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A STUDY ON AUTOMATIC SEGMENTATION OF LIVER REGION FOR TUMOR DETECTION AND GRADING OF TUMOR USING TUMOR BURDEN PARAMETER

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Abstract*:* This paper presents segmentation techniques for liver tumor segmentation from abdominal/liver CT scan images using region growing approach. Gaussian filtering is used to remove the noise from the CT scan images. Region growing, Otsu, Clustering and FCM techniques, respectively, are used for the segmentation of abdomen / liver structure. Morphological operations are used for post processing purpose. Tumor is segmented from CT image by performing thresholding operations. Experiments are performed on clinical data and tumor burden is calculated to present the severity of the tumor in images for all the segmentation methods studied.

Keywords: Region growing, Otsu, Clustering, FCM, Morphological operations, Tumor burden

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INTRODUCTION

Liver cancer is the fifth most frequently diagnosed cancer and third highest death cause cancer in the world. Liver cancer incidence rates about three times higher in men than in women, and have doubled in each sex over the past two decades from 2007 to 2011. The overall rate is increased by 3.4 % per year [1]. The World Cancer Research has estimated that up to one- third of the cancer cases that occur in economically developed countries like the US are related to overweight or obesity, physical inactivity, and/or poor nutrition [2].

Imaging techniques namely Computed Tomography (CT), Magnetic Resonance Imaging (MRI) or Positron Emission Tomography (PET) provide the accurate anatomical information of liver/abdomen images under investigation. Computed Tomography is widely used for imaging abdominal organs for diagnosis, planning and three-dimensional rendering. This technique is more useful to radiologist and surgeon for the measurement of organ and 3-D visualization. The Computed Tomography (CT) is widely used imaging technique because of fully automated which is readily available, faster, safe, comfortable and performs operations without human interference.

Tumor segmentation from liver/abdomen images is an important prerequisite for surgical interventions planning. Segmentation of liver tumor is very difficult and challenging task due to homogeneity, high intensity, characteristics of image, different shapes of the liver and similarity between abdomen / liver tissues and nearby organs of liver [4]. Also medical images are complex in nature and noisy, therefore liver and tumor segmentation is very difficult.

I. Related Work

Researchers have proposed different methods for tumor segmentation from abdomen/liver images. Nader et al. [5] have proposed rough segmentation and refined segmentation approach to segment liver structure. Region labeling is used to detect lesions roughly and then snake technique is performed to get refined tumor. Applying knowledge based discriminative rule tumor classification is done to differentiate between possible tumor and any other defect in CT slices. Paola et al. [6] presented automatic methods to segment abdomen/liver from abdominal CT data. A comparison of automatically detected abdomen/liver volume to the manually traced abdomen/liver boundaries by expert has been discussed. Takeshi et al. [7] proposed a method to extracts blood vessel in the liver using a threshold. Mathematical morphological dilation is then applied to segment the liver region; liver region is extracted using a threshold. Yufei et al. [8] proposed a method based on region growing approach. In this method preprocessing was done by using anisotropic filter and Gaussian function to form a liver likelihood image for further processing. Next, region growing method is combined with the centroid detection and intensity distribution analysis. Mathematical morphological operation is then used to extract liver region. Xing et al. [9] proposed interactive method for tumor segmentation from Computed Tomography (CT) scans. After preprocessing, CT volume is partitioned into a large number of catchment basin under watershed transforms along with liver parenchyma segmentation and liver contrast enhancement. SVM classifier is used to extract tumor from liver. Finally, morphological operations are used to refine the rough segmentation results of SVM classification. In this paper, we present a study on tumor segmentation from liver/abdomen CT scan images based on region growing, Otsu, Clustering and FCM techniques, respectively. Tumor burden is used as parameter to describe the severity of the disease and comparison of the methods is presented in terms of tumor burden value obtained.

II. Proposed Method

The workflow of the proposed system consists of the following steps:

i. Gaussian filtering to remove the noise.

ii. Region of interest (ROI) i.e. liver region is to found with the help of region growing method.

iii. Post-Processing by using morphological operations.

iv. Liver / Abdomen segmentation.

v. Tumor segmentation.

vi. Computation of Tumor burden.

