EE574:3D Liver Vessel Segmentation

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Abstract— **Vessel segmentation is one of the challenging tasks in the field of image analysis. This paper gives a comprehensive study for liver vessel segmentation of 3D images. The main goal is to segment the liver vessels in a given 3D DICOM image of the abdomen. We proposed a cascaded liver segmentation structure such that we first extracted the liver region from the abdomen, then vessel enhancement is performed in order to refine the tubular structures in the extracted liver region. Then, we apply thresholding to detect initial contour which is later used for the initialization of the level set active contour. Lastly, we applied a level set active contour to segment the vessels inside the liver. In this study, we examined various techniques for each of the segmentation structure cascade such as vessel enhancement and level set active contour. Finally, we compared these techniques and select the most appropriate ones to build up our final segmentation structure.**

I. INTRODUCTION

Vessels segmentation of volumetric medical images has increasingly gained acceptance in current clinical practice. The segmentation can be used to generate three-dimensional visualizations and models of the vessels' branching structure and its pathologies to support diagnosis and planning of surgical procedures. Liver vessels segmentation is known to be a challenging task due to the low contrast and the complex branching structure. Many methods are developed for vessel segmentation in the literature. However, segmentation methods vary depending on the imaging modality, application domain, method being automatic or semi-automatic which means that there is no single segmentation method that can extract any type of vascular structures. In the field of liver vessel segmentation, we categorize the state-of-the-art vessel detection or enhancement techniques roughly into integral-based and derivative-based methods, both with the addition of multi scale techniques. The integral-based methods, including matched filters [1], [2], wavelets [3], geometrical moments [4], and model-based inferencing methods [5] are especially useful for finding locations or center lines of vascular structures. However, they do not generate good measures for points away from center lines. Therefore, they either cannot provide accurate estimates for the size or volume of vascular structures or they need extra procedures to have better measures so that the post processing is required.

Among derivative-based methods, Hessian operator based methods [6], [7], [8] are popular as its eigensystem captures the characteristics of tubular structures. The idea behind eigenvalue analysis of either Hessian or orientation tensor is to extract the principal directions in which the local structure of the image can be decomposed. This directly gives the direction of smallest curvature, which is the direction of the tubular structure, and avoids the time consuming line filters in multiple orientations. However, these methods are not valid at branching points, because the assumption of the characteristics of the eigen structure does not hold. The decomposition is not valid when there is no longer a simple dominant eigenvector present especially when images are noisy. To be more specific, [7] has proposed multi scale filtering for the segmentation of curvilinear structures in three-dimensional medical images. This method involves convolving the image with Gaussian filters at multiple scales and analyzing the eigenvalues of the Hessian matrix at each voxel in the image to determine the local shape of the structures in the image. For example, if the voxel corresponds to a linear structure such as a bright vessel the eigenvalues would be different than if the voxel corresponds to a planar structure, speckle noise, or no structure. Another method uses the eigenvalues to define a candidate set of voxels which could correspond to the centerlines of vessels [8]. Multi scale response functions are evaluated at each of these voxels to determine the likelihood that the voxel is a vessel of various diameters. The maximal response over all choices of diameters is retained at each voxel and a surface model of the entire vascular structure is reconstructed from knowledge of centerlines and diameters. A final method which obtains the segmentations by thresholding uses anisotropic diffusion such as Perona-Malik filter to remove noise without removing small vessels. [6] proposed a different multi scale approach based on medial axes which uses assumption that the centerlines of the vessels often appear brightest to detect these centerlines as intensity ridges of the image. Then, the width of a vessel is determined by a multi scale response function.

