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ARTICLE

AUTOMATIC SEGMENTATION OF LIVER TUMOUR IN CT IMAGES USING SPATIAL FCM AND UNIFIED LEVEL SET METHOD

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ABSTRACT

An organ that is vital in order to survive is the liver. It is however quite prone to several diseases such as hepatic tumours. These tumours are routinely investigated by the use of Computed Tomography (CT) mainly for the evaluation of primary and secondary hepatic tumours prior to surgery. In the case of large amount of data however, it is challenging to do a manual segmentation of the CT images. Here, fully automated techniques that require minimal or no supervision remove the need for manual segmentation. This paper evaluates Spatial Fuzzy C Means (FCM) clustering as compared to unified level set method to segment the liver from CT images.

KEY WORDS
Spatial FCM, Clustering, Tumor, Liver, Unified Level Set (MEA)

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INTRODUCTION

The liver constitutes for one of the vital organs present in the human body. It carries out several functions such as detoxification, synthesis of protein and manufacturing of bio chemicals essential for digestion. The liver lies in the right upper quadrant of the abdomen just below the diaphragm. As the liver carries out several functions and due to its location in the abdomen it has been noted to be prone to masses. Here the masses may be either benign or malignant. The detection of these masses are now reliant on the advancements made in imaging modalities such as Magnetic Resonance Imaging (MRI), CT, and digital mammography to name a few. This technology serves to image the many complexities of the human anatomy [1]. In this regard, CT allows for the surgeon to determine the presence, size, location and extent of involvement, making CT the most preferred for hepatic tumours. From the abdominal CT, the liver has been previously segmented using various techniques like FCM, graph cut and adaptive threshold. Along the same lines a researcher JeongjinLeea et al [2] depicted a level-set method for segmentation. This technique involves the use of level-set speed images that determine the initial hepatic boundary. This is done by coupling the level-set speed images to a two-step Seeded Region Growing (SRG). Of the two steps, in the first step if the iteration number of the specified curvature is determined to be too small then the SRG segregates the CT images into a smaller number (also with the increase in the iteration number). From this, the liver boundary is seen to be smoother and can be more easily detected. The calculation time is also increased.

Graph cuts were developed by Jean Stawiaski et al [3] for the purpose of image segmentation. This technique use the graphs based on input data and find a global optimal cut. The graph is construucted by each voxel being assigned with a node. This algorithm was seen to have issue with locating the liver border as the border is darker than the rest if the liver and hence it marks the liver on the whole as a tumour. The accuracy hence was lowered. Adaptive threshold along with morphological was proposed by S.S.Kumar et al [4] for image segmentation of the liver. He also proposed the FCM for the segmentation of hepatic tumours. It was determined that the FCM only measures the grey area values hence decreasing the accuracy. On the other hand, Fast Discrete Curvelet Transform (FDCT) gives textural information of the extracted tumour by making use of artificial neural network classifier. The classification rate thus obtained was 93.3%. Artificial neural networks however need a more diverse training in real time situations. Classification with local binary pattern images for categorising normal and abnormal liver images with cancer was proposed by Vijayalakshmi et al [5]. Non- overlapping segments of 8X8 of liver images are obtained. Further, to extract the features of texture and other appropriate features Legendre moments and forward selection algorithm is applied. The images are then classified using the neighbourhood minimum distance decision rule and Euclidean distance classifier. Hsue et al [6] ascertained that computer aided detection using growing algorithm can be used for liver segmentation of CT images. Following this, the CT images are transformed into a digital signal through DWPD (Discrete Wavelet Packet Decomposition) after which REDUCT sets are employed to segregate the given features and reach a classification.
Xing Zhang et al [7] evaluated automatic segmentation with the employ of optimal surface detection using a statistical shape model. This technique uses the concepts of graph theory that enables for the shape of the liver to be localised using a Hough transform after which the shape model deforms in order to conform to the shape of the liver. A brute force manner is then applied for the scale and rotation of the object. This manner however is associated with a high cost and requires a 6-D parameter. YrjöHäme et al [8] proposed semi-automatic liver tumour segmentation with a hidden Markov field model measure. It uses a non-parametric distribution. Post processing is also including as part of the technique to curtail the overflow to the adjacent tissue. The accuracy is decreasing for low contrast images. Sergio Casciaro et al [9] made a