A. Preprocessing:-

Gaussian filter is used to remove noise and get the region of interest i.e. liver / abdomen region.

$$G(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x2+y2}{2\sigma^2}} \qquad 1)$$

Where, x represents distance from the origin in the vertical axis and y represents distance from the origin in the horizontal axis with standard deviation as a parameter of the Gaussian distribution [5].

Let I be the liver / abdomen image which contains the primal intensity information of the liver / abdomen.

$$I = I_0 \, e^{\frac{|I_0 - \mu^2|}{2\sigma^2}} \qquad 2)$$

Where I represent liver / abdomen likelihood image, μ is Average intensity of liver / abdomen region, and σ , the Standard deviation of corresponding intensity of liver / abdomen region.

B. Region Growing Method:-

This region based segmentation technique partitions an image into a set of connected homogeneous regions of specific criteria such as intensity value, area, shape and texture. The purpose of detection of region is to provide the possibility to characterize the detected object by parameter analysis (shape, size and position etc.). Region growing method is based on the clustering of neighboring pixels of a region that verify a specific assumption [10]. This is one of the most popular techniques for segmentation due to simplicity, fast and better result for liver and tumor segmentation. The region growing techniques requires a seed point to start with and utilizes similarity constraints to partition the space.

Region growing algorithm works as follows,

i. Select seed pixels within the image [11].

ii. Select similarity criteria on the basis of grey level intensity or color.

iii. The regions are grown by appending each seed with neighboring pixels having predefined properties similar to seed pixel in to the region.

iv. This process still continues until no more pixels are met the criteria for allocation into the regions.

Application of this algorithm to CT images results in identification of abdomen/liver structure. The next step is to find out the tumors. When tumors are extracted from the regions, percentage of total tumor in abdomen/ liver region can be calculated by Tumor Burden [8].

C. Otsu Method

This method selects the threshold value by minimizing the within-class variance of the two groups of pixels which is separated by the thresholding operator. The separability of two classes is given by-

$$n(k) = \frac{\sigma_B^2(k)}{\sigma_G^2} \qquad 3)$$

AND

$$\sigma_B^2(k) = \frac{m_G\, P_1\,(k) - m(k)^2}{P_1\,(k)[1 - P_1\,(k)]} \qquad 4)$$

The optimum threshold is that value of k that maximizes $\sigma_B^2(k)$ [14].

Image is preprocessed by applying a high pass filter and median filter is applied to the image and segmentation is done. It is implemented using the graythresh function, a threshold value is found and since tumor region is highly illuminated region, a value of 0.3 is added to the threshold value computed so it can correctly diagnose the tumor area. The final threshold value is obtained by converting preprocessed image in to a binary image. The image is segmented and is ready for post processing to obtain final tumor image which involves repeated use of dilation and erosion operation.

D. Clustering Method

It is a simplest unsupervised learning algorithm. It mainly used to determine the natural spectral grouping present in the dataset. K-means algorithm partitions the image into k clusters (1, 2, -------, k), characterized by their centers or means. The center of every cluster is measured as the mean of all the instances belonging to that cluster. The main idea is to define k centroids for each cluster and placed in a cunning way because result varies from location to location. Therefore, place them as possible far away from each other. The next step is to take every point belonging to a given dataset and associate it to the nearest centroid. When no point is pending, first step is completed and an early group age is done. At this point, recalculate k new centroids as centers of the clusters resulting from the previous step. For k new centroids, a new binding has to be done between the same data points and the nearest new centroids. As a result loop has been generated and k centroids change their location step by step until no more changes are done [16]. K means algorithm is mainly used to partition an image into k cluster.

The k means algorithm consist of following steps [15]-

i. Place k points into the space represented by the objects that are being clustered. These points represent initial group centroid.

ii. Assign every object to the group that has the closest centroid.

iii. When all objects have been assigned, recalculate the position of the k centroids.

iv. Repeat step 2 and 3 until the centroids no longer move.

