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Research Article

Learning-based Improved Seeded Region Growing Algorithm for Brain Tumor Identification

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Abstract: This paper presents a novel approach to segment Magnetic Resonance Image (MRI) of Brain and identification of brain tumor from the brain MRI. The presented work is based on a novel approach that identifies brain tumor from brain MRI in two stages: initially a brain MRI is processed from generation of threshold T2 and PD image of a brain MRI using Seeded Region Growing algorithm, finally, both images are processed further to classify into tumor images or normal images by using Markov Logic (ML) algorithm. Classification on the basis of tumor's existence or not in a brain MRI is performed by subtracting a tumor-affected image from a standard image and the resultant image spots to ascertain the existence of tumor in the image. The proposed approach was tested with various datasets of MRI. Results of this research using the designed approach marked out better than the other existing approaches as results are 96.71% for SNR 5DB and 99.96% for SNR 10DB.

Keywords: Brain MRI, tumor detection, region growing, seed pixel, Markov logic

1. INTRODUCTION

The domain of image processing and analysis has gone through a lot of transition in last couple of decades. A large number of algorithms and methodologies have been introduced to gain higher accuracy of information extraction from images and a lot of success has also been achieved in analyzing the images especially the medical images. However, accuracy has been a major concern in all such methods and techniques used to extract information from the medical images as this diagnosis is dependent on such analysis and a slight mistake in analysis can risk a life. In such type of medical image analysis, image segmentation plays a vital role in objects identification [1]. A key focus in such segmentation based analysis is identification of heterogeneous regions within a medical image to locate the abnormalities. For such type of image analysis various types of images are used and Magnetic Resonance Images (MRIs) are most commonly used for such purpose [2]. MRI provides rich information of various body organs such as brain and such images can be very helpful in achieving higher accuracy in analysis. Typically, medical disorders are diagnosed by using brain MR images. Moreover, taxonomy of different parts of a brain image and the changes in the volume of human brain caused by the aging factor can also be vigorously considered.

There are few approaches which are used to identify various segments of a brain MR image. Region growing is a typical algorithm used for segmentation of brain MRIs since this algorithm mainly divides an input image into small separated areas and such an area is mainly termed as a *seed* [3]. Moreover, the boundaries among these distinguishing contiguous areas are also analyzed. Analysis phase comprises on the areas with sturdy boundaries, ignores the weak boundaries and the neighbor regions are merged together. Such

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boundaries analysis is performed iteratively until no more boundaries are further possible to draw [4]. Surface layers of a brain image are extracted suing this algorithm [5, 6].

This paper proposed a novel approach to identify brain tumors from brain MRI. Since, a typical brain MR image exhibits multiple-model information such as axial, coronal and sagittal [7]. However, the neurosurgeon and radiologist typically find it difficult to manually understand brain tissue structures separately and a good neurosurgeon and radiologist needs to examine the tissue structure disease diagnosis such as brain tumor identification. However, an automated or semi-automated approach of information extraction from brain image can help in a great way. The algorithm presented in this paper is an enhanced version of conventional seeded region growing algorithms used for the segmentation purpose of brain MRI [8-10]. The identifying of various segments is done by this algorithm and each segment is further analyzed to locate possible brain tumor in a MRI. The automatic brain MRI segmentation algorithm is dependent on the seeded region growing and pixel methods for extraction of threshold PD and T2 image, while Markov Logic is used to classify a MRI as a normal brain image or tumor effected brain image.

2. MATERIALS AND METHODS

The used approach is based on seeded region grown algorithm for segmentation of various parts of a brain image. Following is the explanation of the algorithm that extracts T2 and PD threshold images from a MRI image and afterwards the output of seeded region grown algorithm is further processed by Markov Logic algorithm for the sake of classification. The detailed architecture of the used approach is shown in Fig. 1.

Fig. 1 elaborated the used method that pre-processes the input MR images of brain and then performs segmentation using seeded region growing method and afterwards classification of MR images is performed using Markov Logic Networks (MLN). Following were the steps of the used algorithm for segmentation and classification:

Step I. Extraction of the cerebrum region with the help of three methods i.e. (a) thresholding, (b) region growing segmentation, and (c) masking functions.

