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Automatic Intensity Graph Method for Brain and Tumor Segmentation Using Density Measures

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Abstract:
Brain and tumor segmentation has been supported by different methodologies earlier, but struggles with identifying the spatial deformations and identifying the exact boundary regions of the tumor which affects the classification accuracy. We propose a new automatic intensity graph method for brain and tumor image segmentation. Despite its simplicity, this application utilizes the best features of combinatorial graph cuts methods in vision: global optima, practical efficiency, numerical robustness, ability to fuse a wide range of visual cues and constraints, unrestricted topological properties of segments, and applicability to N-D problems. The proposed graph based method also utilizes the region properties for the segmentation problem. At the first stage intensity normalization is performed with the histogram equalization techniques, and then the image is converted into gray scale and based on the gray values similar valued pixels are grouped and constructed as a graph. The segmentation performed with the intensity graph method produces efficient results. Once segmentation is performed, different segmented region is represented with different color values. Obviously the region affected with tumor has different intensity values, using which the tumor tissues are identified.

Keywords: *Image Segmentation, Graph theory, Histogram equalization, Intensity values*

1. Introduction

In recent years, digital images have become increasingly prevalent throughout society. Many governmental, legal, scientific, and news media organizations rely on digital images to make critical decisions or to use as photographic evidence of specific events. This proves to be problematic, as the rise of digital images has coincided with the widespread availability of image editing software. At present, it is not difficult for an image forger to alter a digital image in a visually realistic manner. To avoid both embarrassment and legal ramifications, many of these organizations now desire some means of identifying image alterations so that the authenticity of a digital image can be verified. As a result, the field of digital image forensics has been born.

A brain tumor is an abnormal growth of cells in the brain, which can be cancerous (malignant) or noncancerous (benign). Is defined as any intracranial tumor created by abnormal and uncontrolled cell division, normally in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells, myelin producing Schwann cells), lymphatic tissue, blood vessels blood) in the cranial nerves, in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers primarily located in other organs tumors (metastases). Brain tumors (true) are usually located in the posterior fossa in children and in the anterior two thirds of the cerebral hemispheres in adults, although it can affect any part of the brain.

Texture is a set of components present in an image with various intensities. Normally the intensity in the image and the objects does not have uniform intensity, so that the region of the objects in the image is unbound and hard to extract the object boundary. The texture analysis is the process of normalizing the uniformity of intensity in the image and helps to extract the object or its feature from the image. The reason why the intensity of the image has to be uniform is for the retrieval of image from large set of image or finding a specific object from a group of objects or for face recognition and etc… There is no bound for the application of image processing in real world , now a days the image processing techniques are more useful in many areas of our regular life.

The segmentation technique helps medical image solutions in higher frequency and it has more impact on medical image processing. The image segmentation process has been used in variety of medical problems from identifying born crush to brain tumors. Generally the image segmentation performs the grouping of pixels in different ways also supports the medical problems in many ways. The segmentation process and implication of segmentation has been studied in large scope for lung cancer identification by many researchers.

The histogram equalization technique helps the segmentation process for higher segmentation quality. Using the equalized histogram the uniform region of the image can be identified, also the non uniform regions can be identified. The segmentation process has also applied on the area of content based image retrieval and image classification and indexing processes.

Graph theory an mathematical solution for different problems, here we use graph theory to get connected components for image segmentation. A graph is an abstract representation of a set of objects, where several pairs of the objects are connected by links. It is a mathematical structure and is used to model pairwise relations between objects from a certain collection. The segmentation of image can be performed using the graph theory and the method of graph cut.

2. Background

There exists various methods for segmentation of brain tumors and we discuss few of them here according to our problem.

Tumor-Cut: Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications [2], present a fast and robust practical tool for segmentation of solid tumors with minimal user interaction to assist clinicians and researchers in radio surgery planning and assessment of the response to the therapy. Particularly, a cellular automata (CA) based seeded tumor segmentation method on contrast enhanced T1 weighted magnetic resonance (MR) images, which standardizes the volume of interest (VOI) and seed selection, is proposed. First, they establish the connection of the CA-based segmentation to the graph-theoretic methods to show that the iterative CA framework solves the shortest path problem. Furthermore, an algorithm based on CA is presented to differentiate necrotic and enhancing tumor tissue content, which gains importance for a detailed assessment of radiation therapy response.

Automatic segmentation of brain tumors in magnetic resonance images [5], presents an automatic method for segmentation of brain tumors in MRI. We use images of patients with glioblastoma multiform tumors. After pre-processing and removal of the regions that do not have useful information (e.g., eyes and scalp), we create a projection image for determining the primary location of the tumor. This image provides an overall view of the tumor. Then, we grow the primary region to segment the entire tumor. This method is automatic and independent of the operator. It segments low contrast tumors without requiring their exacta tissue boundaries.

