Automated Segmentation of Suspicious Regions in Liver CT using FCM

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ABSTRACT
In this study, an automated segmentation approach is proposed that segments the liver from input CT images of the liver, and cluster the components into different clusters, separating the liver from any detected suspicious region for further analysis and diagnostics. The proposed methodology relies on two stages mainly; firstly, the liver is segmented from the input CT image by separating it from other organs in the CT scan. This is done via a group of preprocessing stages such as morphological filtering, thresholding and boundary extraction algorithms. Secondly, the output from this stage is further processed using a FCM clustering technique to segment the pixels into different clusters. The proposed methodology is tested on a wide range of dataset liver CT scan images of both normal and infected livers. The success rate of the proposed methodology reached 93.3% for infected livers, which proves the reliability of the proposed methodology and paves the way for further investigation.

Keywords
Fuzzy Clustering Mean (FCM), liver cancer, image processing, segmentation.

1. INTRODUCTION
Dependency upon automated tool for study and analysis of the different imaging modalities used in different applications is increasing. For different imaging techniques such as X-rays, computed tomography (CT) or magnetic resonance imaging (MRI), the ability of the radiologist determines the productivity of the interpretation and consequently the diagnosis [1]. Different diagnostics related to liver treatments are primarily based upon CT, being a vital point in the decisions based upon the visualization of the patient in 3D. CT images are used extensively in medical diagnosis for the fact of their noninvasive behavior and their multi-parameter imaging. In any CT scan the major challenge is the segmentation step due to many different artifacts that may appear in the image, thus most segmentation results are unsatisfactory [2].

Most image segmentation techniques for liver CT depend upon threshold techniques, which mainly depend upon the regional property of the image. Other techniques may depend on the neighborhood properties and use the texture analysis approach [3]. It has been found out that local segmentation techniques perform better than global segmentation ones. This mainly can be attributed to increased sensitivity to small area features [4].

Different research efforts have been exerted along the years to solve the problem of liver segmentation from CT images. In [5] researchers presented a CT liver image diagnostic classification system that detects, extracts and the CT liver boundary and further classify liver diseases. The proposed system consisted of a detect-before-extract (DBE) system to find the liver boundary integrated with a neural network liver classifier mainly designed to distinguish normal liver from infected one.

Other efforts relied on statistical approaches such as [6], in which researchers presented an automated process based on an evolutionary algorithm, a statistical shape model (SSM) and a deformable mesh to solve the liver segmentation problem. The proposed technique integrated both global and local search advantages in two subsequent stages to evaluate the parameters of the deformable mesh. The proposed system results are comparable to a human rater in 60% of the cases tested.

Watershed techniques for segmentation were studied in [2], where researchers used a comprehensive edge detection approach being the watershed algorithm and the region merging approach. The proposed approach handled the problem of over segmentation in a much efficient way. Their results reflected that this approach can be used to achieve better liver cancer CT region segmentation.

Approaches relying on contrast enhanced techniques such as [7] proposed a fully automatic method for liver segmentation from CT images. This method depends mainly on an advanced region growing approach whose output is further improved using various pre- and post-processing steps. The results achieved could successfully segment liver in most cases; however some cases failed as they excluded very large lesions.

Some approaches used hybrid techniques to tackle such problem. In [1], researchers proposed a hybrid approach for liver segmentation from CT data. Their approach consisted of four stages; firstly an intensity-based partition is applied to obtain soft-tissue regions. Secondly, texture classification based on region is used for classification of tissues and generating probability images. Thirdly, an initial region of the liver is defined from probability images. Finally, a 95% confidence interval is used to determine the intensities of the initial regions to detect the liver in the subsequent images And recently, in [8] researchers proposed a sophisticated hybrid system capable of segmenting liver from abdominal CT and detect hepatic lesions automatically. Results based on two different datasets and experimental results reflected the robustness and effectiveness of the proposed system. The proposed system is fast as well with ability to segment liver from abdominal CT in less than 0.15 second/slice. In this study, an automated technique for liver segmentation from CT images is proposed after a set of pre-processing techniques applied to the input image. Then a Fuzzy C-Mean (FCM) clustering technique is used to segment the liver into 3 groups detecting the tumors as well.

The rest of this paper is organized as follows; section 2 describes the proposed methodology in this study in more details. In section 3, experimental procedures and results are presented. Section 4 concludes this study with the conclusion as well as the future recommendations.

2. PROPOSED METHODOLOGY

In this study, a two-stage algorithm is proposed to segment the liver from the input CT image, then followed by a FCM stage to segment the suspicious regions from the segmented liver image. In the subsequent paragraphs, details of the two stages will be described in more details

2.1 Liver Segmentation

The input to this stage is the original CT image of the abdominal region including the liver along with other organs. The desired output from this stage will be the segmented liver image.