Step II. T2 weighted images are processed to

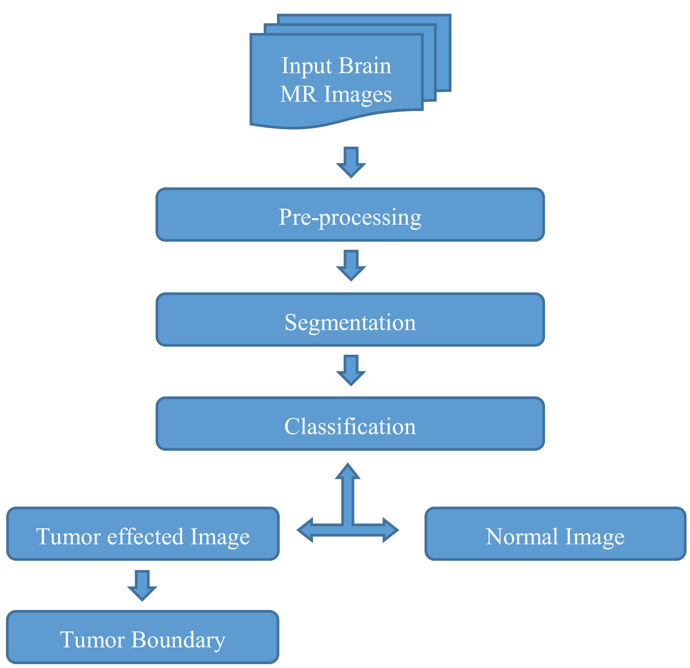


Fig. 1. Architecture of the used approach.

detect Cerebrospinal Fluid (CSF) region by using adaptive thresholding.

Step III. The iterative thresholding method is used to get the ventricular region which is depicted in the middle of the cerebrum, and also extracted the region growing segmentation ventricular.

Step IV. Classification of white and grey matter form the PD images.

Step V. Identification of tumor in the axial slice of the brain MRI.

The tumors in brain are identified by the seeded region growing algorithm after segmenting the various parts of brain MRI [11]. Though, these seeded region growing implementations lack accuracy because of heuristic way of threshold dependent classification.

2.1. Cerebrum Region Classification

Classification of the cerebrum region is the first step where a T2 weighted image is used with single threshold [13]. Here, background is segregated from the brain tissues shown in MRI. Afterwards, the following steps are performed to extract the Cerebrum Region. First, the threshold value from the histogram analysis is computed. In this proposed scenario, the background region pixel values are below 30, while the 32 is the threshold value which will separately identify the tissues of brain with the noise in background. Fig. 2 shows the output image produced by this method.

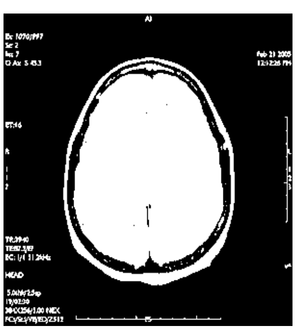


Fig. 2. Threshold value of T2 weight.

In second step, the Region Growing Segmentation (RGS) technique [14] is used for the cerebrum region extraction. The inactive big white region of the threshold image is grown after the extraction of cerebrum region. In this technique, we provide: (a) values of seed pixels; (b) the middle pixel value of the threshold image; and (c) divide the image width (W) and height (H) by 2.

Third step is the masking in which we extract the Cerebrum Region. We made a cerebrum mask in previous step. The cerebrum region is comprised on the pixels which are having 255 intensities (i.e. white pixels). The application of masking [15] on the original T2 weighted image results in the extraction of cerebrum region form the T2 weighted image (Fig. 3).

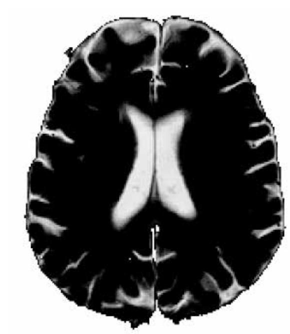


Fig. 3. Extracted cerebrum region.

