Medical Image Segmentation Using Modified K Means And Cellular Automata Algorithms

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ABSTRACT

Segmentation is widely used in medical industry to get abnormal growth data from the medical image like MRI and CT .In this paper, I present a fast and robust practical tool for segmentation of solid tumors with minimal user interaction .K Means based seeded tumor segmentation method on contrast enhanced T1 weighted magnetic resonance (MR) images, is proposed. And the result is compared against Cellular automata based tumor segmentation method. Seed points are selected as the intersection of maximum white points row wise and column wise . First the seed pixels of tumor and background are fed to the algorithm. Using this seeds, the algorithm finds the strength maps for both tumor and background image .This maps are then combined to get the tumor probability map. Comparison studies on both clinical and synthetic brain tumor datasets for both this methods demonstrate performance of the proposed algorithm(K Means)in terms of, its efficiency and accuracy.

General Terms

Image processing ,Segmentation

Keywords

Brain tumor ,Segmentation, Medical image ,Cellular Automata,   Modified K Means.

I.   INTRODUCTION

Early imaging methods, have been abandoned in recent times. And opened way for non-invasive, high-resolution techniques, such as CT Scan and MRI.) In CT or MRI results Neoplasms will show as separately colored masses . In the literature there are many attempts for brain tumor segmentation. Recent trend in the area, is to be able to combine information from different sources to obtain a better segmentation. But, attempts to develop better algorithms from the image processing perspective that work on a particular MRI protocol continue in parallel.

Standard K-Means algorithm was introduced in 1967 .K-Means is an algorithm which rely on hard assignment of information to a given set of partitions or clusters . At every iteration of the algorithm, each member value is assigned to the nearest cluster based on intensity parameter such as Euclidean distance. The clusters are then re-calculated based on the given hard assignments. On each successive iteration, a member value can change clusters, thus altering the values of the cluster at ech iteration. Compared to other clustering algorithms K-Means algorithms typically converge to a solution very quickly.

In this paper, we examine CA algorithm for image segmentation. Then we examine the K means method for brain tumor segmentation .Finally we compare the results. Following a brief background on seeded segmentation methods in Section II, I present frameworks for brain tumor segmentation in Section III,and compare their performance Section IV, followed by conclusion in Section V.

II.   BACKGROUND

A .Cellular Automata (CA)

Cellular automata is a computer algorithm .It was first proposed by Von Neumann and Ulam . In this each individual cell is in a specific state .The cells changes state depending on the states of neighbors determined by a update rule . The state of any cell depends only on the states of the local neighbors found on the previous step. The update rules are same for all cell.

Cellular automaton (CA) is a triple denoted by $A = (S\ N\ \delta)$. where S is called the state set .And N is the neighborhood. $\delta: S_N \rightarrow S$
 is the local transition function .The states of the neighbor is denoted by S_N .Various methods are using CA in image processing problems Eg: image enhancement, image filtering, edge detection , and image segmentation algorithm Grow-cut. Grow-cut method uses a continuous state cellular automata. Image pixels correspond to cells . The state set is denoted by $S(\theta l C)$ .Which consists of a strength value θ in a continuous interval $[01]$ and a label l .The image feature vector is denoted by C. The seed points are initialized by assigning corresponding labels with a strength value between 0 and 1.

B. Modified K Means In Image Segmentation

Modified K-means is a popular algorithm for Segmentation. It devides data set into k sets. Each data point belongs to its nearest center, depending on the minimum distance. Modified K Means is a method to improve the standard K-means algorithm related to several aspects. Standard K-means algorithm consists of four steps: First step is initialization then classification, computational and convergence condition. There are two basic versions of K-means clustering .They are non-adaptive version and adaptive version. Non adaptive version was introduced by Lloyd and adaptive version was introduced by Macqueen .Among this Adaptive k-means clustering is the most frequently used . This is based on Eucledian distance. Adaptive k-means clustering is very similar to gradient descent algorithm .In this only the winning cluster considered and adjusted at each learning step.

III.   METHOD

In this section, the complete segmentation framework to segment brain tumors and the necrotic regions enclosed is presented in detail..