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comparitive study on two methods namely graph cut method,active contour method for liver segmentation. For 3D liver images, both the techniques proved efficient and it was proved for tumour segmentation. This method results in high computation time. Xiaoqi Lu et al [10] proposed modified region growing method in which the source images are pre-processed using a non-linear mapping method for liver segmentation which highlights the liver region. Bing Nan Li et al [11] proposed a unified level set method (LSM) tumour segmentation. This method avoids boundary leakage. It overcomes the disadvantage of both region based LSM and edge based LSM and provides high accuracy of 97%.

Liver segmentation through constrained convex variation model was tested by JialinPenget al [12]. This method was associated with over segmentation as it was involved in categorising those structures that had weak borders as well.

Li C et al [13] proposed a level set model with likelihood and constraint for segmentation of the liver shape. The method was however found to be only useful for the healthy liver. Xiao Song [14] proposed removing the ribs, spine and kidney structures along with a smooth filter to enhance the contrast of images by a thresholding operation. Besides this, the researcher also proposed a FMM (Fast Marching Method) with an automatic seed point process of selection. ABC (Artificial bee colony) using a clustering optimisation algorithm to segment liver from CT images was verified by AbdallaMostafa [15]. Here the centroids from each cluster are calculated using mathematical morphological operations. This enables for the removal of sharp edges of other organs as well as flesh regions. Following this enhancement of the image was achieved by using growing approaches.Nuseiba et al [16] proposed a Distance Regularization Level Set (DRLS) model that employs a contour method which is edge-based for liver segmentation. The main advantage is that it guides the direction of the contour to evolve with the contours of the liver. Xuechen li et al [17] proposed spatial fuzzy clustering for liver segmentation coupled with the level set method. In this method, spatial constraints are included in the objective function which is minimised through spatial FCM which optimises the membership function resulting in an accuracy of 99.86%.

MATERIALS AND METHODS

This paper depicts the modules for segmenting the tumour from the liver in CT images in figure 1. In this work, spatial FCM is used for liver segmentation from abdominal CT images. This method helps in accurate segmentation. Then the tumour from the segmented liver is extracted using Unified Level Set Method and spatial FCM and the comparison is made between the techniques.

CT- Abdomen images

⇓

Liver segmentation using Spatial FCM

⇓

Segmentation of liver tumour
- Spatial FCM
- Unified Level Set Method

Fig. 1: Proposed methodology.

Liver segmentation

The segmentation of liver is difficult due to the fact that the CT image includes other organs like spleen, pancreas, kidney etc. which are very close to the liver. The liver is extracted from the CT image using Spatial FCM clustering. It is an iterative optimization algorithm which aims to reduce the objective function. Initially the algorithm starts with FCM clustering which then incorporates spatial constraints in the membership function and then the iteration proceeds.

The process of fuzzy clustering implies each data point to be belonging to more than one cluster and not as if all points belong to a single cluster as a whole. Hence, clustering points may be found to be less in the cluster edges and more at the core centre (when the points in the centroid are as close, it implies minimisation of cost function and hence pixels away from the centroid are of high membership values). The membership function reveals the pixel probability of pixels in a specific cluster. However, the standard FCM utilises the value of grey level intensity which could be overcome in the spatial FCM which encompasses the pixel level spatial information.

Spatial FCM algorithm is presented as ,

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Let X=(x1, x2, ….,xn) denotes an image with n pixels tobe segregated into c clusters

1. Initialize the membership matrix (u_{ij})
2. Select the number of clusters
3. Calculate cluster centre using,

$$C_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \quad (1)$$

The parameter m controls the fuzziness of the resulting partition.

4. Update the Membership matrix as

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} (d_{ij} / d_{kj})^{2/(m-1)}} \quad (2)$$

Where $d_{ij}=||c_i - x_j||$ represents the distance between the individual cluster center and pixel value i.e Euclidean distance.

