Optimized region growing segmentation algorithm for MR Brain Images

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ABSTRACT

Background: Image Segmentation is an important and challenging factor in the medical image processing. Objective: This paper describes a new segmentation method that modifies the region growing method. It make use of texture constraint in addition to intensity constraint to grow the region for the purpose of segmentation. Also it was optimized using genetic algorithm (GA) i.e., it uses GA for choosing intensity and texture constraint. Texture image is obtained from LBP image. At first the film artifact and noise are removed and the image is enhanced using Gaussian filtering and normalization. Secondly, features are extracted from the image and it is classified using KNN classifier. In the third phase optimized region growing (ORGW) segmentation was done, if the image is abnormal. Finally the image is compared with the ground truth image and the segmentation accuracy was calculated. Results: Work was carried out for many images. The segmentation accuracy is 0.7531% for RGW method and it is 0.9357% for ORGW Conclusion: This automatic detection of brain tumor through MRI can provide the valuable outlook and accuracy of earlier brain tumor detection.

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INTRODUCTION

One of the challenging medical image analysis methodologies is the automated brain disorder diagnosis with MR images. The abnormal tumor portion in brain is segmentation and is used to separate image into regions. These tumors are inhomogeneous, un sharp, and faint (Angel et al., 2011). Image segmentation is one of the most difficult tasks in image processing which determines the quality of the final result of the image analysis. The process of dividing an image into different regions such that each region is homogeneous is termed as image segmentation (Angel et al., 2012). Textures are replications, symmetries and combinations of various basic patterns, usually with some random variation (Angel et al., 2013a). Two innovative modified region growing algorithms have been proposed in (Angel et al., 2013b). In the first modification: texture and intensity based modified region growing (TIBMRG), 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: texture, intensity and orientation based modified region growing (TIOBMRG), 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.

Segmentation refers to partitioning an image into meaningful regions, in order to distinguish objects (or regions of interest) from background. There are two major approaches, region-based method (such as region growing, split/merge using quad tree decomposition) in which similarities are detected, and boundary-based method (such as thresholding, gradient edge detection), in which discontinuities are detected and linked to form boundaries around regions. Segmentation of nontrivial images is one of the most difficult tasks in image processing (Mehdi, 2010). In recent years, medical image segmentation problems has been approached with several solution methods 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). They have different range of applicability. Their small size, partial volume effects, anatomical variability and the lack of clearly defined edges are the challenging factors in segmenting the brain MRI images. In order to find reliable and accurate algorithms for solving this difficult problem several efforts have to be taken (Shafaf, 2010). For the inhomogeneous, un sharp, and faint images that show an intensity pattern that is different from the adjacent healthy tissue, a segmentation based on texture properties is proposed.
in Frithjof (2008). One of the important analysis in many applications of image processing for classification, detection, or segmentation of images is texture analysis. Gray level co occurrence matrices approach is the most popularly used texture measures in this concern (Pietikanen).

The rest of this paper is organized with methodology, experimental results and performance evaluation. Finally it is concluded with a conclusion.

Methodology:

The total process is as follows: 1) Input a MRI head data, 2) Perform Gaussian filtering and normalization, 3) Perform feature extraction, 4) Classification using KNN classifier, 5) Perform ORGW segmentation and 6) Evaluate performance. The optimized region growing segmentation process is shown in Fig. 1.

**Methodology:**

1. Input a MRI head data
2. Perform Gaussian filtering and normalization
3. Perform feature extraction
4. Classification using KNN classifier
5. Perform ORGW segmentation
6. Evaluate performance

**Database (Image Acquisition):**

The images obtained from MRI may be of three types: axial, sagittal or coronal Images. To access the real medical images like MRI, PET or CT scan and to take up a research is a very complex because of privacy issues and heavy technical hurdles. The MRI data is obtained from the publicly available sources for our work. We have used 59 images of which 39 are abnormal and 20 are normal.