A.   Tumor-Cut Algorithm

Steps of the proposed cellular automata based tumor segmentation algorithm is as follows First, (a) The image is traversed from left to right and top to bottom and maximum white point intersection is found which is taken as seed point (b) Using this seed point a VOI is selected and assign foreground and background seeds .Where foreground as in blue color and background in red color .(c) to (d) Cellular Automata algorithm is run on the VOI for each two sets of seeds that is for foreground and for back ground and obtain strength maps for foreground (c) and background (d) and (e) two strength maps obtained in the previous step for foreground and back ground are combined and obtain the tumor probability map P_T (f) Initialize the level set surface at $P_T = 0.5$ and the use this map P_T is to evolve the surface that converges to the final complete segmentation map (g). (h)Choose enhanced and necrotic seeds .At last , (i) segment the necrotic regions of the tumor using Cellular automata based method with the seeds (enhanced and necrotic seeds)
 .

B.   Adapting Transition Rule To Tumor Characteristics

In the tumor segmentation application, MRI volume voxels in 3-D are correspond to the cells or nodes in cellular automata framework. In 3-D a 26-cell cubic neighborhood is used. Where intensities are used as image features. Most of the foreground seeds fall in a ring enhancing region around a dark necrotic core in the seeded tumor segmentation application over contrast enhanced T1-weighted MRI .

C.   Modified k-means

Modified K-means algorithm is a modified algorithm for standard Kmeans which is based on the optimization formulation and a good Iterative method. The steps of this algorithm represented as below

1) At First Divide the image pixels into K parts: As shown below

$$\cup_{k=1}^{k} sk\ , sk1 \cap sk2 = \emptyset, k1 \neq k2$$

2) Calculate initial clustering centers by using the below equation

$$X^{(0)}_{(k)} = \sum d(j) / /sk/, \; k = 1, \ldots, k$$

3) Find the distances of pixels from cluster center . Decide membership of the pixel in each one of the K clusters as per the minimum distance from cluster center.

4) Using the iterative formulas in step 5 find out the new cluster center

5) Until there is no change in the cluster center repeat step 3 and 4 .

6) Traverse the image form right to left and from top to bottom. And findout the point where maximum white points intersect. Take this as seed point

7) Decide in which cluster the seed point belong to and color that cluster in red

IV. EXPERIMENTAL RESULT

The Edges of the CA cluster will not be having tumor cells normally. But K-Means gives more accurate result .It includes only the affected cells.
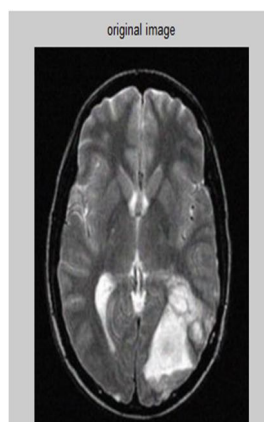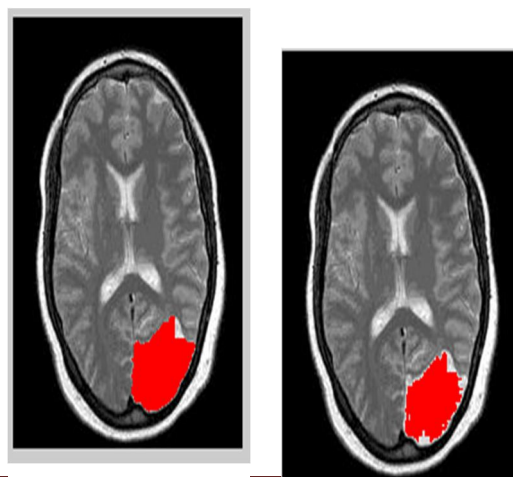

Figure 1 Original Image

Figure 2 CA Result

Figure 1 K Means

V. CONCLUSION

Here we presented two segmentation algorithms for the problem of tumor delineation which exhibit varying tissue characteristics. These algorithm needs very less user interaction .These can be widely used in clinical practices. Compared to CA algorithm K means algorithm shows less computation time and the result is more accurate. In CA result the boundaries of tumor cluster will not be having affected cells .But in the K Means the cluster boundaries also contains affected cells

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