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Segmentation and Classification of MRI Segment in Medical Automated Learning System

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Abstract: *In the process of region localization, images are processed in multiple orders to finalize the segmentation region. In progress to region segmentation, the evolved regions are majorly been discarded due to loss of intermediate information's. These information losses are generated due to trace pixel enlargement or natural discontinuity. The second observing factor in region segmentation is the marking of small region patterns which are derived due to misclassification of actual and detected regions. the complexity of detection logic, due to recurrent coding is an additional factor to observe. In this paper, a new recurrent coding approach of region segmentation is proposed, overcoming the issue of region marking, discontinuity issue and small region miss-classification. The suggested approach is a simpler and robust to region detection, test over different MRI samples.*

Key word: *Region marking, recurrent morphology, image segmentation, MRI samples.*

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I. Introduction

Computer aided diagnosis systems for detecting effected tumor regions in biological study have been investigated using several techniques. In recent years, the occurrence of brain tumors has been on the rise. Unfortunately, many of these tumors will be detected too late, after symptoms appear. It is much easier and safer to remove a small tumor than a large one. About 60 percent of glioblastomas start out as a lower-grade tumor. But small tumors become big tumors. Low-grade gliomas become high-grade gliomas. Once symptoms appear, it is generally too late to treat the tumor. Computer-assisted surgical planning and advanced image-guided technology have become Increasingly used in Edge surgery [1-5]. The availability of accurate anatomic three-dimensional (3D) models substantially improves spatial information concerning the relationships of critical structures (eg, functionally significant cortical areas, vascular structures) and disease [6]. In daily clinical practice, however, commercially available intra operative navigational systems provide the surgeon with only two-dimensional (2D) cross sections of the intensity-value images and a 3D model of the skin. The main limiting factor in the routine use of 3D models to identify (segment) important structures is the amount of time and effort that a trained operator must spend on the Preparation of the data [9]. A brain tumor is a disease in which cells grow uncontrollably in the brain. Brain tumors are of two main types : 1) Benign tumors 2) Effected tumors Benign tumors are incapable of spreading beyond the brain itself. Benign tumors in the brain usually do not need to be treated and their growth is self limited. Sometimes they cause problems because of their location and surgery or radiation can be helpful. Effected tumors are typically called brain tumor. These tumors can spread outside of the brain. Effected tumors of the brain will always develop into a problem is left untreated and an aggressive approach is almost always warranted. A substantial methodological framework including new data analysis method was developed in [10] to meet the challenge of working with big data. Effected imaging phenotypes determined by MRI providing a mean of panoramic and noninvasive surveillance of oncogenic pathway activation for patients treatment was presented. In [11], to summarize and compare the methods of automatic detection of brain tumor through Magnetic Resonance Image (MRI), different stages of Computer Aided Detection (CAD) system was presented. In [12] a method to segmentation EEG signal for detection of primary brain tumor detection, in combination of wavelet transform is presented. Uncertainty in the EEG signals is measured by using the Approximate Entropy. This observation leads to the process of tumor detection based on EEG analysis. [13,14] Describes a Matlab implementation, to detect & extraction of brain tumor from MRI scan images of the brain. Incorporates with noise removal functions, segmentation and morphological operations which are used for MRI image coding. The approach of automated segmentation of the proposed approach was outlined in this work. In [15] an artificial neural network (ANN) approaches by Back propagation network (BPNs) and probabilistic neural network (PNN) was presented. The method is developed to classify the type of tumor in MRI images of different patients with Astrocytoma type of brain tumor. Wherein most methods were developed for segmentation of regions from a given MRI sample, les focus is made on its localization.

Localization of the mass elements in the MRI sample could minimize the overhead coming for processing the whole sample. With this objective a simpler however robust approach of mass localization in MRI sample using recursive Morphological approach with its fusion is suggested. In the approach of segmenting such region, a walker based approach was suggested in [16]. This logic presents a simpler approach of region segmentation via boundary region tracking. In the process of orientation based filtration Gabor wavelets are predominantly been used. In [17], a Gabor based filtration logic is been developed towards region localization. However the orientation and scaling factor at each level results in large processing overhead, to minimize the processing overhead, in this paper a recurrent processing of multi level wavelet filter using Gabor transformation is suggested. To present the suggested approach, the rest of the paper is outlined into 5 sections, where section 2 present the approach conventional Gabor wavelet coding for region localization. The suggested approach of recurrent Gabor modeling is presented in section 3. Section 4 outlines the experimental results, and the conclusion is outlined in section 5.

