Liver Vessel Segmentation Using Graph Cuts with Quick Shift Initialization

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Abstract—Accurate liver vasculature segmentation can provide guidance for doctors to do surgical planning for liver tumor resection. Due to the low contrast level between small vessels boundary and background tissues, complete extraction of liver vessel structures has become a challenging task. In this paper, we propose a method to achieve small vessel extraction by an iterative regional updating process. The gradient vector flow field is first calculated. The vector field has large magnitudes around vessel boundaries with the vectors pointing towards the center of the vessel. Quick shift clustering is then applied to group image voxels with similar intensities into patches. The divergence feature is combined with the clustering result to obtain seed regions that are parts of vessel structures. Next, the seed regions are used as initialization of the graph cuts segmentation. In order to perform segmentation using local intensity information to deal with intensity inhomogeneity, quick shift clustering is applied a second time to group spatially neighboring voxels into local regions. Graph cuts is then applied based on regional intensity distribution. The final result is obtained by iteratively performing regional graph cuts until the change between consecutive binary masks drops below a threshold. The proposed method is compared with global graph cuts, demonstrating the capability of segmenting the complete vessel network. The comparison with manual segmentation shows that the proposed method can also extract small vessel structures that are not available in the manual result.

Keywords—Liver vessel segmentation, gradient vector flow, quick shift, graph cuts

1. INTRODUCTION

Liver vessel segmentation is important in liver clinical operations, especially in surgical planning. An accurate structure of the liver vasculature can be helpful in guiding the planning of tumor resection so that the blood supply of the liver would be minimally influenced during and after surgery. Due to the complex vessel structures, various vessel sizes, orientations and branchings, distortion caused by the presence of tumor, noise and artifacts, and poor contrast because of the inhomogeneity of the contrast agent, accurate segmentation of liver vessel structures is a difficult and challenging task.

A few approaches have been proposed to segment liver vasculatures. Wang et al. [1] incorporated Frangi’s vesselness filter response [2] and line direction information into the fuzzy C-means framework to classify voxels into either background or vessel clusters. Chi et al. [3] proposed a context-based voting mechanism to segment the vessel structures and separate different vessel systems. Homann et al. [4] performed graph-based analysis on the segmented result of global graph cuts [5] to exclude non-vessel structures. Esneault et al. [6] proposed a 3D geometrical moment model to fit at selected points to give local information of vessel likelihood which served as the additional energy term in subsequent graph cuts segmentation. Bauer et al. [7] proposed a tube detection filter to enhance vessel structures. They then implemented a constrained graph cuts using shape prior from the centerline and radius information of the roughly extracted vessel trees. Kaftan et al. [8] used graph cuts to obtain a segmentation of large vessels from clusters identified by a hierarchical classifier. They then performed tracking at every end point of the segmented vessel tree to obtain the final result. Friman et al. [9] fit a vessel template model to the vascular structures to perform tracking based segmentation.

In this paper, a segmentation framework based on regional update scheme is proposed. The divergence of gradient vector flow field is calculated as a feature indicating vessel structures. A clustering process based on quick shift is then applied to partition the 3D volume data into over-segmented patches. The divergence response is incorporated into the clustered data to obtain seed regions which are definite parts of vessels using rough thresholding. In order to deal with contrast variation caused by intensity inhomogeneity, the clustering process is run the second time to obtain under-segmented regions. For each region that contains a seed patch, the graph cuts method is applied to obtain a local segmentation result. All the local results are combined and used as initialization for the next iteration of graph cuts. The final result is obtained by iteratively updating the binary mask regionally until convergence.

The rest of the paper is organized as follows. Section II presents detailed descriptions for each step of the segmentation framework. Experimental results obtained using the proposed method are shown in Sec. III. The conclusion is given in Sec. IV.
II. PROPOSED METHOD

A. Overview

The steps of the proposed method are shown in Figure 1. In this work, we assume that a liver mask is available, and the method is applied directly in the region of interest determined by the liver mask. The divergence of the Gradient Vector Flow (GVF) is first calculated as the feature. Next, the quick shift clustering is applied to group image voxels into patches according to their intensity values. Seed regions are then selected from the patches based on the feature responses. After that, the quick shift clustering is run a second time to obtain super-voxels using spatial information. Using seed regions and super-voxel information, graph cuts is employed locally to produce the final result.

B. Gradient vector flow

The Gradient Vector Flow (GVF) [10] has been widely used as the external force to evolve an active contour. It is defined as the vector field \( V(x) \) that minimizes:

\[
\mathcal{E} = \int \int \mu |\nabla V(x)|^2 + |\nabla f|^2 |V(x) - \nabla f|^2 \, dx ,
\]

where \( \mu \) is a regularization parameter, and \( f = G * I \) is the Gaussian smoothed image \( I \).

The resulting GVF has large magnitudes near the vessel boundaries with the vectors pointing inwards. In order to utilize this information to indicate vessel structures, a straight forward way is to calculate the divergence:

\[
\text{div}(V(x)) = \nabla \cdot V(x)
\]

By calculating the divergence of GVF, vessel structures can be identified as the vector field’s sinks. On the other hand, regions surrounding vessels have small GVF magnitudes, hence producing almost homogeneous divergence.

A rough thresholding is applied on the divergence map to separate vessel regions from surrounding tissues. The threshold value \( \tau_v \) is selected empirically such that adjacent vessels are isolated from one another instead of merging into a single large region. False positives are allowed and will be dealt with in the next step.

C. Quick shift clustering

Quick shift [11] is an iterative mode seeking algorithm that identifies modes in a set of data points. A mode is the densest location in a certain search space of the data points. Quick shift first estimates a kernel density as:

\[
P(x_i) = \frac{1}{N} \sum_{j=1}^{N} K(D(x_i, x_j)),
\]

where \( K(x) \) is the kernel function, \( D(x_i, x_j) \) is the distance between point \( x_i \) and \( x_j \). It then extends the search path to the next point by moving the center of the kernel window to the nearest neighbor of \( x_i \) at which there is an increment of density \( P \):

\[
y_i = \arg \min_{j(P(x_i) \leq P(x_j))} D(x_i, x_j),
\]

When all the points are connected with one another, a spatial threshold is used to separate modes. Different clusters of the data points can then be identified.

In this work, quick shift is first implemented to obtain over-segmented images favoring voxels with similar intensities. Since voxels contained in each patch have very close intensity values, a patch can be considered as part of the vessel structures if its mean intensity is higher than a pre-set threshold value. To obtain definite vessel regions, the divergence information is incorporated. The decision making procedures are summarized below.

1. Select an isolated region in the thresholded divergence map.
2. Find the position of the local minimum of the divergence values in the selected region.
3. Find the patch in the over-segmented images that contains the local minimum.
4. If the mean intensity of the patch is greater than the threshold \( \tau_v \), the patch is identified as a seed region.
5. Repeat 1-4 until all regions are processed.
6. Delete single-point regions to avoid false detection due to noise.

The result of the above procedures is a set of seed patches that are definite parts of vessel structures. These seeds are then used to initialize the graph cuts segmentation step.

Fig. 1 Flowchart of the proposed method.