2.2 Classification of the Cerebrospinal Fluid (CSF)

The next stage is the classification of CSF region. To identify this region in the T2 weighted image, the used threshold is calculated from the histogram [16]. Here, T2 weighted image is used to construct a histogram with the help of cerebrum region pixels. The 40% threshold (T_{csf}) value is set in this histogram as per suggested by the similar studies

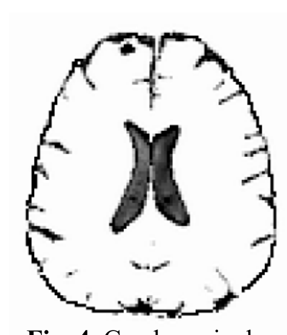


Fig. 4. Cerebrospinal fluid (CSF) regions.

[17, 18]. Here, the extra ventricular CSF is identified as the region in vicinity of cerebrum region.

The CSF Region is presented by the white pixels. Then the masking is applied on the Cerebrum image and extracts the Cerebrospinal Fluid Region from the MR T2 weighted image.

2.3 Classification of White and Grey Matter

In this phase, the white and gray matters are classified. The following sequence of operations is used in this phase. First step is the loading of MR PD-weighted image [19].

Fig. 5. PD-weighted image.

Now mask is made for the cerebrum only by excluding ventricular part. After this we have both cerebrum and ventricular masks. The cerebrum mask pixels with 255 intensities (i.e. white pixels) and the ventricular mask pixels have not 255 intensity (i.e. not white pixels) are the pixels of cerebrum region in the PD-weighted image. Now we will apply this mask on the PD-weighted image

Fig. 6. Cerebrum region of the PD-Weighted image

for the extraction of cerebrum region by excluding the ventricular region [16].

There might be two eminent peaks in the histogram, when we make a histogram of the cerebrum region of PD-image. However, due to the degraded image quality, the reliable results are not achieved. In our approach, the region in vicinity of CSF region is classified as the gray matter. Here, the PD weighted image pixels are used to estimate the intensities and are used to compute the threshold [20] Tgm as shown in equation (5):

$$Tgm = \mu - \tfrac{1}{2}\,\delta \qquad (5)$$

Where δ is the standard deviation and μ is the mean of the pixel intensities. We threshold the T2 weighted cerebrum image that is constructed in the first step after the calculation of Tgm. The white and gray mater mask are made by the threshold image. In WG mask, the white region falls under the gray matter and the black region is located in

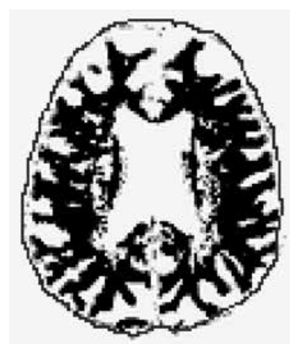


Fig. 7. Threshold image.

the white matter.

2.4 Tumor Detection using Markov Logic

For the detection of tumor, histogram based Markov Logic is used. The used Markov Logic algorithm used histogram based dominant feature to classify the extracted brain into four classes such as (i) Gray Matter (GM), (ii) White Matter (WM), (iii) Cerebrospinal Fluid (CSF), and (iv) tumor. Initially, the used algorithm is trained for a set of input brain MR images having tumors. We proposed a learning based addition to the existing seeded region growing algorithm to make it quick, intelligent and accurate. The Markov logic network [12] [represents k^{th} joint distribution (equation (1) given below] is incorporated with the existing seeded region growing algorithm to enhance the learning ability.

$$P(X=x)=\frac{1}{Z}\prod \phi k\,(x_{\{k\}}) \quad \text{(Eq. 1)}$$

In Eq. 1, the set of variables which are $X \epsilon (X_1, X_2, \ldots, X_n)$ is the representation for joint distribution of model. In typical Markov Logic network, a set of pair (F_i, w_i) is used to represent a predicate and a predicate in first order logic is represented by F_i and a real number depicts w_i that is weight of the predicate/formula.