II. Region Localization- Gabor Modeling

Gabor filters have been presented in several works on image processing; however, most of these works are related to segmentation and analysis of feature. Gabor filter were proposed for directional decomposition and analysis of linear components in images using multiresolution Gabor filters. Multiresolution analysis by using Gabor filters has natural and desirable properties for analysis of directional information in images; most of these properties are based upon biological vision studies as described previously. Other multiresolution techniques have also been used with success in addressing related topics such as feature analysis and segmentation and image enhancement. For feature classification which uses a tree-structured wavelet transform for decomposing an image where, image decomposition is performed by taking into account the energy of each subimage instead of decomposing subsignals in the low-frequency channels. If the energy of a subimage is higher than a certain fixed threshold value, then the decomposition procedure is applied again; else, the decomposition is stopped in that region. Different tree structures are used which are highly depends upon the value of the threshold. A 2-D Gabor function is a Gaussian modulated by a complex sinusoid. It can be specified by the frequency of the sinusoid and the standard deviations and of the Gaussian envelope.

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right] \quad (1)$$

Gabor wavelet represents a bank of Gabor filters normalized to have dc responses equal to zero and designed in order to have low redundancy in the representation are obtained by dilation and rotation of $\psi(x,y)$ as in (1) by using the generating function

$$\begin{gathered} \psi_{m,n}(x,y) = a^{-m}\psi(x',y'), a>1, m,n = integers \\ x' = a^{-m}[(x-x_0)cos\theta + (y-y_0)sin\theta] \\ y' = a^{-m}[-(x-x_0)sin\theta + (y-y_0)cos\theta] \end{gathered} \quad (2)$$

Where (x_0,y_0) center of the filter in the spatial domain;$\theta = n\pi/K$ total number of orientations desired; and scale and orientation, respectively. The scale factor in (2) is meant to ensure that the energy is independent. Gabor wavelets in the frequency domain is defined as

$$\Psi(u,v) = \frac{1}{2\pi\sigma_u\sigma_v} exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \quad (3)$$

The design strategy used is to project the filters so as to ensure that the half-peak magnitude supports of the filter responses in the frequency spectrum for the non-effected region as compared to the region with architectural distortion. By doing this, it can ensured that the filters will capture the maximum information with minimum redundancy. The obtained output for the gabor filter at different orientation reveals the orientation in one particular direction, an average gabor output is derived given by,

$$K_{avg} = |\sum I(x,y)| \quad (4)$$

where$I(x,y)$ is the gabor output obtained at each orientation.

III. Recurrent Gabor Modeling

For the selection of tumor region from the obtained magnitude image the spectral variation in each orientation is observed. The spectral density varies at average density of 3-4 units for the tumor region, where as a spectral density variation with tumor region is observed to be at 1-2 variation. The extracted region is then further processed for tumor region extraction based on the directional filter based approach. For the obtained spectral bands based on the Gabor output the orientation field, the details were derived by,

$$\theta(x,y) = -\frac{\pi}{2} + K_{avg}\frac{\pi}{K} \qquad (5)$$

The average estimated orientation field is then used for the designing of a directional filter for the estimation of the region which is directionally different from the original region.

To extract the tumor regions, a logical ANDing operation over obtained eight orientations were carried out, where each orientation is transformed to a bi-level logic using global thresholding as illustrated. Thresholding is a simple technique for image segmentation. It distinguishes the image regions as objects or the background. Although the detected regions are consisting of tumor regions and non-tumor regions in every detail component resolution, they can distinguish due to the fact that the intensity of the tumor regions is higher than that of the non-tumor regions. Thus, an appropriate threshold can be selected to preliminarily remove the non-tumor regions in the resolution component sub-bands. A dynamic thresholding value is calculated as the target threshold value *T*. The target threshold value is obtained by performing an equation on each pixel with its neighboring pixels. Two mask operators are used to obtain mask equation and then calculate the threshold value for each pixel in the 3 resolution resolution. Basically, the dynamic thresholding method obtains different target threshold values for different resolution images. Each resolution component resolution $e_s$is then compared with *T* to obtain a binary image ($\boldsymbol{e}$). The threshold *T* is determined by,

$$T = \frac{\sum(e_s(i,j)Xs(i,j))}{\sum s(i,j)} \qquad (6)$$

Where,

$$s(i,j) = \max(|g_1 ** e_s(i,j)|, |g_2 ** e_s(i,j)|) \qquad (7)$$

and,

$$g_1 = [-1\ 0\ 1], g_2 = [-1\ 0\ 1]^t$$

In Eqn. 7, "* *" denote two-dimensional linear convolution. Figure.1 below shows an example of a 5×5 resolution component resolution *(e_s)*. The masked matrix element S(P8) is calculated as given in Eqn. 7.

$$\begin{pmatrix} p_1 & p_2 & p_3 & p_4 & p_5 \\ p_6 & p_7 & p_8 & p_9 & p_{10} \\ p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ p_{61} & p_{17} & p_{18} & p_{19} & p_{20} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} \end{pmatrix}$$