After obtaining the vessel detection and enhancement, a variety of approaches have been published for the consequent analysis of vascular images and vessel segmentation. These approaches can be categorized into three parts as region growing, active contours and centerline based methods. In region growing techniques, object is incrementally segmented by starting from seed points or regions located inside the object and then adding neighboring voxels based on some inclusion criteria. Active contours evolve a curve based on different forces including external forces, derived from the image, and internal, model-based forces, constraining the contour geometry and its regularity. They can be classified

as parametric active contours and implicit active contours with level set technique. Centerline-based techniques focus on directly extracting the vessel centerline. Therefore, they may not capture the complete volume information unless there is a higher-level information such as underlying direction and scale information. In this paper, we emphasized on the active contour with level set implementation based liver vessel segmentation. For example, curve evolution schemes with level set methods proposed by Caselles et al. [9] have become an important approach in computer vision. This approach is an extension of classical active contour models [10] and it uses partial differential equations to control the evolution of an initial boundary estimate toward the true object boundary. [11] uses gradient vector flow active contours to detect skeletons of volumetric objects. This work could be used to model shapes of vessels by computing the connected skeletons of vessels in a smooth and highly centered way. Another level-set based method is proposed by [12]. They used an iterative curve evolution approach to model the boundaries of vessels. In their approach, an energy criterion function based on intensity values and local smoothness properties of the vessel walls is iteratively minimized. They make an assumption that the vessels can be modeled as tubes with varying widths. They evolve 1D curves in a 3D volume and then estimate the radius of the vessels locally using the inverse of principal curvature. The advantage of this technique is that it does not require pre-segmented data.

The paper is organized as follows: Section 2 gives a review of the methods examined to build up the final liver vessel segmentation structure. Additionally, the final segmentation structure is simply described to give details of the mathematics behind them. Section 3 is devoted to the experiments and results of these approaches and also the comparison of them. The paper is finalized with a conclusion in Section 4.

II. METHODOLOGY

We separated the liver vessel segmentation problem into three parts such as vessel enhancement, initial active contour prediction and vessel segmentation through an active contour with level set implementation. As we mentioned above, we examined various techniques for these parts. Hence, this section first describes the vessel enhancement techniques. Then, the initial contour detection steps are illustrated. Lastly, it describes the active contour level set approaches used. As the result of examination over different approaches, the final liver vessel segmentation structure can be shown in Fig. 1.

A. Vessel Enhancement

In vessel enhancement part, we tried three popular approaches such as Regularized Perona-Malik diffusion filter, Frangi's approach and Manniesing's approach which is one of the recent techniques.

1) Regularized Perona-Malik Diffusion Filter: This approach is used in [8] that P-M filter addressed this issue by using the general divergence diffusion form to construct a nonlinear adaptive denoising process, where diffusion can take
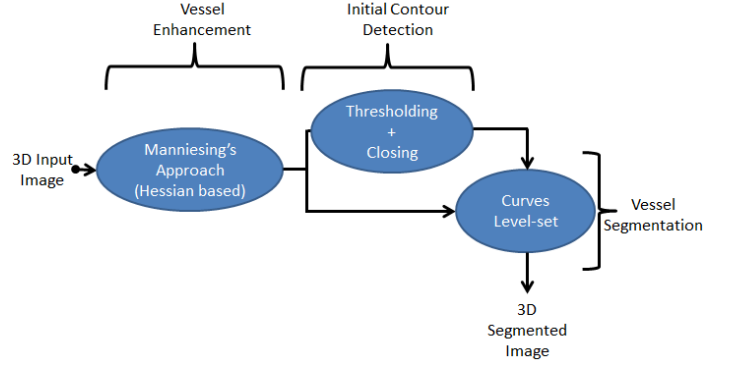

Fig. 1.   Liver vessel segmentation system overview, the names inside the blue boxes are the selected approaches among all.

place with a spatially variable diffusion in order to reduce the smoothing effect near edges.The general diffusion equation, controlled by the gradient magnitude, is of the form:

$$I_t = div(c(|\nabla I|)\nabla I), \tag{1}$$

where in the P-M case, c is a positive decreasing function of the gradient magnitude. Two functions for the diffusion coefficient were proposed: $c_{PM1} = (1 + (|\nabla I|/k_{PM})^2)^{-1}$ and $c_{PM2} = exp((|\nabla I|/k_{PM})^2)$. It turns out that both have similar basic properties (positive coefficient, non-convex potentials, ability for some local enhancement of large gradients. Some drawbacks and limitations of the original model have been mentioned in [13]. They have shown the ill-posedness of the diffusion equation, imposed by using the P-M diffusion coefficients, and proposed a regularized version where the coefficient is a function of a smoothed gradient:

$$I_t = div(c(|\nabla I * G_\sigma|)\nabla I). \tag{2}$$

Hence, we thought that it can be useful for our case.