E. Fuzzy C-Means Algorithm

This algorithm [17] is the most popular method used in image segmentation because it has robust characteristic for ambiguity and retain much more information than hard segmentation method [18]. The fuzzy c means algorithm was first introduced by Dunn [19] and extended by Bezdek [17]. Test pixel in this algorithm is allowed to be the member of two or more clusters with different membership coefficient. This algorithm is an iterative in nature, generates fuzzy partition matrix and requires cluster center along with objective function. Cluster center value and objective function are updated for every single iteration and stopped when difference between two successive object function values is less than some predefined threshold value is less than some predefined threshold value. This algorithm produces an optimal C partition by minimizing the weighted within group sum of squared error objective function [20] and are shown as given below,

$$J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (V_{ik})^q \; d^2\,(X_k\,,\; V_i) \qquad 5)$$

Where, $x = \{x_1, x_{2,} - - - x_n\} \subseteq$ R dataset

n= number of data items

c= number of clusters; $2 \leq c < n$

V_{ik} = degree of membership of X_k in i^{th} cluster

q= weighting exponent of each fuzzy member

V_i= prototype of center cluster i

A solution of the object function J_{FCM} is carried through iterative process, which is explained as follows.

1. Assign the values for c, q and threshold value ϵ. Also initialize the partition matrix $U = [v_{ik}]$.

2. Initialize the cluster centers and a counter p.

3. Calculate the membership values and store in an array.

4. For each iteration calculate the parameters a_i^p and b_i^p till all pixels are processed where

$$a_i^p = a_i^p + V_i X_k$$

$$b_i^p = b_i^p + V_i$$

5. After each iteration update cluster center and compare it with the previous value $(U^b - U^{b-1})$

6. If the difference of comparison is less than the defined threshold value stop iteration else repeat the procedure.

F. Post-Processing – Morphological Operations

The abdomen/liver and tumor segmentation may contain holes, gaps, protrusion and connected neighbor tissues. To remove this, mathematical morphological operations such as opening, dilation and filling are performed [5].

Opening: - The opening of set A by structuring element B, denoted $A \, o \, B$ is defined as,

$$A \, o \, B = (A \, \Theta \, B) \oplus B \qquad 6)$$

Where, Θ and ⊕ denote erosion and dilation respectively. Thus, the opening A by B is the erosion of A by B, followed by a dilation of the result by B. Opening removes the small objects from the foreground , placing them in the background, eliminates thin protrusion, smoothens the contour, break narrow isthmuses and also it is used to find specific shapes in an image [23].

Dilation: - Dilation is mainly used for expanding an element A by using element B. Dilation helps in clearing the border of the image. Dilation of A by B is, denoted $A \oplus B$, is defined as,

$$A \oplus B = \{ Z \,|\, (B)_z \cap A \neq \emptyset \} \qquad 7)$$

This equation is based on obtaining the reflection of B about its origin and shifting this reflection by Z.

The above equation 7) may be rewritten as,

$$A \oplus B = \{ Z \,|(B)_z \cap A \subseteq A \} \qquad 8)$$

Filling: - Filling is used to fill the gaps and holes in the binary image. Filling is defined as,

$$F(x,y) = \{ 1 - I(x,y), if\ (x,y) is\ on\ the\ border\ of\ I$$

O, Otherwise. 9)

Where, I is a binary image.

F is a marker image [19].

G. Tumor segmentation

After segmenting the abdomen/liver from the CT image, tumor is detected from the liver image. Intensity of the tumor in the abdomen/liver part is different, so threshold value is set to detect the tumor part from the abdomen/liver part. The threshold value is different for different images. If the value of an area is greater than threshold value then it indicates as a tumor region in the abdomen/liver part [5].

H. Tumor burden

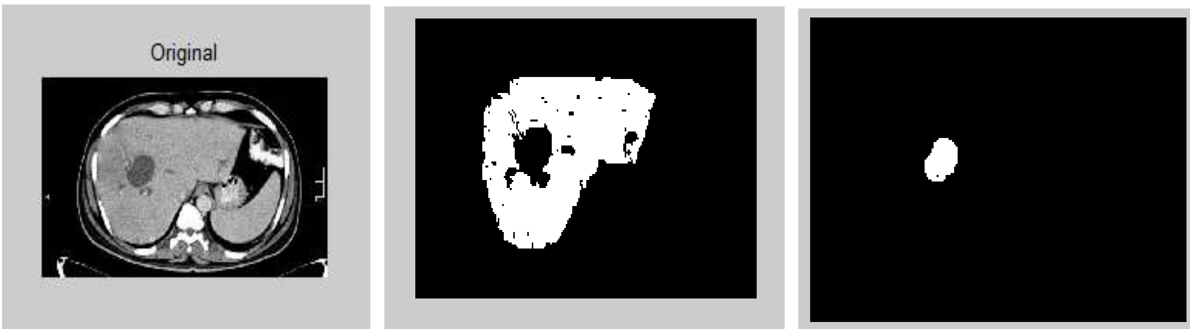
The percentage of the total tumor present in the abdomen/liver is known as tumor burden, which helps in monitoring the evaluation of disease. It helps in distinguishing whether the tumor is cancerous or non-cancerous [13]. It is calculated by using the following formula,