Figure 1. 5×5 resolution component sub-band *(es)*

$$s(p_8) = \max(|p_9 - p_7|, |p_{13} - p_3|) \qquad (8)$$

Applying similar operations to each pixel, all S (i, j) elements can be determined for each resolution component sub-band. Using Equation 6 threshold 'T' can then be computed, and the binary edge image ($\boldsymbol{e}$) is then given by

$$e(i,j) = \begin{cases} 255, if\ e_s(i,j) > T \\ 0, otherwise \\ 1 \end{cases} \qquad (9)$$

The fundamental enhancement needed in MRI is an increase in contrast. Contrast between the brain and the tumor region may be present on a MRI but below the threshold of human perception. Thus, to enhance contrast between the normal brain and tumor region, a Segmentation filter is applied to the digitized MRI resulting in noticeable enhancement in image contrast. Segmentation filters work by increasing contrast at edges to highlight fine detail or enhance detail that has been blurred. It seeks to emphasize changes. The most common Segmentation filter uses a neighborhood of 3*3 pixel. For each output pixel it computes the weighted sum of the corresponding input pixel and its eight surrounding pixels. The weights are positive for the central pixel and negative for the surrounding pixels. By arranging the weights so that their sum is equal to one, the overall brightness of the image is unaffected. For the tumor region extraction, we use morphological operators and the logical operator to further remove the non-tumor regions. In tumor regions, vertical edges, Horizontal edges and diagonal edges are mingled together while they are distributed separately in non-tumor regions. Since tumor regions are composed of vertical edges, horizontal edges and diagonal edges, tumor regions can be determined to be the regions where those three kinds of edges are intermixed. Tumor edges are generally short and connected with each other in different orientation. Morphological dilation and Erosion operators are used to connect isolated candidate tumor edges in each block of the binary image. For the tumor region extraction, we use morphological operators and the logical operator to further remove the non-tumor regions. In tumor regions, vertical edges, Horizontal edges and diagonal edges are mingled together while they are distributed separately in non-tumor regions. Since tumor regions are composed of vertical edges, horizontal edges and diagonal edges, tumor regions can be determined to be the regions where those three kinds of edges are intermixed. Tumor edges are generally short and connected with each other in different orientation. Morphological dilation and Erosion operators are used to connect isolated candidate tumor edges in each block of the binary image. Erosion is one of the two basic operators in the area of mathematical segmentation. It is typically applied to binary images. The basic effect of the operator on a binary image is to erode away the boundaries of regions of foreground pixels.

For the feature selection a hybrid GA approach is presented. The feature selection selects the best features from the hybrid feature extraction. The classification involves consideration of the dataset before transferring the data to a classifier. It is recommended to consider only an important feature for selection. Hence, it is useful for choosing the significant and relevant features in this brain tumor detection. Furthermore, the feature selection is used during the classification to find the important feature that decreases the workload of the classifier and enhances the classification accuracy. In this research, KNN based GA minimizes the redundancy within input voxels and defines more relevance between input/output voxels. Then, the fitness function is calculated for input voxel subsets by using KNN that maximizes the mutualdata between the voxels. At last, the crossover &mutation operators are utilized to detect the most active voxels by reducing there dundancy-based Fitness Function (FF). The GA selects the subset of features as the chromosomes and every chromosome is sent to the DNN for computing fitness value. The DNN classifier employs each chromosome as a mask for capturing the features. The DNN classifier defines a fitness value of each and every chromosome and GA utilizes these fitness values for the chromosome computation process. At the final stage, the GA finds an optimal subset of the feature.

IV. Experimental Results

For the implementation of automated recognition system a data set collected from different source for various class of MRI image is considered. Figure shows the database considered for the implementation. The collected MRI images are categorized into four distinct classes with each as one type of tumor. The MRI scan are scanned and passed for implementation, to locate the tumor region.