5. The objective function is defined as

$$J = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \quad (3)$$

6. The spatial function is defined as

$$h_{ij} = \sum_{k \in NB(x_j)} U_{ik} \quad (4)$$

where *NB*(x_j) represents a square window centered on pixel x_j in the spatial domain.

7. The spatial function is incorporated in to the membership function as

$$U_{ij}' = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{ij}^{p} h_{ij}^{q}} \quad (5)$$

Where, p and q are parameters to control relative importance of spatial and membership function. Convergence is identified by making a valid comparison between all changes that occurs are the centre of the cluster in a dual step mode. The liver region is segmented and is fed as input to the tumour extraction phase.

Tumour segmentation

From the segmented liver, tumour is extracted using spatial FCM and unified level set method. The unified level set method is discussed in this section. Edge based LSM is applicable only for CT images with clear and distinct boundaries. Region based LSM is applicable even for CT images not having clear boundaries but it is not applicable to detect object of interest with low contrast. To overcome the disadvantage, a unified level set method is proposed where boundary leakage can be avoided. This method integrates image gradient, region competition and prior information for CT liver tumour segmentation. The probabilistic distributions of liver tumours are estimated by fuzzy clustering and are utilized to improve the object indication function, defined by the directional balloon force and regulated region competition.

The algorithm for unified level set method is as follows

1. Assign the controlling parameters (α, β, γ, λ). (α, β, γ, λ value ranges from 0 to 1).
2. Estimate the object of interest (P_{rk}).
3. Compute the object indication function and signed balloon function.

$$E(\gamma, g_i, g_p) = \exp(-\max\{\gamma g_i, (1-\gamma) g_p\}) \quad (6)$$

Where $g_i = \dfrac{g(\omega) - \min(g(\omega))}{\max(g(\omega))}$

$$g(w)=\frac{1}{1+\left|\nabla\left(G_\sigma * \omega\right)\right|^2}$$

G_σ *w represents the convolution of image with Gaussian kernel.

$$G(\beta, \sigma_0, P_{rk})=[1-2\beta(1-P_{rk})]\,\sigma_0 \quad (7)$$

4. Initialize the dynamic interface

$$\varphi_0=-4\epsilon[0.5-(P_{rk}>0.5] \quad (8)$$

5. Compute the mean curvature k, dirac function δ_τ (φ), heaviside function (H_ϵ(φ)).

6. Compute the force of region competition.

$$R= P_{rk} - \sum_{j\neq k} P_{ri} \quad (9)$$

7. Evolve the dynamic interface with temporal step size.

$$\varphi(v,t+\Delta t)=\varphi(v,t)+\Delta tF \quad (10)$$

$$=\alpha\,\delta(\varphi)\,E(k+\lambda G)+(1-\alpha)\,\delta(\varphi)R \quad (11)$$

8. Repeat from step 5 until the result is satisfactory.

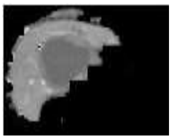
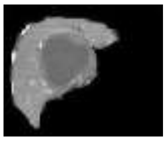
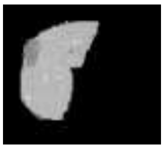
RESULTS AND DISCUSSION

Several sources such as scan centre, internet along with corresponding ground truths for segmentation was used to collect CT images for the research. The liver segmentation and tumour of the abdominal CT images can be analyzed qualitatively and quantitatively by comparing with the ground truth from medical experts to evaluate the performance. The qualitative is done by visual analysis. Accuracy, sensitivity and specificity are calculated for quantitative analysis. These are the terms which statistically measure the performance of the test.

Liver segmentation

Liver segmentation from the abdominal CT image is carried out using Spatial Fuzzy C Means clustering method. Twenty one images, out of 4 sample images, the corresponding segmented liver images and ground truth images are shown in [Table 1] and the quantitative results is shown in [Table 2].