2) Frangi's Approach: This vessel enhancement algorithm is based on anisotropic diffusion scheme guided by vessel likelihood at pixel level. It is basically a smoothing filter with the strength and direction of diffusion is determined by a "vesselness" measure. Vesselness is measured by analyzing the eigen system of the Hessian matrix. In the literature, several vesselness functions have been proposed but we used Frangi's vesselness function as shown in Eq. (3) [7]. In the case of bright vessels on a dark background, for increasing magnitude, the order of eigen values of a Hessian matrix are as follows:

$$|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$$

Frangi's vesselness function is composed of three components formulated to discriminate tubular structures from blob-like or plate-like structure

$$V_F(\lambda) = \begin{cases} 0, \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ (1 - e^{\frac{-R_A^2}{2\alpha^2}}) \cdot e^{\frac{-R_B^2}{2\beta^2}} \cdot (1 - e^{\frac{-S^2}{2\gamma^2}}), \text{o.w} \end{cases} \tag{3}$$

where

$$R_A = \frac{|\lambda_2|}{\lambda_3}, R_B = \frac{|\lambda_1|}{\sqrt{|\lambda_2 \lambda_3|}}, S = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}$$

in which R_A differentiates between plate and line like structures, R_B accounts for deviation from a blob like structure, and S differentiates between foreground (vessel) and background (noise). The parameters α, β and γ are weighting factors determining the influence of R_A, R_B and S which means that they control the sensitivity of the vesselness measure. The vesselness response is calculated at multiple scales by computing the Hessian with Gaussian derivatives at multiple scales. At every voxel location, the vesselness output with the highest response is selected.

3) Manniesing's Approach (VED): Frangi's vesselness function discussed above is not continuous and can not be used in the diffusion process since vesselness function is not smooth at the origin, and therefore cannot directly be used to construct a vesselness diffusion equation. Hence, Manniesing et al. [14] proposed a smoothed version of Frangi's vesselness function as shown below.

$$V_S(\lambda) = \begin{cases} 0, \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ (1 - e^{\frac{-R_A^2}{2\alpha^2}}) \cdot e^{\frac{-R_B^2}{2\beta^2}} \cdot (1 - e^{\frac{-S^2}{2\gamma^2}}) \cdot e^{\frac{-2c^2}{|\lambda_2||\lambda_3|}}, \text{o.w} \end{cases}$$
(4)

For a multi scale analysis, the vesselness function is computed for a range of scales and the maximum response is selected.

$$V = max_{a_{min}} \le \alpha \le \alpha_{max} V_s(\lambda)$$

Next, based on the new smoothed vesselness function several scale spaces can be constructed. Actually, this method is similar to the work of Weickert who introduced "edge enhancing diffusion" [15] and "coherence enhancing diffusion" [16] based on the eigensystem of the structure tensor. The objective here is to construct a scale space that preferably preserves vascular structures. Therefore, a diffusion tensor is defined in such a way that diffusion is promoted along the vessel but prohibited perpendicular to the vessel.

$$D = Q\lambda'Q^T$$

where Q is a matrix containing eigen vectors of the Hessian matrix and λ' is a diagonal matrix containing the following elements

$$\lambda_1' = 1 + (w - 1)V^{\frac{1}{S}}$$

$$\lambda_2' = \lambda_3' = 1 + (\epsilon - 1)V^{\frac{1}{S}}$$

where ϵ, w and S are algorithm parameters. Using this tensor definition, a diffusion equation is formulated as follows

$$L_t = \nabla \cdot (D\nabla L)$$

Hence, vascular structures will be enhanced by evolving the image according to the above diffusion equation.

B. Initial Contour Detection

Before we move on to the active contour level set segmentation, we need to predict the locations of the liver vessels because the active contour segmentation methods require an initial contour or seed points. Therefore, the second part of our segmentation structure is called as the initial contour detection. It takes the output of the vessel enhancement step as input and produces the predicted vessel locations.

