Universal Fast Marching Method to Identify Liver Image

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Abstract. Liver segmentation is of prime importance in modern liver disease diagnosis and analysis. In our paper, random section of liver image is chosen and its histogram is achieved. From histogram, liver pixel intensity range is obtained. Using the range value, threshold segmentation is carried out which detaches the liver from its adjoining organs. Median filter is employed to curtail the noise. The sigmoidal function is applied to improve anatomical structures of image. Then the image is converted into binary called as speed function. The novel algorithm is designed to locate the start points within speed function without user intervention. These start point evolved outwardly using Fast Marching Method till complete periphery of liver is reached. The proposed algorithm is compared with popularly used segmentation algorithms. The results show that proposed segmentation algorithm is robust in approach.

Keywords: Computed Tomography, Fast Marching Method, Liver segmentation, Magnetic Resonance Imaging, threshold based segmentation.

1. Introduction
Segmentation is a process of dividing the image into meaningful divisions. In medical images, segmentation algorithm is basically used either to separate required organ from its neighbouring organs or put outline for intended organ [1-2].
Liver is an obligatory organ which is accountable for numerous chemical actions that human body needs and it generates chemicals that are used by different parts of human body. For a healthy body, healthy liver is much necessary. The liver is threatened by many diseases like cancer, fatty liver, cirrhosis, etc. The diseases in the liver spread very fast because of its anatomical structures and rich in its biochemical environments.
Liver segmentation is primary requirement for computer based disease analysis and diagnosis. Separating liver from abdominal scanned images is quite tedious task since edges are blurry, huge pixel intensity variation from one patient to another as well as variation of pixel intensity inside the liver image because of diseases or may be due to hereditary problem and close proximity with neighbouring organs. Thus segmentation method based on edge, region, threshold, feature and parameter fails to detect
the liver image accurately in scanned images. As well as different segment algorithms are used for different modalities like CT, MRI, PET, etc.

The proposed segmentation algorithm first studies the liver pixel intensity dispersion by picking haphazard section of liver. Then liver pixel intensity range is acquired using its histogram. Threshold based segmentation is carried out using this range which precisely isolates liver image from CT/MRI scan images.

2. Related Work

Numerous segmentation algorithms have been suggested by authors which provides good results on particular application. Shenhai Zheng [3] integrates global guassian intensity analysis and local statistical features in level set framework to achieve coarse liver image. The improved Chan-Vese model is used to improve the liver outline. Ankur Biswas [4] propose liver segmentation method in which thresholding is employed to take out liver from abdominal CT scan images. Two geometric contours are initialized which grow using level set method to detach liver from CT scan image accurately. Sangeeta [5] employed Neutrosophic Set (NS) theory to isolate the liver from its neighbouring organs and Chan-Vese (C-V) model to spot liver boundary. Sangeeta [6] used NS theory to segment liver from abdominal CT scan image. A novel step is followed to identify start points inside liver which progress outwardly to spot liver boundary using Fast Marching Method (FMM). Sangeeta [7] used threshold based segmentation to separate liver from CT and MRI scan images and boundary is marked by improved C-V model. L Merg [8] designed liver and liver tumour segmentation algorithm based on 3D dual path multi-scale Convolutional Neural Network. To refine the segmentation results, conditional random field was used which eliminated false segmentation points in the segmentation results. Budak [9] constructed liver and liver tumor segmentation model using two deep Encoder-Decoder Convolutional Neural Network [EDCNN]. An EDCNN separates liver image from CT scan which is input for training of a second EDCNN. The second EDCNN the segment the tumour region within the liver ROI regions as predicted by the first EDCNN. This model produced an average DICE score of 95.22% for test set of CT images.

3. Methodology

Step1: The acquired image is in 1019 X 682-pixel matrix. To speed up the algorithm, the dimensions are reduced to 512 X 512-pixel matrix.