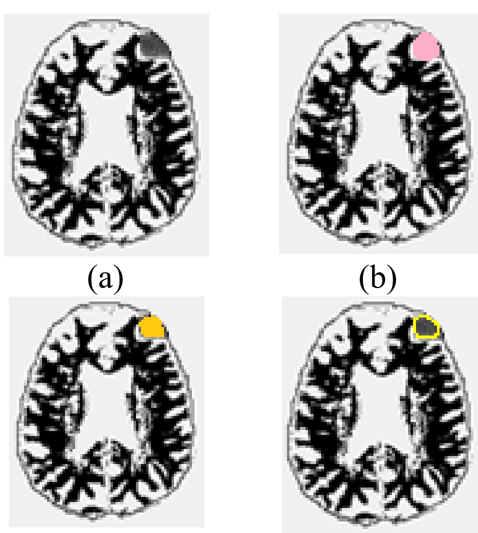
To update the weights of the used formula, statistical relational learning approach is incorporated by combining probability with the traditional first-order logic. Here, a typical Markov Logic Network (MLN) with a set of weights and formulas that can be represented as below [12]:

$$P(X=x)=\frac{1}{Z}\exp\left(\sum_j w_j f_j(x)\right) \quad \text{(Eq. 2)}$$

The weights of the equation (2) are dynamically updated by using diagnolized Newton Method with weight update formula given in equation (3):

$$w = w + D^{-1}g \quad \text{(Eq. 3)}$$

The various parts of MRI are accurately classified by the help of such weights.Here the classification is on the basis of tumor's existence or not in a brain MRI is performed by subtracting a tumor affected image from a standard image and the resultant image spots the possible tumor's existence in the image. Fig. 8 shows results of the classification by highlighting the identified area that can be a tumor. The output is depicted in terms of manual segmentation on the axial slice and the segmentation of tumor along the boundary identified on the axial slice.



(a) (b) (c) (d)

Fig. 8. Segmentation results: (a) Slice of the original image; (b) Manual segmentation on the axial slice; (c) Segmentation of tumor; (d) Boundary identified on the axial slice.

The existing algorithm roughly draws the boundary of the identified tumor. However, the accuracy of tumor identification is higher as compared to other approaches that is discussed in the following section.

3. RESULTS AND DISCUSSION

The proposed approach was tested by performing a set of experiments initially on the simulated brain MR images and then testing the performance on the standard MR images taken from BrainWeb. The results are given in Table 1 and Table 2. Results highlight that the MLSRG technique for 5 dB and10 dB are quite better than the previously used approaches such as FISRG, *K*-means and FAST. The segmentation results of MR images with previous algorithms such as FISRG, *K*-means and FAST algorithms are tabulated in Table 1.

Table 1. Comparative results with the previous techniques applied on simulated images [8].

Previous techniques	SNR 5dB	SNR 10 dB
MLSRG	96.71%	99.96%
FISRG	96.04%	98.80%
K-Means	82.86%	92.02%
FAST	72.48%	99.98%

Table 2 shows the results of segmentation of MR images from a BrainWeb (standard database) tested with MLSRG, FISRG, *K*-means and FAST algorithms.

Table 2. Comparative results with the previous techniques on MRI taken from BrainWeb

Previous techniques	SNR 5dB	SNR 10 dB
MLSRG	91.35%	97.12%
FISRG	89.24%	95.68%
K-Means	82.47%	88.60%
FAST	74.22%	84.85%