**Pre-processing (Gaussian filtering and Normalization):**

As a first stage of the segmentation problem it is often necessary to filter the main edges of the image while rejecting much of the gradient noise that leads to over segmentation (Bredon, 2007). Pre-processing and enhancement techniques are used to improve the detection of the suspicious regions in MRI. The Pre-processing stage is used for reducing image noise, highlighting edges, or displaying digital images. The Pre-processing Techniques such as Content Based model, Fibre tracking Method, Wavelets & Wavelet Packets, and Fourier transform technique. Olivier et al. designed a new Standard Imaging Protocol for brain tumor radiotherapy. In this regard, a Gaussian filter was chosen. This filter has several advantages including its ability to perform edge enhancing and noise rejection simultaneously. 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 standard deviation $\sigma$ is called the cut off frequency ($f_c$) and is defined as:

$$f_c = \frac{f}{\sigma}$$

In image processing, normalization is a process that changes the range of pixel intensity values. Normalization is sometimes called contrast stretching or histogram stretching. In more general fields of data processing, such as digital signal processing, it is referred to as dynamic range expansion.

**Feature Extraction:**

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately (Singh). Texture features such as mean, standard deviation, entropy, skewness, kurtosis, correlation, energy, and homogeneity are extracted. Calculation of the texture features are given in below:
Mean: \( \mu = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} x(i, j) \)  

(2)

Entropy: \( e = -\sum_{w} p_w \log_2(p_w) \)  

(3)

Where, \( K \) – Number of rows in the image, \( L \) – Number of columns in the image and \( x''(i,j) \) – pixel value at point at location \( (i,j) \).

\( p_w = \frac{q_w}{mn} \)  

(4)

Where, \( p_w \) - Probability of the grey level, \( q_w \) - Total number of pixel with \( w^{th} \) grey level and \( K \) - Total number of grey levels.

Skewness: \( S_{ij} = \left( \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{(x(i, j) - \mu(i, j))^3}{S} \right) \)  

(5)

Kurtosis: \( HO = \left( \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{(x(i, j) - \mu(i, j))^4}{S} \right)^{1/2} \)  

(6)

Standard Deviation: \( S = \left( \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (x(i, j) - \mu(i, j))^2 \right)^{1/2} \)  

(7)

Contrast: \( C = \sum_{i=1}^{K} \sum_{j=1}^{L} \left( x''(i, j) \right) \)  

(8)

Homogeneity: \( HO = \sum_{i,j} \frac{x(i, j)}{1+|i-j|} \)  

(9)

Where, \( m \) - Number of rows of the given input image, \( n \) - Number of columns of the given input image.

**Classification:**

The nearest-neighbour method is perhaps the simplest of all algorithms for predicting the class of a test example. The training phase is trivial: simply store every training example, with its label. To make a prediction for a test example, first compute its distance to every training example. Then keep the \( k \) closest training examples, where \( k \geq 1 \) is a fixed integer. Look for the label that is most common among these examples. This label is the prediction for this test example. This basic method is called the kNN algorithm. These are the two major choices to make: the value of \( k \), and the distance function to use. One example kNN classification is given in Fig. 2. The most common distance function is Euclidean distance.

\[ d(x, y) = \|x - y\| = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \]  

(10)

**Fig. 2:** Example kNN classification.

The kNN only requires 1) an integer \( k \), 2) a set of labelled examples (training data) and 3) a metric to measure ‘closeness’. In the example in Fig 3 we have three classes and the goal is to find a class label for the unknown example \( x_u \). In this case we have used the Euclidean distance and a value of \( k=5 \) neighbours. Of the 5 closest neighbours, 4 belong to \( \omega_1 \) and one belongs to \( \omega_3 \), so \( x_u \) is assigned to \( \omega_1 \), the predominant class. Initially the kNN classifier is trained with the features that are extracted in the previous step. A classifier is used
to classify the input MRI images into tumor or normal. In MATLAB the ‘knnclassify’ function is used to classify the images into a normal one or pathological (abnormal) one.