Step2: The liver pixel density distribution varies from one person to another person; it also varies throughout the liver part in medical scan images. There is no definite range of intensity values for liver part. Hence, it is crucial to find pixel range for liver part. In proposed algorithm, this is done by picking random section of liver to learn pixel density dispersion. A histogram of only picked liver part is obtained. From histogram, pixel intensity range is achieved, further highest pixel intensity value \( T_{max} \) and smallest pixel intensity value \( T_{min} \) is derived.

Step3: Apply threshold segmentation using \( T_{min} \) and \( T_{max} \). The threshold function is defined in equation (1).

\[
I = \begin{cases} 
I & \text{if } T_{min} \leq I \leq T_{max} \\
0 & \text{Otherwise}
\end{cases}
\]  
(1)

Where I is intensity level of image. This threshold function separates liver image from its neighbouring organs like kidney, spleen, heart, ribs, gallbladder and pancreas.

Step4: The noise is reduced by applying median filter of size (3 x 3).

Step5: In the next step, anatomical structures are enhanced by sigmoidal function which is represented in equation (2).
$$S_f = T_{\min} - T_{\max} \frac{1}{1+e^{-(I-A)/B}} + T_{\min}$$

Where: $T_{\min} =$Minimum pixel intensity value of liver part; $T_{\max} =$Maximum pixel intensity value of liver part; $A =$ Pixel intensity level to be enhanced; $B = (T_{\min} + T_{\max}) / 2$; $I =$ Intensity level of image.

**Step 6:** Small regions are removed by image erosion morphological operation.

**Step 7:** Convert the obtained image into binary image which is called a speed function.

**Step 8:** Generate the start points automatically within area of the liver.

**Step 9:** The start points and speed function are inputs to FMM. These start points grow outwardly using FMM [10-16] until it detects complete periphery of the liver. This marks liver periphery in CT/MRI scan images.

The proposed model for marking the border of liver image in CT scan and MRI is demonstrated in figure 1.

### 4. Automatic Start Points Selection

We conducted large-scale investigational experiments to find the impact of start points. The position of start points within liver part and number of start points have great impact on the performance of the FMM. Most of the algorithms identify the start points manually which involve user intervention. We recommend an automatic method which locates the start point automatically within the liver area. To find out start points, subsequent steps are pursued.

**Step 1:** Find out centroid of liver as $(cx, cy)$.

**Step 2:** Choose $d_i=20$ which is chosen experimentally.

**Step 3:** Points $(cx, cy),(cx, cy+d_i),(cx+d_i, cy),(cx+d_i, cy+d_i)$ positioned inside liver are chosen as start points i.e.

### 5. Experiment and Results

The experiment dataset includes 50 MRI scan images and 50 CT scan images which are offered by M/S “CT scan Center”, Hubbali, Karnataka, India. Every scan consists of 40-150 slices. Every slice of CT and MRI scan is a 1020 X 682 size colour image.

The outcomes of CT scan and MRI scan images are shown in figure 2 and 3 respectively. Figure 2(a), (b) and (c) present the original CT scan image, picking random part of liver and histogram of picked liver part respectively. Figure 2(d), (e), and (f) threshold based segmentation result, liver periphery marking using FMM and standard image, respectively for CT scan images. Figure 3(a), (b) and (c) present the original MRI scan image, select random part of liver and histogram of selected liver part respectively. Figure 3(d), (e), and (f) threshold based segmentation result, liver periphery marking using FMM and standard image, respectively for MRI scan images.
6. Comparison with Existing Methods
To evaluate the performance of novel model to identify liver border in abdominal CT and MRI scan images, it is compared with one of the popular region based segmentation method (a). Chan-Vese (C-V) model [17] with specifications: initial contour location= [325,335; 345,335], number of iteration=175 and \( \mu=0.110 \); (b) Chunming Li et al [18] designed a level set based segmentation method intended for MRI scanned images. This method is also called as LSE (Level Set Evolution) model. The analysis of this method was executed on the medical images with specifications: \( \mu=1.01 \), \( \epsilon=1.01 \), step time=0.101, \( \sigma=4 \), initial contour position= [165,225; 185,235], number of iterations=11; (c) Chunming Li et al. [19] proposed a novel segmentation method based on energy fitting. This technique of segmentation is also called as Region-Scalable Fitting (RSF) model. The analysis was carried out with specifications: \( \sigma=3.23 \), \( \epsilon=1.01 \), \( \mu=1.01 \), step time=0.11 \( \lambda_1=1.01 \), \( \lambda_2=1.01 \), number of iterations=24, initial contour position = [165, 210; 185, 210].
Figure 2. Experimental outcomes of proposed method for CT scan image; (a) 2D CT scan images; (b) pick arbitrary part of liver; (c) histogram of arbitrarily picked liver part; (d) results of threshold based segmentation for CT scan images; (e) periphery of liver marked in CT scan images; (f) reference image of CT scan.