Table 1: Liver segmentation using spatial FCM

Abdominal	Segmented Liver image	Ground Truth Image
		
		

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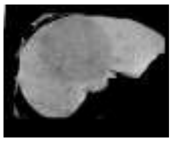
		

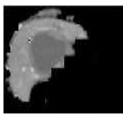
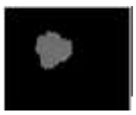
Table 2: Liver Segmentation using Spatial FCM–Quantitative Analysis

Image	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	90.3	89	96
2	89	87	95.3
3	92	89.5	97.8
4	91.3	90.2	97.3

Tumour segmentation

The tumour region is extracted from the segmented liver using Spatial Fuzzy C Means technique and Unified Level Set Method. Out of twenty sample liver images, 4 images are corresponding segmented tumour images for both the techniques. Ground truth images are shown in [Table 3] and the quantitative result is shown in [Table 4].

Table 3: Liver tumour segmentation using spatial FCM and unified level set method

Segmented Liver Image	Liver tumour segmentation using Spatial FCM	Liver tumour segmentation using Unified level set method	Ground truth image
			

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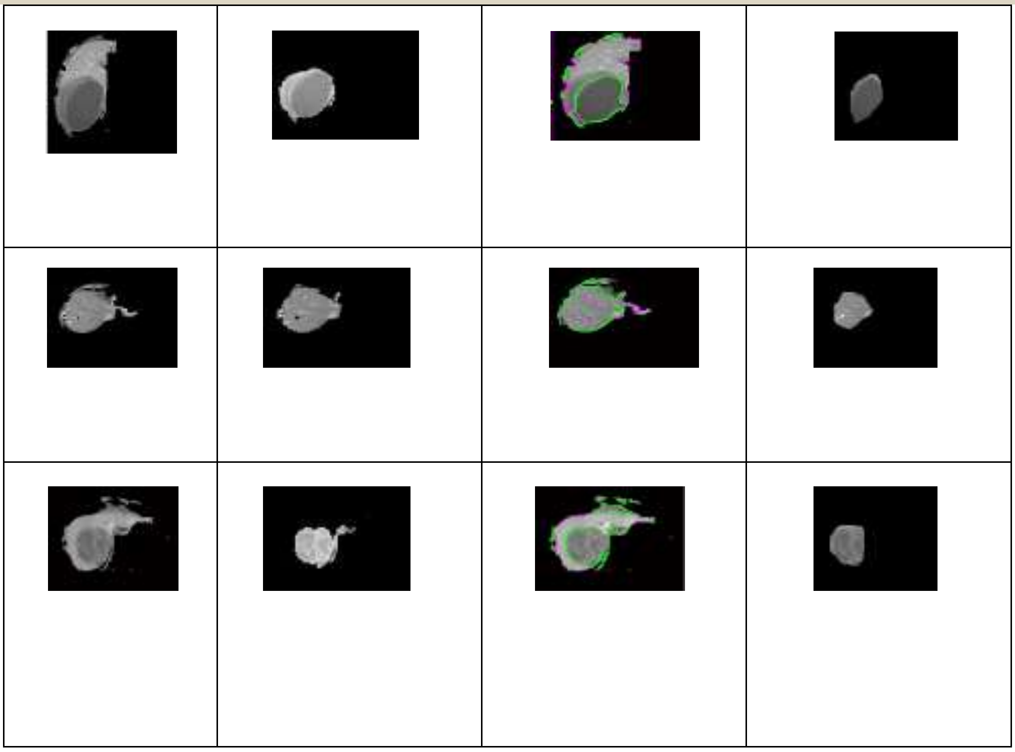

Table 4: Liver Tumour Segmentation using Spatial FCM and unified level set Method - Quantitative Analysis

Image	Unified level set method			Spatial FCM		
	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	92.5	90	95	93	93.2	97.5
2	89.3	88.7	93.5	93.9	92	95.2
3	82.7	77.2	85.5	94.3	95	97.8
4	89.5	88.2	93.6	92.7	94.5	96.3

CONCLUSION

In this research, the liver segmentation and tumour segmentation is implemented. The automatic liver and tumour segmentation proves to be efficient which can make computation feasible and less time consuming. The liver segmentation accuracy ranges from 91.4-97.8% which is achieved by means of spatial FCM, for tumour segmentation, accuracy ranges from 91-98.3% which is achieved by means of spatial FCM and for accuracy ranging 85-96.5% is achieved by using unified level set method.

CONFLICT OF INTEREST

There is no conflict of interest.