$$Tumor\ Burden = \frac{Sum\ of\ the\ area\ of\ total\ tumor\ in\ liver}{Area\ of\ the\ liver} * 100 \qquad 10)$$

III. Experimental Results:-

For validating the proposed technique, the dataset of images are collected from PRISM Medical Diagnostic, Solapur, Maharashtra. Experiments are carried out on CT images stored as jpeg image of size 1366 * 768 pixels using core i3 processor. The proposed method shows fast and reliable segmentation as shown in Fig. 1. and TABLE I presents tumor burden values for various images in terms of percentage. Severity of the tumor determined in abdominal CT images is broadly classified in to three groups such as Mild, Moderate and Severe. The range is defined as, Mild= 0-2 tumor burden, Moderate= 2-5 tumor burden and Severe= 5 and above tumor burden.

i. Region Growing Results



(a) (b) (c)

Fig. 1. (a) Original CT Image; (b) Liver Segmentation Image; (c) Tumor Segmentation Image.

TABLE I. **Tumor Burden Analysis using Region Growing Method**

Sr. No.	Images	Tumor burden (%)	Tumor Classification
1	Image 1	1.1239	Mild
2	Image 2	1.1403	Mild
3	Image 3	0.8960	Mild
4	Image 4	5.3589	Severe
5	Image 5	0.8049	Mild
6	Image 6	No Tumor Found	----
7	Image 7	No Tumor Found	----
8	Image 8	0.6092	Mild
9	Image 9	1.4084	Mild

10	Image 10	13.6429	Severe
11	Image 11	0.4470	Mild
12	Image 12	0.5992	Mild
13	Image 13	13.7544	Severe
14	Image 14	1.1538	Mild
15	Image 15	3.7159	Moderate
16	Image 16	2.5480	Moderate
17	Image 17	2.4031	Moderate
18	Image 18	0.5957	Mild
19	Image 19	0.4845	Mild
20	Image 20	1.1445	Mild
21	Image 21	1.0236	Mild
22	Image 22	1.4850	Mild
23	Image 23	4.5347	Moderate

ii. Otsu Method :-

(a) (b) (c)

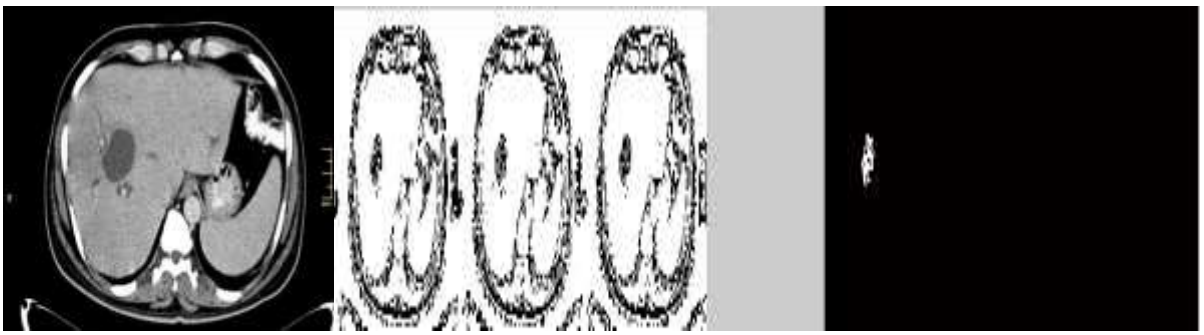
Fig. 2. (a) Original image; (b) Segmented image; (c) Tumor Segmentation image.

