, A, RE, ε and £ of sample image1.

Segmentation Methods	Image 1					
	Co	**Cor**	**A**	**RE**	**Coefficient of Similarity**	**Spatial overlap**
Texture	89.75%	88.45%	88.5%	13.5%	1.1350	0.9344
RegionGrowing	68.75%	89.75%	89%	29.09%	0.7091	0.8045
IBTRG	93.75%	94.65%	94.1%	5.68%	1.0569	0.9116
IOBTRG	93.43%	93.15%	94.08%	5.93%	1.0594	0.9560

Table 7. Co, Cor, A, RE, ε and £ of sample image2.

Segmentation Methods	Image 2					
	Co	**Cor**	**A**	**RE**	**Coefficient of Similarity**	**Spatial overla p**
Texture	49.35%	84.13%	80.38%	13.58%	1.1358	0.4621
RegionGrowing	64.11%	89.5%	85.35%	3.13%	0.4652	0.4995
IBTRG	75.77%	93.93%	92.35%	-54.4%	0.9687	0.9755
IOBTRG	94.059%	93.75%	93.5%	-50.04%	0.7248	0.7304

Table 8. Co, Cor, A, RE, ε and £ of sample image3.

Segmentation Methods	Image 3					
	Co	**Cor**	**A**	**RE**	**Coefficient of Similarity**	**Spatial overlap**
Texture	89.7%	88.97%	89.2%	7.78%	1.0779	0.6582
RegionGrowing	89.3%	88.83%	88.89%	8.48%	1.0606	0.4748
IBTRG	92.45%	92.66%	93.45%	-34.18%	0.9605	0.7672
IOBTRG	90.60%	93.60%	92.83%	-52.51%	0.9647	0.8219

Table 9. Co, Cor, A, RE, ε and £ of sample image4.

Segmentation Methods	Image 4					
	Co	**Cor**	**A**	**RE**	**Coefficient of Similarity**	**Spatial overlap**
Texture	85.77%	89.08%	88.17%	1.78%	0.8684	0.8745
RegionGrowing	89.2%	88.88%	89.15%	2.828%	0.8837	0.7705
IBTRG	92.77%	93.23%	92.39%	-34.4%	0.7562	0.7712
IOBTRG	92.05%	91.25%	92.51%	-30.54%	0.7825	0.7656

Table 10. Co, Cor, A, RE, ε and £ of sample image5.

Segmentation Methods	Image 5					
	Co	**Cor**	**A**	**RE**	**Coefficient of Similarity**	**Spatial overlap**
Texture	86.82%	85.58%	86.32%	2.69%	0.8456	0.8921
RegionGrowing	87.82%	78.29%	84.77%	1.378%	0.8327	0.7185
IBTRG	92.84%	92.83%	93.54%	-43.24%	0.8923	0.8341
IOBTRG	92.65%	92.47%	92.95%	-20.54%	0. 8752	0.8766

Table 11. ε, and £ of sample image 6.

Segmentation Methods	Image6	
	Coefficient of Similarity	**Spatial overlap**
Region Growing	0.7366	0.7965
Texture	0.8423	0.8032
IBTRG	0.8512	0.8123

Table 12. ε, and £ of sample image 7.

Segmentation Methods	Image7	
	Coefficient of Similarity	**Spatial overlap**
Region Growing	0.7308	0.7826
Texture	0.8378	0.8145
IBTRG	0.8467	0.8237

The input image, manually segmented, region growing based, texture based and IBTRG segmented images are shown below in Figure 4. The overall accuracy of the proposed methods are shown below in Figure 5. It is 93.16% for IBTRG and 93.17% for IOBTRG.

a) The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 6.

b) The input image, ground truth image, region growing, texture, IBTRG and IOBTRG segmentations of image 7.

Figure 4. The Segmentation results of images 6 and 7.

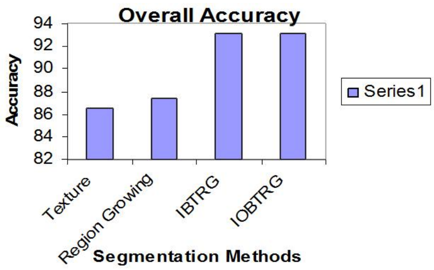


Figure 5. Overall accuracy.

5. Conclusions

In the method proposed by H.B. Kekre *et al.* [9], probability and entropy are used for grouping pixels into different regions. They form the images of probability and entropy and are then displayed. Since the values of probabilities were very low, normalization was performed before detection of tumor. It gives better segmentation results as compared to GLCM. Shi and Malik [20] proposed Unsupervised Hybrid Classification for Texture Analysis (UHCTA) algorithm and compared it with LBP) and GLCM. It is found that UHCTA method has more classification accuracy than the other methods while using different window sizes. The average window size for UHCTA is 91.6% which is higher than the 85% and 86.6% of LBP, and GLCM respectively. Region growing segmentation is purely based on image regions. Modified region growing segmentation algorithm performs segmentation based on the intensity and orientation constraints. But it cannot address the intensity in homogeneity problem. Texture has the property of homogeneity. Thus, the intensity in homogeneity problem can be addressed by adding texture constraint in addition to intensity and orientation constraints. Segmentation based only on texture also yields imprecise results. Texture combined with modified region growing increases segmentation accuracy than region growing, texture and IBTRG. The overall accuracy is 93.16% for IBTRG and 93.17% for IOBTRG. But for texture segmentation and region growing segmentation it is only 86.51 and 87.43% respectively, that was less than the proposed methods. However, the elapsed time is high for the proposed method which can be reduced further in future. Also the overall accuracy can be increased using any optimization algorithms.

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