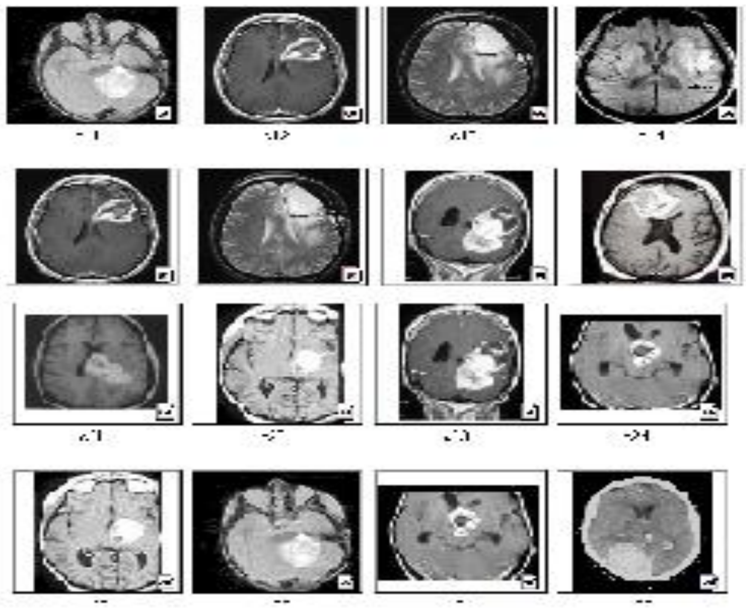
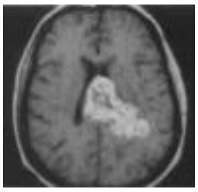


Fig.2 The set of test sample used for localization

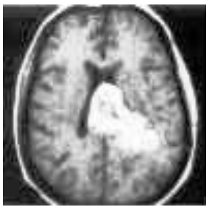
For every MRI image, the proposed approach tends to segment the region with exact tumor. The obtained results are shown below:

Original Query MRI image to test



(a)

Histogram equalized image

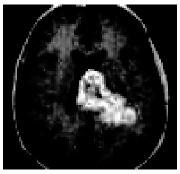


(b)

Figure 3. (a) Original Test sample (b) Histogram equalized image

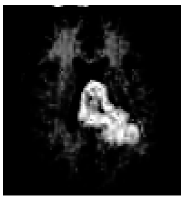
Figure.3 (a) represents the original MRI image used for testing. Initially, to enhance the illumination and to eliminate the noise effect, the histogram equalization is applied and the obtained histogram equalized MRI image is shown in figure.3 (b).

Intensity Maped image



(a)

Extracted Region without outer Skull Region



(b)

Figure 4. (a) Intensity Mapped Image (b) Boundary region extraction

Figure.4 (a) shows the intensity mapped MRI image. Intensity mapping is done here to obtain the uniform intensities at each and every pixel thus; the region with abnormal intensities will be highlighted. This will reduce the segmentation complexity. After mapping intensity, the image is subjected to the extraction of a region with outer skull region .

To evaluate the performance of the developed approach following parameters are used.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

Where,

TP = True positive (Correctly identified)
FP = False positive (Incorrectly identified)
TN = True negative (false, Correctly identified)
FN = False negative (false, incorrectly identified)

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For the given simulation model, four classes with each class having 5 subjects, forming total of 20 subjects is used for training. During testing process, a query sample is given and the extracted features are passed to SVM classifier.
Along with accuracy, to show the enhancement of propose approach and also to compare the proposed approach with earlier approaches, few more metrics such as sensitivity, specificity, Recall, precision and F-measure was evaluated with following mathematic expressions.
Sensitivity measures the proportion of positives that are correctly identified as such.

$$Sensitivity = \frac{TP}{TP+FN} \tag{14}$$

Specificity measures the proportion of negatives that are correctly identified as such.

$$Specificity = \frac{TN}{TN+FP} \tag{15}$$

Precision is the fraction of identified instances that are correct, while recall is the fraction of correct instances that are identified.

$$Recall = \frac{TP}{TP+FN} \tag{16}$$

Table 1: parametric Observation

Test sample	Method	Accuracy (%)	Sensitivity	Specificity	Recall
Class 1	Direct mapping	55.670	0.220	0.608	0.220
	Clustering	62.500	0.315	0.752	0.315
	Threshold GA modeling	70.000	0.444	0.909	0.444
Class 2	Direct mapping	49.484	0.432	0.712	0.432
	Clustering	58.1341	0.458	0.854	0.458
	Threshold GA modeling	69.500	0.524	0.946	0.524
Class 3	Direct mapping	55.670	0.420	0.762	0.420
	Clustering	63.824	0.452	0.886	0.452
	Threshold GA modeling	70.840	0.484	0.924	0.484
Class 4	Direct mapping	58.360	0.446	0.738	0.446
	Clustering	65.420	0.558	0.824	0.558
	Threshold GA modeling	72.820	0.582	0.908	0.582

V. Conclusion

This paper outlines a segmentation method based on recursive process of dilation and erosion. The approach is a simpler and effective mode of coding towards image region localization and recognition in MRI processing. Towards the automation of MRI processing, the process overhead is kept minimized by processing on a smaller structuring element. The recursion process leads to higher estimation accuracy of the exact localization region. This leads to better performance in segmentation process. The processing overhead is observed to be lower and the region localization is processed over a binarized coefficient sample. In the recurrent process converges to a isolated region detection of probable tumor region, which is covered in larger region growing with smaller mass regions.

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