Multi-pathways CNN for robust vascular segmentation

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ABSTRACT

Vascular structures are important information for education purpose, surgical planning and analysis. Blood vessels of the organ is a task that required an experienced users in order to achieve accurated result. The large variations of its structure, and properties of image are make the vessels segmentation become more and more complicate and hard to recognize even on experienced users. In this paper, we introduce a deep artificial neural network architecture for automatically vessel segmentation of computed tomography (CT). Our network consists of multiparallel deep convolution neural networks. Each network extract the features from difference planes to maximize a segmentation accuracy. To solve the problem of model fail to segment the clinical data which have more various constrains, we add normalization process as preprocessing. The experimental results, our network can obtain 0.879 of dice coefficient which better than stage-of-the-art methods which normally use to extract the vessels.

Keywords: Vessel Segmentation, Automatic Segmentation, Deep leaning, Medical Imaging, 3D Imaging

1. INTRODUCTION

Understanding of vessel structure can improve the success rate of accurate organ analysis, diagnostics, and surgical operation. Although many segmentation of blood vessel methods and techniques have been developed, the performance of the existed approaches usually vary depending on the modality, applications domain, and other factors. Due to the dependencis, many methods have been proposed such as Frangi,\textsuperscript{1} level-set from G. Pizaine,\textsuperscript{2} graph cuts from Y. Boykov.\textsuperscript{3} Therein, there are mainly two categories: automatic, and semi-automatic methods, which have been proposed to extract the vessel structure.

Region growing is a well-known semi-automatic pixel/voxel based segmentation method, which basically depends on the similarity of intensity and spatial proximity.\textsuperscript{4–6} Due to the large variety of vessel intensity in medical image, region growing usually lead to over- or under- segmentation.

Multi-scale filter method has been widely used to extract vessel structure in various applications. This method is automatic efficient strategy by integrating three dimensional structures in multiple scans and can provide acceptable result for different medical data. A line enhancement filter compress with different orientations and scales, for emphasizing cylindrical structure of the vessel, are firstly use, called as multi-scale approach,\textsuperscript{1} and then follows with other image operations like thresholding, component analysis, and connected component to produce the image segmentation.\textsuperscript{7} Y. Sato et al\textsuperscript{8} proposed an improvement of the three-dimensional multi-scale line filter. The method is used to segment the curvilinear in medical data using the information which obtain from the second derivative of the filtered multi-scale images by Gaussian kernels on obtained with an adaptive orientation selection.

Recently, deep learning architecture has been demonstrated the powerful ability in computer vision tasks by automatically learn hierarchies of relevant feature directly from the input data. The deep convolutional neural network has been successfully applied for image classification and object detection, especially for ImageNet classification competition, which is the most successful network for image classification since 2012.\textsuperscript{9} Apart of

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classification, segmentation methods also proposed and success to apply such as FCN. However, FCN not well perform on small and detailed object like vessel which mostly curse the problem of over- or under- segmentation.

In medical image processing, U-net (2 dimensional) and V-net (3 dimensional) have been proposed to perform a segmentation task. Both methods use the concept of convolution and deconvolution. While convolutional extract features from image, deconvolutional transform the feature into segmentation result. Although these methods achieved promising results for large organ segmentation, it is difficult to be efficiently used for vessel extraction because vessel has detailed structure and only small parts appeared on the image.

Motivated by the existed conventional vessel extraction approaches and deep learning framework, we propose an automated vessel segmentation using deep learning framework on the transformed vesselness map by multi-scale approach. We consider the segmentation procedure as a voxel-wise classification problem by integrating three plane structure of the focused voxel. The main contributions of our proposed method are summarized as: (1) we propose a novel VesselNet based on deep learning framework for robust vessel extraction, which is a first application of deep learning for vessel extraction; (2) the proposed framework is an architecture with multi-pathways deep neural networks (DNN), which consists of three separately deep convolutional parts to extract discriminated features of sagittal, coronal and transvers (axial) planes, respectively; (3) we propose to use a vesselness probability map image as the input of DNN instead of the raw CT image, which is robust and can be generalized for vessel segmentation of CT data from different imaging devices.