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FINANCIAL DISCLOSURE
None

REFERENCES

[1] Torfinn Taxt, Arvid Lundervold, Jarle Strand, Sverre Holm. [1998] Advances in Medical Imaging,. International Conference on Pattern Recognition.

[2] Jeongjin Leea, Namkug Kimb, Ho Leea, Joon Beom Seob, et al. [2007] Efficient Liver Segmentation Using A Level-Set Method With Optimal Detection Of The Initial Liver Boundary From Level-Set Speed Images. International Journal on Computer Methods and Programs in Biomedicine, 88(1):26-38.

[3] Jean Stawiaski, Etienne Decenci ere and Francois Bidault. [2008] Interactive Liver Tumor Segmentation Using Graph-cuts and Watershed. International Conference on Medical Image Computing and Computer Assisted Intervention.

[4] SS Kumar, RS Moni.[2010] Diagnosis of Liver Tumor from CT Images using Fast Discrete Curvelet Transform.International Journal on Computer Science and Engineering (IJCSE), 02(04): 1-6.

[5] Vijayalakshmi B, Subbiah Bharathi. [2016] Classification of CT liver images using local binary pattern with LegendreMoments. CURRENT SCIENCE, 110(4).

[6] Ching-Hsue,Cheng,Liang-Ying Wei. [2016] Rough Classifier based on Region Growth Algorithm for identifying Liver CT image.Journal of Applied Science andEngineering,19(1):65-74.

[7] Xing Zhang, Jie Tian, Kexin Deng, Yongfang Wu and Xiuli Li [2010] Automatic Liver Segmentation Using A Statistical Shape Model With Optimal Surface Detection. IEEE Transaction on Biomedical Engineering, 57(10).

[8] Yrjö Häme and Mikka pollari.[2012] Semi-automatic liver tumor segmentation with hidden Markov measure field model and non-parametric distribution estimation. International Journal on Medical image Analysis, 16(1): 140-149.

[9] Sergio Casciaro, Roberto Franchini, Laurent Massoptier, et al..[2012] Fully Automatic Segmentation Of Liver And Heaptic Tumors From 3-D CT Abdominal Images: Comparitive Analysis of Two Automatic Method. IEEE Sensors Journal, 12(3).

[10] Lu, Xiaoqi, Jianshuai Wu, Xiaoying Ren, Baohua Zhang, and Yinhui Li.[2014] The study and application of the improved region growing algorithm for liver segmentation. Optik - International Journal for Light and Electron Optics, 125(9): 2142–2147.

[11] Bing Nan Li, Chee Kong Chui, Stephen Chang, Sim Heng Ong .[2012] A New Unified Level Set Method For Semi-Automatic Liver Tumor Segmentation On Contrast-Enhanced CT Images. International Journal on Expert Systems with Applications, 39:9661-9668.

[12] Jialin Peng, Ye Wang and Dexing Kong.[2013]Liver Segmentation Using Constrained Convex Variational Model.International Journal on Pattern Recognition Letters.

[13] Li C, Wang X, Eberl S, Fulham M, Yin Y, Chen J, Feng DD.[2013] A likelihood and local constraint level set model for liver tumor segmentation from CT volumes.IEEE transactions on biomedical Engineering, 60(10).

[14] Xiao Song, Ming Cheng, Boliang Wang, Shaohui Huang, Xiaoyang Huang, and Jinzhu Yang.[2013] Adaptive fast marching method for automatic liver segmentation from CT images. Medical Physics, Vol. 40, No. 9.

[15] Abdalla Mostafa, Ahmed Fouad,Mohamed Abd Elfattah.[2015] CT Liver Segmentation using Artificial Bee Colony Optimization. Procedia Computer Science. 60: 1622-1630.

[16] Nuseiba M. Altarawneh, Suhuai Luo, Brian Regan, Changming Sun.[2015] A modified distance regularized level Set model for liver segmentation from ct images. Signal & Image Processing: An International Journal (SIPIJ) 6(1).

[17] Xuechen Li, Suhuai Luo, Jiaming Li.[2013] Liver Segmentation from CT Image Using Fuzzy Clustering and Level Set. International Journal of Signal and Information Processing, 4: 36-42.

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