Initial contour detection step is based on simple image morphology operations. Firstly, a simple binary thresholding is applied which means that if the intensities of the pixels are below a certain threshold, they are set as background pixels, otherwise they are considered as foreground, vessel, pixels as shown in Fig. 7. We observed that there exists disconnections along the vessels in some parts of the vessels after thresholding is applied. Therefore, we decided to apply closing operation in order to reduce these disconnections. Closing operation first dilates the foreground pixels so that the vessels enlarge and the gaps between the disconnected vessel parts are filled and then it erodes the vessel pixels in order to shrink the vessels and also remove the noisy pixels. The final output of the initial contour detection can be shown in Fig. 8.

C. Level-set Active Contour Segmentation

1) The Gradient Vector Flow with Level-set Approach: The gradient vector flow active contour was introduced by Xu and Prince [17]. It was developed in order to increase the capture range and improve ability of snakes to move into boundary concavities. A snake that minimizes energy functional, E, must satisfy the Euler equation,

$$\alpha x''(s) - \beta x''''(s) - \nabla E_{ext} = 0. \tag{5}$$

This can be thought of as a force balance equation

$$F_{int} + F_{ext}^{(p)} = 0. \tag{6}$$

where $F_{int} = \alpha x''(s) - \beta x''''(s)$ and $F_{ext}^{(p)} = -\nabla E_{ext}$. The internal force F_{int} discourages stretching and bending while the external potential force $F_{ext}^{(p)}$ pulls the snake toward the desired image edges. In GVF approach better external force representation is presented. External forces can be divided into two classes: static and dynamic. Static forces are those that are computed from the image data, and do not change as the snake progresses. Standard snake potential forces are static external forces. Dynamic forces are those that change as the snake deforms. New static external force field is defined $F_{ext} = v(x, y)$ which is called gradient vector flow field. To obtain the corresponding dynamic snake equation potential force $-\nabla E_{ext}$ is replaced with $v(x, y)$ yielding

$$x_t(s, t) = \alpha x''(s, t) - \beta x''''(s, t) + v. \tag{7}$$

The parametric curve solving the above dynamic equation is called a GVF snake. It is solved numerically by discretization and iteration, in identical fashion to the traditional snake. Although the final configuration of a GVF snake will satisfy

the force-balance Eq. (6), this equation does not, in general, represent the Euler equations of the energy minimization problem. This is because $v(x, y)$ is not an irrotational field. The loss of this optimality property, however, is well compensated by the significantly improved performance of the GVF snake.

In particular, the gradient vector flow field to be the vector field is defined as $v(x, y) = [u(x, y), v(x, y)]$ and minimizes the energy functional

$$\epsilon = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + ||\nabla f||^2 ||v - \nabla f||^2 \mathrm{d}x\mathrm{d}y \quad (8)$$

where u_x, u_y, v_x and v_y are the spatial derivatives of the field, μ is the blending parameter, f is gray level or binary edge map which can be obtained by means of edge detection. In this equation, the first term is the diffusion term and the second one is the field formation term. Additionally, the parameter μ regularizes the effect of the first term in the integrand, which is a smoothing term derived from the formulation of optical flow [17]. If the original image contains large amounts of noise, μ should be increased in order to compensate. When $||\nabla f||$ is small, the energy of ϵ is dominated by the first term in the integrand which yields a slowly varying field. While if $||\nabla f||$ is large, the second term dominates the energy functional and will be minimized by setting $v = \nabla f$. This leads to the vector field v being slowly varying in homogeneous regions, and at the same time being nearly equal to the gradient of the edge map in regions where the gradient of the edge map is large [18].

Additionally, the level set approach can also be used with gradient vector flow active contour algorithm which brings the advantages described below .