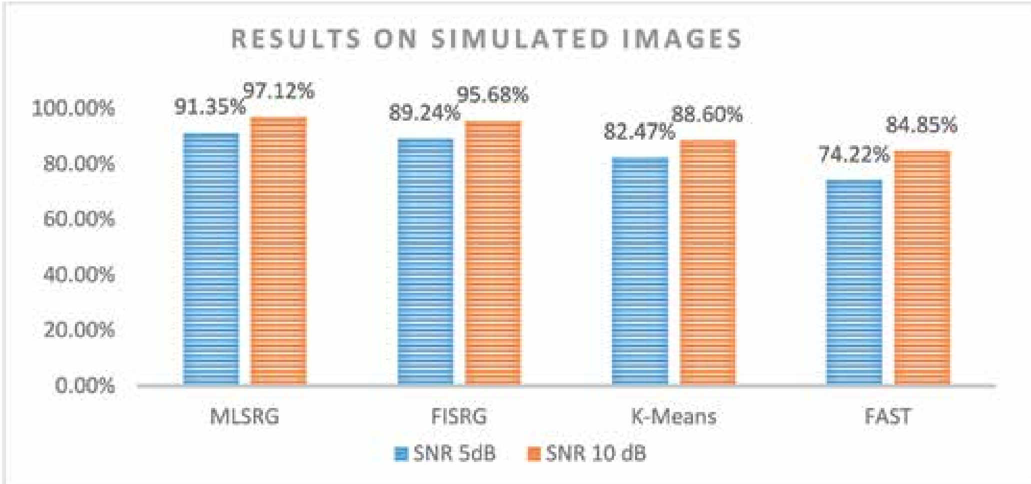


Fig. 9. Result on simulated images.

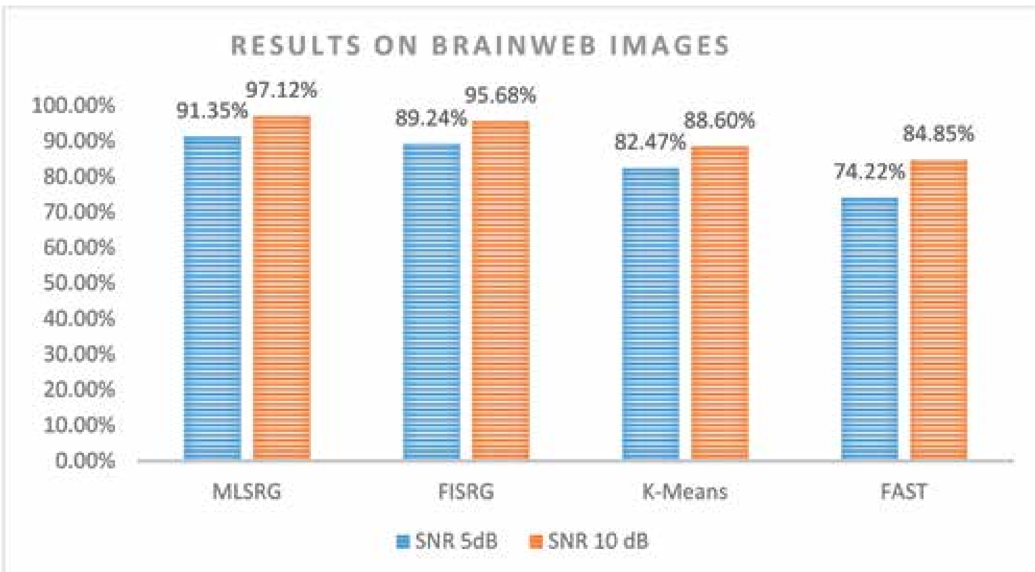


Fig. 10. Result on BrainWeb images.

The accuracy of MRI segmentation with previous three approaches is around 80%; thus, there is is possibility of improvement in accuracy (Table 1, 2; Fig. 9, 10). In this paper, the proposed algorithm is an improved version of existing Seeded Region Growing algorithms [8]. The presented system is not only capable of reading spatial information of a brain image but also classifies the various parts of the brain image. This approach classifies various components of brain such as the brain white and gray matter, cerebellum, cerebrospinal region, and ventricular region, etc. There is a wide range of applications of the presented work form data revelation and compression to quantitative analysis of medical images. The presented work can assist in the more precise detection of various changes in the volume of brain caused by the aging factor. The work in such areas can also be a considerable contribution in the ongoing research.

4. CONCLUSIONS

A novel automatic approach is proposed that is capable of reading and classifying the brain MRI images into normal images and tumor effected images. A hybrid segmentation method is used that involvs seeded region growing algorithm for region and boundary detection of brain T2 image; then Markov Logic classifies the image to find out the possibility of tumor. The segmentation is done by structural approach, such as seeded region growing algorithm. The performance of said algorithm can be improved by incorporating the Markov Logic-based learning ability. The results of the experiments using the designed approach marked out better than the existing approaches as results are 96.71% for SNR 5DB and 99.96% for SNR 10DB.

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