The strucutre of our paper is organized as follows. Section 2, we describe our framework including vesselness map calculation with multi-scale approach and the multi-pathways architecture of the deep network. Experimental results of the proposed framework and conclusion are described in sections 3 and 4, respectively.

2. VESSEL SEGMENTATION METHOD

In image processing, image segmentation is the process of partitioning an image into several segments, in which we classify pixels with similar features into the same segment. In our proposed deep learning based vessel segmentation, we use a trained deep neural network to classify each voxel into vessel or non-vessel classes. The advantage of the deep learning based method is that the network will automatically extract the useful features for classifications. In addition to use the deep learning method for classification, we also proposed to use a vesselness probability map (a multiscale filter enhanced image) as input of the network.

2.1 Vesselness probability map (conventional)

In order to make our network suitable for clinical data, which have various range of intensity, and factor. We transform an intensity value into probability value form.

To normalize a medical image, multiscale-scale method is the method that used to extract the vessel probability from line information. The method has been proposed by A.F. Frangi, which the value of vessel can obtain by follows

\[
V(\sigma) = \begin{cases} 
0, & \text{if } \lambda_2 > 0 \text{ or } \lambda_1 > 0 \\
(1 - \exp\left(\frac{R_\alpha}{\alpha^2}\right)) \exp\left(\frac{R_\beta}{\beta^2}\right)(\exp\left(\frac{R_\gamma}{\gamma^2}\right)), & \text{otherwise}
\end{cases}
\]  

(1)

where \(\alpha, \beta, \gamma\) are parameters used to balance between plate \((R_\alpha)\), blob \((R_\beta)\), and background \((\gamma)\), and can be calculated as follows

\[
R_\alpha = \frac{\lambda_2}{\lambda_1}, \\
R_\beta = \frac{\lambda_3}{\lambda_2\lambda_1}, \\
\gamma = \sqrt{\sum_{j \leq 3} \lambda_j^2},
\]
To train vessel network, we use vesselness probability map data to generate 2D orthogonal (sagittal, coronal, and transverse) patches of size $s^2$ centered on the target voxel. The network’s output is a probability of vessel for each voxel which can form into probability image.

2.2 Vessel Net
We argue that segmentation image is gather from the classified pixel/voxel, therefore we construct a deep convolution network for pixel/voxel classification. To complete the vessel classification task that suitable to clinical data.

2.2.1 Vessel network architecture
Conventional deep neural networks can be considered as a one-pathway network. The input of the is a 2D or 3D image (3D image usually used for medical images). In this paper, we proposed a three-pathways patch based network for vessel segmentation from a 3D medical data. The effectiveness of our proposed network architecture will be shown in Sec. 3. Our network architecture is shown in Fig. 1. It consists of three separately convolutional networks to extract features of sagittal, coronal, and transverse plans, respectively. Three features from each network are concatenate and used in a fully connected layer. The represented features are learnt by 2D convolutional and pooling layers. A complex features are captured when each network finish their own process. All output feature are combined to gate at the top layer and network start learn a correlation using fully connected layers.

2.2.2 Learning Method
The network is trained by a mini-batch method, which stochastic gradient decent algorithm (SGD)\textsuperscript{13} are used as learning optimization method. The update function with momentum $m$ and learning rate $\alpha$ at iteration $t$ is given by

$$\Delta w_i^{lr}(i) = -\alpha \frac{\partial E}{\partial w_i^{lr}} + m \Delta w_i^{lr}(t-1),$$  \hspace{1cm} (2)

The hidden layer of each network $r$ including two set of 2D convolutional and max pooling layer. The activation from convolutional represent local features at different position in an image which the output features of each layer $l$ was controlled by learnable kernels $k$. The output is then given by

$$O_i^l = \varphi\left(\sum_k W_k^{lr} O_{(l-1)r}^k + b^{lr}\right),$$  \hspace{1cm} (3)

where $W_k^{lr}$ is weight matrix and $b^{lr}$ is represented the scalar bias. The activation function denotes as $\varphi$ which we used rectifier linear unit (RELU) for all neurons of the network. The reason of using RELU function is to avoid the vanishing gradient problem.\textsuperscript{14}
\[ \varphi(x) = \max(0, x), \]  

While the most of neurons in our network use RELU function, the output layer uses a softmax activation function. The softmax function are used to interpolated the inputs \( z \) into \([0,1]\) and the output can be used as probabilities.