Figure 3. Investigational outcomes of proposed technique for MRI scan images; (a) 2D MRI scan images; (b) Pick arbitrary part of liver; (c) histogram of arbitrarily picked liver part; (d) results of threshold based segmentation for MRI scan images; (e) periphery of liver marked in MRI scan images; (f) reference image of MRI scan.

Figure 4 presents comparison outcomes of proposed technique with existing technique. The figure (a), (b), (c), (d) and (e) show 2D MRI scan, result of C-V model, result of RSF model, LSE model and proposed model for MRI scan respectively. The figure (f), (g), (h), (i) and (j) show 2D CT scan, result of C-V model, result of RSF model, LSE model and proposed model for CT scan respectively.

The liver has indistinguishable edge and pixel intensity distribution inside the liver varies from one section of liver to another section and it varies from one patient to another. Hence, all three existing algorithms have limitation, ensuing in vague detection of liver image. In this work, first pixel density variation inside the liver is analyzed by picking random section of liver and hence achieves exact liver separation from neighbouring organ.
Figure 4. Comparison of proposed technique with existing technique.

The fig (a), (b), (c), (d) and (e) show 2D MRI scan, result of C-V model, result of RSF model, LSE model and proposed model for MRI scan respectively. Fig (f), (g), (h), (i) and (j) show 2D CT scan, result of C-V model, result of RSF model, LSE model and proposed model for CT scan respectively.

In the state-of-art that we have considered for comparison, the authors have to decide the position of initial curve and count of iterations on trial and error bases. These parameters influence the outcome of the segmentation method/model. Within anticipated technique, there is no human intercession to identify the initial contour position and count of iterations. As soon as liver periphery is recognized, results will be demonstrated on the computer screen.

RSF model, LSE model, C-V model and the anticipated model have been experimented on 50 MRI and 50 CT scan images. The segmentation accuracy for proposed model and state of art has been determined for 50 MRI and 50 CT a are illustrated in figure 5 and 6 respectively.

7. Segmentation Performance Evaluation Metric

The segmentation method has many applications like industry, medical images, business, etc. Nowadays, many segmentation methods are available. It is difficult to decide which segmentation algorithm has to be used [20-22]. This is because no universal segmentation method available which provides best result for all types of applications. For different applications, different types of
segmentation methods are suitable [23-25]. Selection always depends upon type of data that is provided to segmentation methods. The evaluation metric(s) helps us to select one of the best segmentation algorithms for particular application. This is done by comparing the outcome of proposed model against standard image. The standard image is obtained by manual segmentation which is verified by practicing doctor.

7.1. Accuracy:
The quantity of match between standard image and algorithm segmented image is measured by metric called as accuracy. The accuracy is defined as follows.

\[
\text{Seg. Accuracy} = \frac{\text{ASP}}{\text{AP}}
\]

Where \(\text{ASP}\) = Quantity of satisfactorily classified pixels in segmented region and \(\text{AP}\) = Amount of Pixels in machine segmented image.