Brain Tumor Detection Using Color-Based K-Means Clustering Segmentation [6], propose a color-based segmentation method that uses the K-means clustering technique to track tumor objects in magnetic resonance (MR) brain images. The key concept in this color-based segmentation algorithm with K-means is to convert a given gray-level MR image into a color space image and then separate the position of tumor objects from other items of an MR image by using K-means clustering and histogram-clustering.

Brain Tumor Detection from Pre-Processed MR Images using Segmentation Techniques [8] , has been proposed which can be successfully used to detect the brain tumor. This helps in determining the size and location of tumor. Edge based technique and color based segmentation are used. Edge-based segmentation has been implemented using operators e.g. Sobel, Prewitt, Canny and Laplacian of Gaussian operators. The color-based segmentation method has been accomplished using K-means clustering algorithm. The developed algorithm shows better result than Canny based edge detection.

Brain MRI Segmentation for Tumor Detection using Cohesion based Self Merging Algorithm [7] presents an algorithm for brain MRI segmentation to detect the location of the tumor. Segmentation using CSM based partitioned K-means clustering algorithm is applied. It is a self merging algorithm. The noise effect is less. This approach is simple and less complex in computation. The computation time is also very less.

In Multi fractal Texture Estimation for Detection and Segmentation of Brain Tumors [12], A stochastic model for characterizing tumor texture in brain magnetic resonance (MR) images is proposed. The efficacy of the model is demonstrated in patient-independent brain tumor texture feature extraction and tumor segmentation in magnetic resonance images (MRIs). Due to complex appearance in MRI, brain tumor texture is formulated using a multi resolution-fractal model known as multifractional Brownian motion. Detailed mathematical derivation for mBm model and corresponding novel algorithm to extract spatially varying multi fractal features are proposed. A multifractal feature-based brain tumor segmentation method is developed next. To evaluate efficacy, tumor segmentation performance using proposed multifractional feature is compared with that using Gabor-like multiscale texton feature.

A New Approach to Image Segmentation for Brain Tumor detection using Pillar K-means Algorithm [13], presents a new approach to image segmentation using Pillar K-means algorithm. This segmentation method includes a new mechanism for grouping the elements of high resolution images in order to improve accuracy and reduce the computation time. The system uses K-means for image segmentation optimized by the algorithm after Pillar. The Pillar algorithm considers the placement of pillars should be located as far from each other to resist the pressure distribution of a roof, as same as the number of centroids between the data distribution. This algorithm is able to optimize the K-means clustering for image segmentation in the aspects of accuracy and computation time. This algorithm distributes all initial centroids according to the maximum cumulative distance metric.

3. Proposed Method

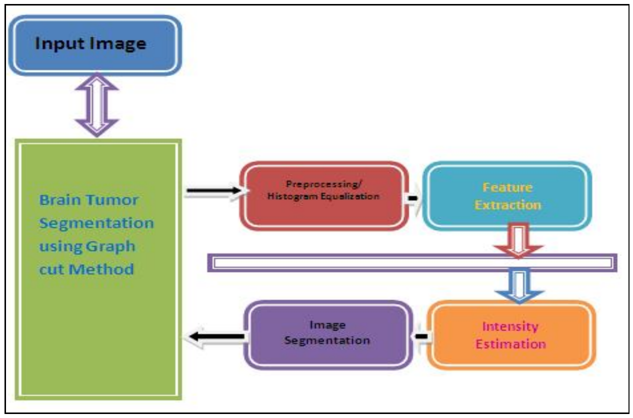

Figure 1

3.1. Histogram Generation

At the First step we have generated the histogram value of the image; we used 64 bit histogram for our purpose. The resultant value is used for the segmentation process. Based on the result of histogram equalization the image is segmented and reconstructed to provide the resultant image. The resultant image is displayed to the user and will be allowed to provide new threshold. Based on new threshold entered the clustering process and segmentation process will be repeated to provide new result. This methodology will be repeated until the user gets satisfied.

3.2. Algorithm

Step1: start
Step2: read input image img.
Step3: load possible intensity values Ivset={0…256}.
Step4: for each value in Ivset
Compute tp=total pixel having intensity value Ivset(i)/ total no of pixels.
End.
Step5: for each pixel p in image Img
Perform transformation by rounding the intensity values nearer.
$T(k) = round(L-1) \sum_{n=0}^{k} p_n$
Compute probability distribution.
P_n – probability distribution
End
Step 6: stop.