TABLE II. Tumor Burden Analysis using Otsu

Sr. No.	Images	Tumor burden (%)	Tumor Classification
1	Image 1	0.7728	Mild
2	Image 2	1.0861	Mild
3	Image 3	1.3549	Mild
4	Image 4	3.9684	Moderate
5	Image 5	0.7861	Mild
6	Image 6	No Tumor Found	-------
7	Image 7	No Tumor Found	-------
8	Image 8	0.6431	Mild
9	Image 9	2.0334	Moderate
10	Image 10	8.5312	Severe
11	Image 11	0.6705	Mild
12	Image 12	0.7750	Mild
13	Image 13	7.3991	Severe
14	Image 14	1.5794	Mild
15	Image 15	4.4548	Moderate
16	Image 16	3.8938	Moderate
17	Image 17	4.8178	Moderate
18	Image 18	0.7148	Mild
19	Image 19	0.5254	Mild
20	Image 20	1.1105	Mild

21	Image 21	0.5540	Mild
22	Image 22	1.9685	Mild
23	Image 23	5.2308	Severe

iii. Clustering Method :-



(a) (b) (c)

Fig. 3. (a) Original CT image; (b) Segmentation Image; (c) Tumor Segmentation Image

TABLE III. **Tumor Burden Analysis using Clustering**

Sr. No.	Images	Tumor burden (%)	Tumor Classification
1	Image 1	0.7098	Mild
2	Image 2	0.7049	Mild
3	Image 3	0.4978	Mild
4	Image 4	2.5310	Moderate
5	Image 5	0.8218	Mild
6	Image 6	No Tumor Found	------
7	Image 7	No Tumor Found	-------
8	Image 8	0.4231	Mild

9	Image 9	1.3137	Mild
10	Image 10	7.5415	Severe
11	Image 11	0.3168	Mild
12	Image 12	0.5655	Mild
13	Image 13	11.9595	Severe
14	Image 14	0.7504	Mild
15	Image 15	4.2727	Moderate
16	Image 16	3.3282	Moderate
17	Image 17	4.6729	Moderate
18	Image 18	0.5750	Mild
19	Image 19	0.8525	Mild
20	Image 20	0.5080	Mild
21	Image 21	1.5424	Mild
22	Image 22	1.5308	Mild
23	Image 23	2.6086	Moderate

iv. Fuzzy C-Means Algorithm :-

(a) (b) (c)

Fig. 4. (a) Original image; (b) Segmented image; (c) Tumor Segmentation Image

TABLE IV. **Tumor Burden Analysis using FCM**

Sr. No.	Images	Tumor burden (%)	Tumor Classification
1	Image 1	0.5209	Mild
2	Image 2	0.7230	Mild
3	Image 3	0.5216	Mild
4	Image 4	2.1467	Moderate
5	Image 5	0.5736	Mild
6	Image 6	No Tumor Found	--------
7	Image 7	No Tumor Found	---------
8	Image 8	0.6073	Mild
9	Image 9	1.2191	Mild
10	Image 10	15.0812	Severe
11	Image 11	0.4089	Mild
12	Image 12	0.3604	Mild
13	Image 13	7.4831	Severe
14	Image 14	0.6644	Mild
15	Image 15	2.4630	Moderate
16	Image 16	3.6464	Moderate
17	Image 17	5.0293	Moderate
18	Image 18	0.4330	Mild
19	Image 19	0.3271	Mild
20	Image 20	0.9494	Mild

21	Image 21	0.4738	Mild
22	Image 22	0.9480	Mild
23	Image 23	3.5953	Moderate

CONCLUSION:-

Effective segmentation of liver/abdomen CT images has been investigated in this paper. Popular segmentation techniques namely region growing, Otsu, Clustering and FCM, respectively, are implemented for the segmentation of abdomen / liver structure. Thresholding is used for tumor segmentation from abdomen/liver. Apart from this morphological operations are used to get fast and accurate abdomen/liver and tumor segmentation. The detected tumor has been graded using tumor burden as parameter. It is evident from the tabular results that region growing approach gives good results compared to other segmentation techniques. Tumor burden values helps in monitoring the severity of disease.

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