The perfect segmentation results segmentation accuracy of 1 i.e. there is 100% similarity between standard image and image from segmentation method. As the segmentation accuracy move away from 1, indicating amount of dissimilarity.

\[\text{Figure 5. Comparison result using Accuracy for MRI scan images.}\]

\[\text{Table 1. Average segmentation accuracy for the anticipated method and State-of-art for MRI and CT scan images.}\]

| Scanned images | Proposed model (in %) | C-V model (in %) | LSE model (in %) | RSF model (in %) |
|----------------|-----------------------|-----------------|-----------------|-----------------|
| MRI            | 74.8                  | 48              | 51.5            | 42.3            |
| CT             | 92.6                  | 40.3            | 45.6            | 40.9            |
7.2. Volumetric Overlie Error (VOE):
The Volumetric Overlie Error between 2 clusters of pixels SALG and SREF is specified in % and stated as $(1 - \text{Jaccard Coefficient}(JC))$ [26, 27]. JC is proportion obtained by intersection and union of algorithm segmented image (SALG) and reference image (SREF). The SREF is acquired by physical separation using paintbrush and verified by doctor. The VOE ranges between 100% to 0%. VOE=100% indicates algorithm segmented image and reference image do not overlap at all and 0% indicates perfect segmentation result by algorithm i.e. algorithm segmented image and reference image overlap on each other. The VOE for proposed model and state of art has been determined for 50 MRI and 50 CT are illustrated in figure 7 and 8 respectively.

![Figure 6. Comparison outcome using Accuracy for CT scan images.](image)

![Figure 7. Comparison of results using VOE for MRI scan images.](image)

![Figure 8. Comparison of results using VOE for CT scan images.](image)
Table 2. Average VOE for the anticipated method and state-of-art for MRI and CT scan images.

| Scanned images | Proposed model (in %) | C-V model (in %) | LSE model (in %) | RSF model (in %) |
|----------------|-----------------------|-----------------|-----------------|-----------------|
| MRI            | 7.4                   | 23.3            | 35.5            | 32              |
| CT             | 5                     | 23.6            | 27.6            | 34.4            |

Table I and II represent average accuracy in % and VOE in % respectively for MRI and CT scan images.

8. Conclusions
In this paper, the authors design the universal liver segmentation technique which is realized on MRI and CT images. In the anticipated method, pixel density variation in the liver image is studied by picking random part of liver image and obtaining the histogram of it. Using this pixel intensity range is achieved. With this, threshold based segmentation is executed which detaches the liver from its neighbouring organs. Subsequently, four starting/seed points are identified automatically which move outwardly using FMM, identifying liver border precisely. This method can be applied to other modalities without any modification. The proposed segmentation algorithm fails to detect liver image accurately in case of diseases exists at the edges. In the future, the authors will focus on segmentation of liver and its tumour.

References
[1] Xiao S, Cheng M, Wang B and Huang S 2013 Automatic Liver Segmentation from CT Images Using Adaptive Fast Marching Method Seventh International Conference on Image and Graphics 897-900
[2] Kumar P S and Latte M V 2019 Fully Automated Segmentation of Lung Parenchyma Using Break and Repair Strategy Journal of Intelligent Systems 28 271-289
[3] Zheng S, Fang B, Li L, Gao M and Wang Y 2015 A variational approach to liver segmentation using statistics from multiple sources Physics in Medicine & Biology 63 025024.
[4] Biswas A, Bhattacharya P and Maity S P 2018 3D segmentation of liver and its lesions using optimized geometric contours Procedia computer science 133 240-247.
[5] Siri S K and Latte MV 2017 Combined endeavor of Neutrosophic Set and Chan-Vese model to extract accurate liver image from CT scan Computer methods and programs in biomedicine 151 101-109
[6] Sangeeta S and Latte MV 2019 A novel approach to extract exact liver image boundary from abdominal CT scan using neutrosophic set and fast marching method Journal of Intelligent Systems 28 517-532
[7] Siri SK and Latte MV 2017 Universal Liver Extraction Algorithm: An Improved Chan–Vese Model Journal of Intelligent Systems 29 237-50
[8] Meng L, Tian Y and Bu S 2020 Liver tumor segmentation based on 3D convolutional neural network with dual scale Journal of Applied Clinical Medical Physics 21 144-157
[9] Budak Ü, Guo Y, Tanyildizi E and Şengür A 2020 Cascaded deep convolutional encoder-decoder neural networks for efficient liver tumor segmentation Medical hypotheses 134 109431
[10] Sethian J 1996 Level Set Methods and Fast Marching Methods, Cambridge University Press 18 89-92.
[11] Sethian JA 1996 A fast marching level set method for monotonically advancing fronts, Proceedings of the National Academy of Sciences, 93, 1591–1595
[12] Sethian JA and Popovici AM 1999 3-d traveltme computation using the fast marching method Geophysics 64 516–523
[13] Sun H, Sun J G, Sun Z Q, Han F X, Liu Z Q, Liu M C, Gao Z H, and Shi X L 2017 Joint 3d traveltme calculation based on fast marching method and wavefront construction Applied Geophysics 14 56–63
[14] Fomel Y 1998 Fast-marching eikonal solver in the tetragonal coordinates In SEG Annual Meeting Society of Exploration Geophysicists 1949-1952
[15] Yatziv L, Bartesaghi A, and Sapiro G 2006 O(n) implementation of the fast marching algorithm *Journal of Computational Physics* **212** 393 – 399