2) Curves Evolution Level-set Approach: In this approach, a level set curve evolution approach [12] is used to model the boundaries of vessels. Level set approach is frequently used for vessel segmentation due to its flexibility in terms of topological changes. Let u be the signed distance function to curve C, then C is the zero level-set of u, and u is an implicit representation of C. Different topologies of C can be represented by the constant topology of u, because evolving C according to $C_t = \beta N$ is equivalent to evolving u according to $u_t = \beta |\nabla u|$ for any function β.

Curves algorithm is an extension of geodesic active contours based on a level set implementation. An energy criterion function based on intensity values and local smoothness properties of the vessel walls is iteratively minimized. Objective is to find the curve that best fits the vessel boundary which can be modeled as a minimization problem over all closed planar curves $C(p)$:

$$\int_0^1 g(|\nabla I(c(p))|)|C'(p)|dp \quad (9)$$

where I is the image and g is a strictly decreasing function.

The method is an extension of geodesic active contours and minimal surfaces. Regularizing force derives from an underlying one-dimensional curve in three dimensions, which

corresponds to the centerline of the tubular structures. However, level set approach defined above does not hold in case of evolving one-dimensional curve in three dimensions, because co-dimension of surface is two and embedding surface u cannot be created in the same way. Curves level set uses image information to create the auxiliary vector field used to evolve one dimensional curves [12].

For one-dimensional curve to evolve in a three-dimensional image, by making an assumption on the existence of an underlying vector field d driving the evolution:

$$C_t = \kappa N - \prod d \quad (10)$$

where $\prod$ is the projection operator onto the normal space of C which is a vector space of dimension two. Then, evolution equation for the embedding space is

$$v_t = \lambda(\nabla v, \nabla^2 v) + \nabla v \cdot d \quad (11)$$

By computing the Euler-Lagrange equations, the curve evolution equation is formulated as

$$C_t = \kappa N - \frac{g'}{g} \prod (H \frac{\nabla I}{|\nabla I|}) \quad (12)$$

where H is the Hessian of the intensity function. Second part is the auxiliary vector field d according to (10). Then, equation for the embedding space is:

$$v_t = \lambda(\nabla v(x, t), \nabla^2 v(x, t)) + \frac{g'}{g} \nabla v(x, t).H \frac{\nabla I}{|\nabla I|} \quad (13)$$

Segmentation is an iterative procedure which takes the current segmentation estimate as zero level set and evolves it according to evolution function in Eq. (12). An initial volume is generated from data as described in Initial Contour Detection part. Curves level set method enables the attraction of evolving surface to edge gradients on other surfaces besides the current one by using image term at each location on higher dimensional manifold. If there are two neighboring tubes and only one is used for the initialization, curves level set can segment both of them. That property of curves level set makes it less sensitive to initialization. Evolving higher-dimensional manifold is periodically reinitialized to be a distance function to its zero level set, because image force invalidates the distance function constraint. Reinitialization should not be too frequent to avoid eliminating the affect of image force.

III. EXPERIMENTS AND RESULTS

This section discusses the experimental results of tried methods for each of three parts in our final liver vessel segmentation structure. Additionally, the effects of parameters in each methods are discussed in order to obtain healthy results. In this section, firstly vessel enhancement methods are examined, then the results of initial contour detection part is described, and lastly the level set active contour algorithms are compared. As a result of these comparisons, we chose the best approaches and we performed some modifications and eventually, we built up our own segmentation.

A. Vessel Enhancement

1) Regularized P-M Diffusion Filter: Regularized P-M filter is the oldest approach among the others we used, the resulting image after we applied this filter is shown in Fig. 2.
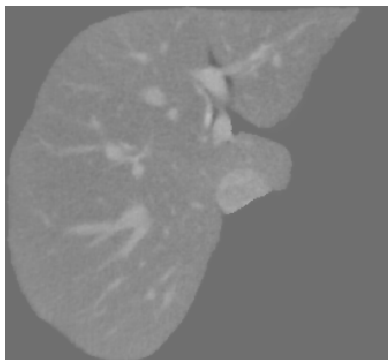

Fig. 2.   The best resulting image obtained by Regularized P-M filter, the parameters are time-step = 0.039, conductance = 10 and iteration number = 5.