4. Feature Extraction

From the preprocessed image we extract the intensity features of each pixel. Each pixel will be computed with mean intensity value. The intensity of the each pixel will be computed using the intensity estimation function. Each pixel intensity values like red, green, blue values are extracted and mean intensity value will be computed for each pixel.

5. Automatic Intensity Graph Based Segmentation

The extracted features of the image is converted into to directional graph, unlike general graph cut method, our does not compute weights which represent the incoming edges. The Edge metric is used to identify the background and foreground objects. The segmentation process generates a node in the intensity graph, and computes the intensity distance between the neighbor pixel values. A link will be generated in the graph, from the pixel node only if the intensity distance is within a limit. We compute the distance between 8 pixels of neighbors. The brain region which is affected by tumor and other region have little change in intensity measures and we will be using those intensity measures to identify the brain tumor. The similar pixels will be grouped and the graph will be painted using a different color in the image and shows the clustered and segmented results. Identifying the brain tumor region is performed using the density measures of the region affected to overcome the false positive results. For each graph and node constructed, we compute the density of pixels covered to identify the region of tumor.

5.1. Algorithm

step1: start
step2: init graph set white region -WG, dark region DG.
step3: read preprocessed image Img.
step4: Feature Image Fi =
step5: for each pixel Pi from Fi

if(Wg.size>0)
compute Intensity Distance

$$\text{ID} = \sum_0^1 Euc(I(Px(R) - Py(R)), I(Px(G) - Py(G)), I(Px(B) - Py(B))))$$

if(ID<White Threshold Wth)
Add Px to Wg.
Wg = ΣPx(Wg)+Py.
set color of pixel =255.
for each neighbor of Py
go to step5.
end.
else
if(Fi(Py)<Wth)
Add Px to Wg.
Wg = ΣPx(Wg)+Py.
set color of pixel =255.
for each neighbor of Py
go to step5.
end.
end.
end.
step6: for each pixel Pi from Fi
if(Dg.size>0)
compute Intensity Distance

$$\text{ID}= \sum_0^1 Euc(I(Px(R) - Py(R)), I(Px(G) - Py(G)), I(Px(B) - Py(B))))$$

if(ID<Dark Threshold Dth)
Add Px to Dg.
Wg = ΣPx(Dg)+Py.
set color of pixel =255.
for each neighbor of Py
go to step5.
end.
else
if(Fi(Py)<Dth)
Add Px to Dg.
Wg = ΣPx(Dg)+Py.
set color of pixel =255.
for each neighbor of Py
go to step5.
end.
end.
end.
Step7: compute density measure for white region.

$$\text{Dm} = \int_1^N Area(Dg)$$

step8: select most density location as tumor region.
step9: stop.

6. Results and Discussion

The proposed method has been implemented and tested with Matlab and we have used variety of data set to test the performance of the proposed approach. We use the well known simplicity dataset of Wang et al. These images are manually divided into 10 categories which are people, beaches, historian buildings, buses, dinosaurs, elephants, roses, horses, mountains, and foods. We conducted the performance comparison between our approach for image segmentation and two comparing algorithms which are Kmeans algorithm and Gaussian Mixture Model (GMM) algorithm. For performing the K-means algorithm, we run 7 times of Automatic intensity graph noticed its average results.

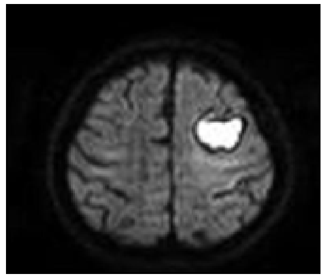

Figure 2: Manually segmented image

- Figure 2, shows the segmented image, which is performed by manual segmentation.

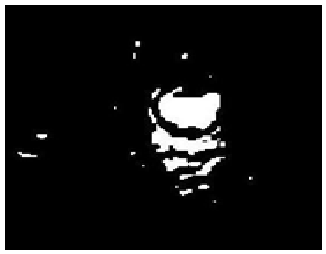

Figure 3: Segmented image with Automatic graph

The figure 3 shows the segmented image obtained from proposed method, it has produced higher efficient results. From figure it is clear that the proposed approach has more impact on image segmentation approaches.

7. Conclusion

We proposed automatic intensity graph based brain tumor segmentation approach, which uses both color texture and shape features for image segmentation. The proposed method has performed histogram equalization to improve the image quality which also normalizes the gray values of the image pixels. Then the features of the image are extracted like intensity values and we compute the mean intensity value for each pixel. From the intensity mean values an intensity graph is generated and segmentation is performed. The proposed approach reduces the problem of false positive results and produces efficient results.

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