In our network, we use negative loglikelihood as our cost function. The cost function can provide better result than common use cross entropy. The function is defined as follows

\[ E(\varphi) = \frac{\sum_{i=1}^{n} \log \left( \sum_{j=1}^{N} x_{ij} y_{ij} \right)}{n}, \]  

3. EXPERIMENTS

The proposed method has been evaluated on IRCAD datasets maintained by French research institute. To generate dataset, we generate ROI of liver region and apply multi-scale to generate vesselness probability. The training set has randomly extracted from the voxel that have value more than designed threshold \( T = \text{mean} - \text{variance} \) in vesselness probability map image without livers boundary while the test set will use all voxel that contain vesselness probability map value \( (T > 0) \) but still eliminate the boundary of liver. The total of training set has a total of 50k voxels from each volume. Each voxel, we extracted a 2523-dimensional input vector consisting of three patches of 2D orthogonal patches of 29 x 29 voxels. The learning rate \( l \) and momentum \( m \) were set to 0.00005 and 0.9, respectively. We used a batch size of 2000 data. Dice coefficient is used as evaluation metric in our experiments.

Figure 2, all one-pathway with one channel networks can segment vessel with not much different from each other, which around 0.81 for 2D CNNs and 0.82 for 3D CNN. With this experiment show that not only axial plane is important for segmentation but another coronal and sagittal also important. The result of one-pathway with three channels network also show the features from each plane cannot be extract with same trained kernels. The dice coefficient of one-pathway with three channels is lower than our network.
Table 1. Comparison of the proposed with state-of-art method using IRCAD dataset

<table>
<thead>
<tr>
<th>Method</th>
<th>Input</th>
<th>DICE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level set(^2)</td>
<td>Processed data</td>
<td>0.73</td>
</tr>
<tr>
<td>Frangi(^1)</td>
<td>Raw data</td>
<td>0.6645±0.089</td>
</tr>
<tr>
<td>Graph cut(^3)</td>
<td>Raw data</td>
<td>0.3445±0.034</td>
</tr>
<tr>
<td>Submodular Graph cut(^{16})</td>
<td>Multiscale data</td>
<td>0.7504±0.043</td>
</tr>
<tr>
<td>Our with Cross-entropy</td>
<td>Multiscale data</td>
<td>0.8498±0.094</td>
</tr>
<tr>
<td>Our with Negative log likelihood</td>
<td>Multiscale data</td>
<td>0.8792±0.087</td>
</tr>
</tbody>
</table>

Figure 3. Performance comparison between two input features of raw intensity and vesselness probability map value. Row indicates different data samples. Six columns: a. CT intensity images; b vesselness probability map images; c. and d. the segmentation results of intensity, and vesselness probability map images, respectively. Red color voxels denote correct vessel result while green color voxels are difference between the ground-truth vessel and the segmented vessel. e. and f. 3D visualization results of both intensity and vesselness probability map images, respectively.

The dice result of conventional graph cut is only 0.344, because the boundary probability term or smoothness term is a term to minimize the cost function. This term can benefit to most segmentation object specifically for large object such as liver, kidney, and lung. However, vessels are detail information which easily eliminated by smoothness term of graph cut. Submodular graph cuts method uses the concept of submodular to give extra cost to the similar edge by add high order tensor to the cut cost.\(^{16}\) We reimplemented the this method for 3D imaging and do experiment based on our implementation because the author of submodular graph cut provide us the code that focus only 2D image. This method can improve from 0.344 dice to 0.75 dice result. Table 1 show the comparison between our method and state-of-art methods. The results of other methods still cannot pass 0.8 of dice coefficient while our method can yield 0.849 and 0.879 of dice results in both loss function types. In figure 3, The method using vesselness probability map is much better than that using the raw intensity, especially for CT volumes having different intensity range (last row).

4. CONCLUSION

We designed a deep neural network to perform automatically segmentation of vessel in liver region image. Our networks features are learned from 2D orthogonal patches which are firstly transform raw data to vesselness probability map using multi-scale method. The transformation can deal with any intensity variation in CT
volume data, which is the problem when use raw intensity data. Our network still has problem in network connectivity and under-segmentation in some region.

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