2) Frangi's Approaches: Frangi's approach is a very popular approach and many studies in the literature utilize this in order to enhance the vessels. We used multi scale approach with Frangi's vesselness function to detect various sized vessels. The vesselness response is calculated at multiple scales by computing the Hessian with Gaussian derivatives at multiple scales in order to obtain the multi scale detection of vessels. The parameter σ used in the algorithm is very critic in the implementation, for example, with a σ value of 0.5, small size vessels are enhanced. If the scale is increased to a σ value of 4.0, large size vessels are enhanced so that to enhance vessels with varying size, the image was run through multi scale filter with a sigma range of [0.5 4.0]. However, as obviously seen from the result, the vesselness measure is highly sensitive to noise pixels. The results of this approach is shown in Fig. 3.
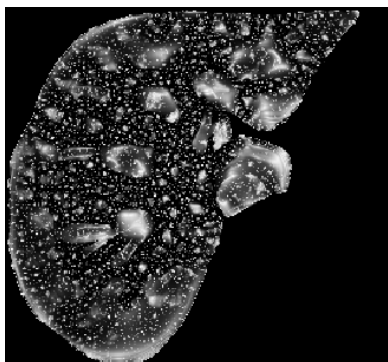

Fig. 3.   The best resulting image obtained by Frangi's approach with $\sigma min = 0.2$, $\sigma max = 10$ and number of scales = 20.

3) Manniesing's Approach (VED): The most obvious application of VED is noise reduction while preserving vessel structures. As it is mentioned in the vessel enhancement part, it uses a smoothed version of Frangi's vesselness function since Frangi's vesselness function is not continuous and can not be used in the diffusion process. Therefore, it overcomes the deficiency of Frangi's approach. In the algorithm, there are two important parameters that affect the results. The first parameter is σ of Gaussian derivatives at multiple scales, and the second parameter is the iteration count, t. Fig. 4 shows the effect of these parameters, in general, with the increase in the number of iterations an increased smoothing effect was observed. Additionally, σ range is important to enhance the small vessels and the large vessels. The best results obtained using this approach is shown in Fig. 5.
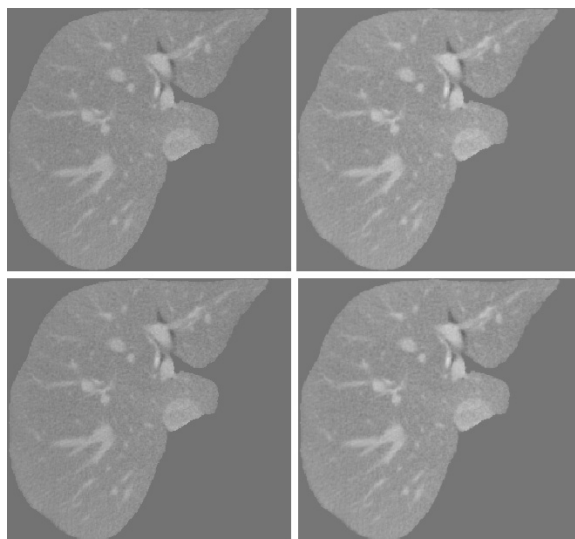

Fig. 4.   Effect of parameter σ and iteration count. The results with $\sigma_{min} = 0.1$, $\sigma_{max} = 1$, step size = 0.2 when iteration count, t = 10(top left) and t = 50(top right). When changing the range $\sigma_{min} = 1$, $\sigma_{max} = 5$, step size = 0.5 and t = 10(bottom left) and t = 50(bottom right).

Fig. 5.   The best resulting image obtained by Manniesing's approach,VED.

Theoretically, there are three characteristic aspects of vessel enhancement to compare. First, its capability of enhancing the continuity of vessel segments, second, the improvement in separation of vessels in maximum intensity projections, and third, its effective blurring of background or non-vessel like structures [14]. When we compare above three approaches, we observed that the best results are obtained through VED. It leads to a good background suppression which is due to the

strong isotropic blurring for non-vessel structures. In addition, VED filters are less affected by noise pixels.