The input image is subjected to multiple pre-processing steps to enhance the ability of the liver segmentation process. Firstly, a morphological filter is used for noise reduction as well as decoupling attached organs. For an input image (*I*), using a structuring element (*B*), the image is once dilated to become I_{dil} and once eroded to become I_{erod} , the average of both dilated and eroded images produces I_{avg} as described in eqns. (1), (2).

$$I_{dil} = I \oplus B$$

$$I_{erod} = I \ominus B \quad (1)$$

$$I_{avg} = \frac{I_{dil} + I_{erod}}{2} \quad (2)$$

The new value assigned to the filtered image I_{filt} at a certain location (i, j) is decided based upon the value of I_{avg} at the same location , as described by eqn (3).

$$I_{filt}(i, j) = \begin{cases} I_{dil} & if\ I(i, j) \geq I_{avg}(i, j) \\ I_{erod} & if\ I(i, j) < I_{avg}(i, j) \end{cases} \quad (3)$$

The output filtered image is then subjected to a thresholding process to be converted to binary image, in order to be further processed. The thresholded image is then cleaned using morphological processes on binary images based upon consecutive opening and closing processes. The main purpose of this cleaning process is to remove the small noise from the binary image. The connected component algorithm is implemented to find out the connected parts in this image. The boundaries of the detected components are extracted afterwards, then the largest boundary is extracted based upon the assumption that the liver is normally the largest organ in the input CT image, which is a valid assumption for our type of input images. Finally a mask is created by region filling algorithm to fill inside the largest boundary only.

The output from this stage (liver segmentation stage) is the result of the element-wise multiplication between the developed mask and the original input. This output image includes only the original values of intensities of the liver, and otherwise is black. The overall algorithm of this stage is summarized in Fig. 1.

2.2 Tumor Segmentation

Based upon the output from stage A, the Fuzzy C-Mean (FCM) clustering technique is adopted to cluster the intensity levels of the image into three main clusters, being the background pixels (black pixels), liver region (light pixels) and suspicious regions (dark pixels). Fuzzy C-Mean (FCM) algorithms have been used extensively and proven effective for the image segmentation applications [9]. In this study, it is used as the main clustering tool to differentiate liver pixels from suspicious regions pixels.

Firstly, the FCM technique is run in order to cluster pixels in the image in 3 main clusters (background, liver, suspicious). After which the original values of the intensity levels of the 3 clusters are restored from the input image. The image containing the suspicious regions is determined based upon the number of elements belonging to each cluster. In this image, the small regions are removed compared to the main suspicious regions, as they will be mainly noise or wrong pixels assigned to this cluster. Finally, the output from this stage is an image including the suspicious regions separated from the liver. The overall algorithm is summarized in Fig. 2. In the following section, details about the different dataset images used to validate the performance of this proposed methodology along with the achieved results will be discussed in more details.

for *each input CT image* do
- **Apply** morphological filter to enhance the quality of the image before further processing, as described in equations (1-3).
- **Convert** image from Grayscale level to binary through applying suitable threshold value
- **Clean** binary image by opening and closing (morphological operations)
- **Apply** connected component algorithm
- **Extract** boundaries of detected components
- **Find** largest boundary, being the liver boundary
- **Create** a mask using region filling algorithm inside largest boundary
- **Multiply** original input image by this mask
- **Output**: Image with only liver segmented

Fig.1: The block diagram for liver segmentation

Input: Output image from stage A

for *each segmented input image* do

Apply FCM algorithm to cluster the intensity levels into 3 different clusters (background, liver and suspicious region)

Retrieve the original values of intensity levels for each cluster

Determine the image that includes the suspicious regions

Clean the image

Return the suspicious region image only

Output: Suspicious regions image

Fig.2: The block diagram for tumor segmentation using FCM algorithm

3. EXPERIMENTS AND RESULTS

The proposed methodology is tested on different dataset images for each of normal and infected livers. Experiments are conducted on a range of images for each to validate the proposed methodology. In the following paragraphs, the output from different stages will be presented, and the summary of the results achieved will be presented at the end of this section.

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Fig.3: Original input image

The first step is the morphological filtering process, where the image is pre-processed for further segmentation, the output of this stage is presented in Fig. 4. The filtered image is then thresholded and further cleaned by morphological operations (opening followed by closing), the result of this process is shown in Fig. 5.

Fig. 4: Output of morphological filter process

Fig.5: Left: output of threshold process, Right: cleaned threshold image

Based upon the cleaned threshold image, the connected components are detected, and then boundary extraction algorithm is implemented. All boundaries of detected objects are extracted and overlaid, and largest boundary is evaluated. Fig. 6 presents the output of this stage, where all boundaries are shown, and largest boundary (liver) is highlighted in red color.