**ORGW Segmentation:**

Segmentation describes separation of suspicious region from background MRI image. Image segmentation algorithms generally are based on one of two basic properties of intensity values: 1) discontinuity and 2) similarity. The ultimate aim in a large number of image processing applications is to extract important features from the image data, from which a description, interpretation, or understanding of the scene can be provided by the machine. Four of the most common methods are: 1) amplitude thresholding, 2) texture segmentation 3) template matching, and 4) region-growing segmentation (Rafael, 2003). The abnormal image was treated to segmentation process. Genetic algorithm is used to choose the texture threshold and intensity threshold so as to increase the segmentation performance. The algorithm is given below:

**Procedure:**

**Input:**

Pre-processed Image

**Output:**

Regions

Step 1: Start

Step 2: Apply LBP operator to the image to get the texture image.

Step 3: Set the intensity threshold $T_I$ and texture threshold $T_T$ by using genetic algorithm.

Step 5: For the image I do

a. Perform histogram equalization (denoted as Hist) of all pixel $P_j$.

b. Extract the most frequent histogram of the image and denote it as $Freq_{Hist}$.

c. Choose any pixel $P_j$ corresponding to the $Freq_{Hist}$ and assume that pixel as seed point SP with intensity $I_P$.

d. If the intensity of neighbouring pixel is $I_N$ and if texture value is $T_N$, then check for intensity constraint $|I_P - I_N| \leq T_I$ and texture constraint $|T_P - T_N| \leq T_T$.

e. If both (intensity and texture) the constraints are satisfied, grow the region to neighbouring pixel. In all the other case the region is not grown to the neighbouring pixel.

Step 6: Stop.

**Experimental Results:**

The proposed MRI abnormality detection and tissue segmentation technique is implemented in the working platform of MATLAB (version 7.12). The input, ground truth, filtered, normalized, LBP, region growing (RGW) segmentation and ORGW images are given in Fig. 3. Experiment was conducted for 59 images of which 39 are tumorous and 20 non tumor.

![Sample MRI Images](image-url)

**Fig. 3:** The input, ground truth, filtered, normalized, LBP, region growing (RGW) segmentation and ORGW segmentation images.
Performance Evaluation:
In order to verify the quality and flexibility of our proposed techniques, we obtain similarity measures to compute the overlap between tumors segments obtained using ORGW and ground truth (GT) obtained using manual segmentation (Kavitha, 2012). The evaluation of brain tumour detection in different images is carried out using the following metrics,
\[ \text{Accuracy} = \frac{(\text{TN} + \text{TP})}{(\text{TN} + \text{TP} + \text{FN} + \text{FP})} \]

Where, TP stands for True Positive, TN stands for True Negative, FN stands for False Negative and FP stands for False Positive. As suggested by above equations, accuracy is the proportion of true results, either true positive or true negative, in a population. It measures the degree of veracity of a diagnostic test on a condition.

Table 1: Segmentation Accuracy.

<table>
<thead>
<tr>
<th>Images</th>
<th>Texture Threshold</th>
<th>Intensity Threshold</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image1</td>
<td>132</td>
<td>170</td>
<td>0.7434</td>
</tr>
<tr>
<td>Image2</td>
<td>129</td>
<td>146</td>
<td>0.7698</td>
</tr>
<tr>
<td>Image3</td>
<td>133</td>
<td>175</td>
<td>0.7392</td>
</tr>
<tr>
<td>Image4</td>
<td>142</td>
<td>169</td>
<td>0.7719</td>
</tr>
<tr>
<td>Image5</td>
<td>124</td>
<td>184</td>
<td>0.7215</td>
</tr>
</tbody>
</table>

Conclusion:
We proposed ORGW algorithm as an improved approach to brain MR image segmentation. By preprocessing the images properly, number of redundant rules which could contain noisy information can be reduced. The kNN classifier classifies the image into normal or abnormal. The genetic algorithm used in the threshold value selection, helps in increasing the segmentation accuracy. The experimental results have shown that ORGW segmentation had produced better results than RGW segmentation. The use of the ORGW segmentation greatly improves the performance of the image segmentation than RGW segmentation. The segmentation accuracy is 0.7531% for RGW method and it is 0.9357% for ORGW. However our work is time consuming so that effective measures can be taken to reduce the time complexity and further to improve the accuracy.

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