As a result, we determined to use Manniesing's VED filter in order to enhance the liver vessels. Although VED results in the best, the small vessels are still could not be captured so that we applied gray-scale dilation in addition to this approach on the output of VED so that we performed an additional enhancement which VED could not capture. Hence, the resulting image after we applied VED plus gray-scale dilation is shown in Fig. 6.

Fig. 6. The resulting image after applying gray-scale dilation operation to the output of VED. 3x3x3 ball structure is used for gray-scale dilation operation.

B. Initial Contour Detection

In this part, we first applied binary thresholding to the image obtained by vessel enhancement part. The value of threshold should be tuned experimentally according to the range of image pixel intensities. The result of thresholding is shown in Fig. 7.
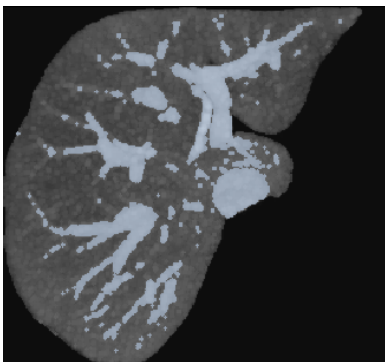

Fig. 7. The resulting image after applying thresholding operation to the output of vessel enhancement part. The threshold value is 160.

As it is seen from the figure above, the resulting image is very noisy and there are some disconnections along the vessels. We applied the closing morphological operation in order to fill these gaps. The resulting image of initial contour detection part is shown in Fig. 8.
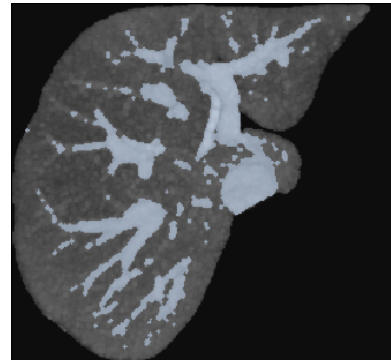

Fig. 8. The resulting image after applying closing operation to the output of thresholding. 3x3x3 ball structure are used for closing operation.

C. Level-set Active Contour Segmentation

Initial contour, in our case the binary mask image, is given to the active contour in order to complete the segmentation. We performed two different active contour with level-set.

1) The Gradient Vector Flow with Level-set Approach: The gradient vector flow active contour begins with the calculation of a field of forces, called the GVF forces, over the image domain. The GVF forces are used to drive the snake modeled as a physical object having a resistance to both stretching and bending, towards the boundaries of the object. The GVF forces are calculated by applying generalized diffusion equations to both components of the gradient of an image edge map. There is an important parameter denoted by μ in Eq. (8). Actually, there are many parameters in the details of the algorithm, however, they do not affect the results much so that they can be fixed. The parameter μ is used to regularize the effect of the smoothing term derived from the formulation of optical flow equation. It should be set according to the amount of noise present in the image such that if the input image is very noisy, then μ should be chosen high. The best results obtained by using GVF is shown in Fig. 9.
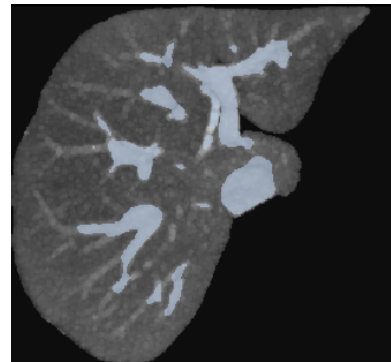

Fig. 9. The best result obtained using GVF, the parameters are $\mu = 1$, propagation = 0.5, curvature = 1 and advection = 1.