Fig.6: Output of morphological filter process extracted boundaries with largest boundary highlighted in red color

Using the largest boundary extracted, a mask is created with ones inside it, and zeros otherwise. By multiplication of this mask with the original input image, the liver is segmented from the input image, as shown in Fig. 7. The segmented liver image is the input for stage B algorithm to extract the different clusters based upon the FCM clustering technique. The required number of clusters is 3 clusters reflecting the background, liver regions and suspicious regions. A minimum acceptable tolerance is defined as a terminating condition for the FCM algorithm until no further improvement is achieved. The results achieved from the FCM algorithm are tabulated in Table.1.

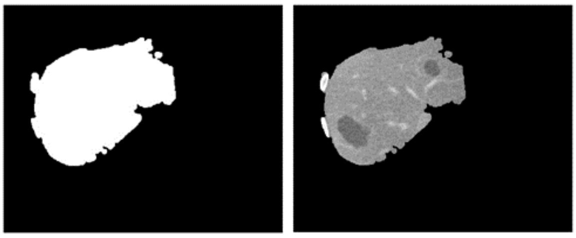

Fig. 7: Left: Mask created, Right: segmented liver image

After the FCM algorithm is finished, pixels assigned to each cluster are segmented, and then the original intensity levels of these pixels are retrieved. The output of the 3 clusters after segmentation is shown in Fig. 8.

As can be seen from the results, the proposed methodology was able to successfully segment the liver from the suspicious regions following the two stages applied on the input image. The proposed methodology is tested on a dataset of 30 infected livers. The images were acquired by different clinics and scanners, the data sets contained a total of 60 in range of 2 lesions per data set. The size of the lesions with average 1.03mm, for infected livers, 3 clusters are extracted, and in the case of normal livers only 2 are extracted, as there will be no suspicious regions detected. Success rates of the proposed methodology over the range of images tested is presented in Table 2.

The average execution time of the proposed approach in this study is 21.32 seconds. This is the average of several runs of the code on different test images

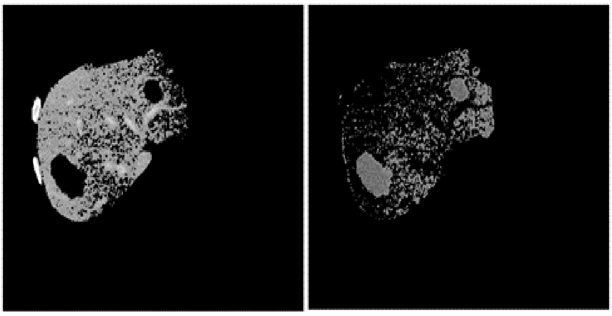

Fig. 8: Left: pixels belonging to liver cluster, Right: pixels belonging to suspicious region cluster

To be able to evaluate the performance of our proposed algorithm, we compare our results with these achieved by segmentation using region based [10]. The comparison is tabulated in Table 3, as can be seen; these results are very satisfactory in other studies

Table.1 Objective Function Values For FCM Algorithm

Iteration count	Objective function	Improvement value
1	3414.299024	
2	2641.819675	772.479349
3	2638.853264	2.96641 1
4	2590.368589	48.484675
5	1916.624911	673.743678
6	227.459498	1689.165413
7	132.178121	95.281377
8	131.884283	0.293838
9	130.132754	1.751529
10	116.549739	13.583015
11	65.554682	50.995057
12	61.138575	4.416107
13	60.18605	0.952525
14	59.968159	0.217891
15	59.906162	0.061997
16	59.885428	0.020734
17	59.877804	0.007624
18	59.87484	0.002964
19	59.873649	0.001191
20	59.87316	0.000489
21	59.872956	0.000204
22	59.872871	0.000085
23	59.872835	0.000036
24	59.872819	0.000016
25	59.872813	0.000006

Table .2 Success Rate of Proposed Algorithm

Type of Liver	No. of images	Success Rate
Normal liver	30	96.67%
Infected liver	30	93.3%

Table .3 Comparison of average Success Rate of Proposed Algorithm (FCM) and Region Based Algorithm

Method	Success Rate	Execution Time
FCM	93.3%	21.32sec
Region based	91.28%	32.38sec

4. CONCLUSION

In this study, an automated segmentation methodology is proposed to segment suspicious regions from liver CT images. The proposed methodology is based upon 2 main stages; firstly, the input CT image is pre-processed using a morphological filter to prepare the image for further processing. The result of this step is further subjected to thresholding process to convert the image to binary format then two cascaded morphological operations are applied (opening then closing) to remove the small regions resulting from the threshold process. Boundary extraction and region fill algorithms are implemented to produce a mask that is further used to extract only the liver from the original input CT image. The second stage uses the output segmented liver image and apply FCM algorithm to cluster the detected pixels into 3 different clusters being the background, liver and suspicious regions pixels. The pixels belonging to each cluster are further extracted from the original input image and presented in separate images to aid the analysis and diagnosis stage, Future efforts include applying an intelligent method to specify the severity of the detected suspicious region, and possibly, specify the type of the infection. On another level, other complicated segmentation procedures may be investigated.

5. REFERENCES

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