[16] Garrido S, Malfaz M, Blanco D 2013 Application of the fast marching method for outdoor motion planning in robotics *Robotics and Autonomous Systems* **61** 106-114

[17] Chan T, and Vese L 2001 Active Contours Without Edges *IEEE Transactions On Image Processing* **10** 266-77.

[18] Chunming L, Huang R, Ding Z, Chris Gatenby J, Metaxas DN and Gore JCA Level Set Method for Image Segmentation in the Presence of Intensity Inhomogeneities With Application to MRI *IEEE transactions on image processing* **20** 2011.

[19] Chunming L, Kao C Y, Gore J C, and Ding Z 2008 Minimization of Region-Scalable Fitting Energy for Image Segmentation *IEEE transactions on image processing* **17** 1940-9.

[20] Kumar PS and Latte MV 2018 Lung Parenchyma Segmentation: Fully Automated and Accurate Approach for Thoracic CT Scan Images *IETE Journal of Research* **66** 370-83.

[21] Walaa HE, Moftah HM, El-Bendary N and Hassanien AE Performance Evaluation of Computed Tomography Liver Image Segmentation Approaches *International Conference on Hybrid Intelligent Systems (HIS)* 109-114

[22] Li X, Aldridge B, Rees J and Fisher R 2010 Estimating the reference from multiple individual segmentations with application to skin lesion segmentation, *Annual Technical Meeting on Medical Image Understanding and Analysis (MIUA)*

[23] Graaf C, Koster A, Vincken K. and Viergever M 2008 Validation of the interleaved pyramid for the segmentation of 3D vector images in Pattern Recognition Letters, transactions on image processing, **17** 469-75

[24] Manisha S and Chouhan V 2012 Objective Evaluation Parameters of Image Segmentation Algorithms *International Journal of Engineering and Advanced Technology (IJEAT)* **2** 2249 – 8958

[25] Kumar PS and Latte MV 2019 Modified and Optimized Method for Segmenting Pulmonary Parenchyma in CT Lung Images Based on Fractional Calculus and Natural Selection In *Journal of Intelligent Systems* **28** 721–732.

[26] Jaesik M, Powell M and Bowyer KW 2004 Automated Performance Evaluation of Range Image Segmentation Algorithms *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* **34** 263-71.

[27] Heimann T, Van Ginneken B, Styner MA, Arzhaeva Y, Aurich V, Bauer C, Beck A, Becker C, Beichel R, Bekes G, Bello F, Binnig G, Bischof H, Bornik A, Cashman P, Ying Chi, Cordova A, Dawant B M, Fidrich M, Furst J D, Furukawa D and Grena L Comparison and Evaluation of Methods for Liver Segmentation from CT Datasets *IEEE Transactions on Medical Imaging* **28** 1251-65.