2) Curves Evolution Level-set Approach: This approach is used to model the boundaries of vessels and frequently used for vessel segmentation due to its flexibility in terms of topological changes. There are three important parameters

that comes from the energy functional. The first one is the propagation which controls how much the curve propagates along the vessel. The second parameter is the curvature term, the larger the curvature, the smoother the resulting contour. Lastly, the third parameter is the advection. The effects of parameters are shown in Fig. 10. We can conclude that the most sensitive parameter is the propagation.
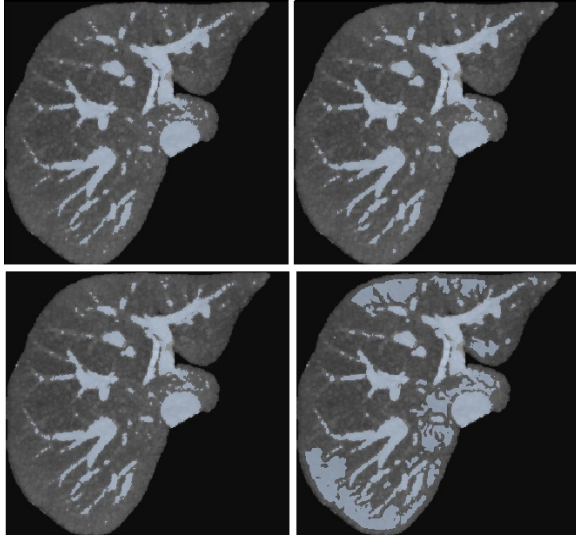

Fig. 10. The resulting images with different parameters. When propagation = 1, curvature = 1 is fixed and change advection = 1(top left) and = 2(top right). When propagation = 1, advection = 2 is fixed and change curvature = 1(top right) and = 2(bottom left). When curvature = 1, advection = 1 is fixed and change propagation = 1(top left) and 2(bottom right).

Fig. 11 shows the best results obtained using this approach.
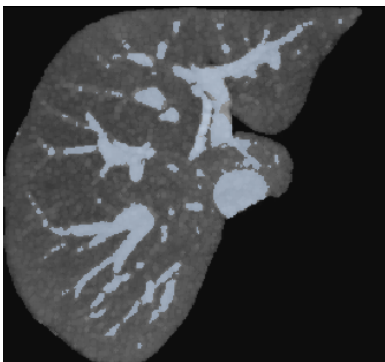

Fig. 11. The best resulting image as the result of Curves evolution with level-set approach, the parameters used are propagation = 1, curvature = 1 and advection = 2.

When we compared the results for this part, the GVF level set approach is less successful for finding the small vessels especially for the ones near to the boundary of the liver. In contrast, Curves level set approach obviously propagates better along the small vessels (see Fig. 11 and Fig. 9). Hence, we determined to use curves evolution level-set approach in our final segmentation structure. To sum up, in the final liver vessel segmentation structure, we start with vessel enhancement using VED and then we apply gray-scale dilation to strengthen the small vessels. Then, we move on to the initial contour detection by applying binary thresholding followed by closing operation. Finally, we segment the vessels using curves level-set active contours.

IV. CONCLUSION

Vessels segmentation of volumetric medical images is a challenging task due to the low contrast and the complex branching structure. Many methods are developed for vessel segmentation in the literature. Vessel segmentation problem can be separated into two sub problems such as vessel enhancement and vessel segmentation. The state-of-the-art vessel detection or enhancement techniques roughly into integral-based and derivative-based methods, both with the addition of multi scale techniques. We emphasized on the derivative based methods. We analyzed three different vessel enhancement methods: regularized P-M diffusion filter, Frangi's Hessian operator based approach and Manniesing's modified version of Frangi's approach. When we compared their overall performance, we observed that Manniesing's approach with multi scale is less sensitive to noise and it produces better results for our case so that we decided to use Manniesing's approach for vessel enhancement. Then, we performed a simple morphological operation in order to strengthen the small vessels. After the vessel enhancement, we applied binary thresholding to predict the locations of vessels. The final step is the vessel segmentation and it can be categorized into three as region growing, active contours and centerline based methods. We emphasized on the active contours with level set implementation. We examined two popular approaches such as the gradient vector flow and the curves level set. The output of thresholding is used as an initial contour to these active contours. When we compared the performance of these approaches, we observed that the curves level set is more accurate to detect the vessels inside the liver.

When we built up our final liver segmentation structure using the selected approaches mentioned above, we obtained very promising results for the vessel liver segmentation. However, the system requires some parameters to produce good results. In our experiments, we observed that exploring the optimal parameters is a huge problem. Unfortunately, they can be determined by making some experimentations on given input images.

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