3D MODEL-BASED METHOD FOR VESSEL SEGMENTATION IN TOF-MRA

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Abstract:
In this paper, an automatic method to segment the blood vessel for 3D MRA (Magnetic Resonance Angiography) is presented. The segmentation process classifies MRA data into two parts: background and blood vessels. The process includes statistical model based on the voxel intensity and MRF model based on the context information of voxels. Both the models were built on 3D voxel, rather than on 2D. The proposed method is tested on the 3D Time-Of-Flight (TOF) -MRA data. The segmentation results give a good performance in extracting blood vessels.

Keywords: Vessel segmentation; Statistical model; Context information; Markov random field

1. Introduction

Accurate 3D cerebrovascular segmentation for magnetic resonance angiography (MRA) images is one of the most important problems for early diagnostics and timely treatment of intracranial vascular diseases. Among three traditional MRA techniques, namely time-of-flight (TOF) MRA, phase contrast angiography (PCA) MRA, and contrast enhanced (CE) MRA, only TOF-MRA is widely used clinically owing to its fast and providing high contrast images. This results in good background signal suppression and can quantify flow velocity vectors for each voxel. TOF-MRA relies on amplitude differences in longitudinal magnetization between flowing static.

Most of the 2D segmentation methods are not suitable for the 3D MRA data. 3D segmentation techniques can be classified as the following four categories: scale space analysis, deformable models [1], statistical model[2], and hybrid methods [3].

In multi-scale filtering, each image is convolving with Gaussian filter at multiple scales to enhance curvilinear structures in the 3D MRA data [4]. The output of this filter is used to define an enhanced set of images in which blood vessels are brightened, whose background noise and planar structures are darkened. Multi-scale filter responses at each of the voxels determine the likelihood that voxels belong to a vessel of a certain diameter. The maximal response over all the diameters is retained at each voxel. Finally, the surface model of the vascular structure is reconstructed from the centerlines and diameters [5]. The main idea of the Deformable models is that an estimate of initial vessel boundary is deformed iteratively to optimize an energy function which of gradient information and the smoothness of the surface. Geodesic active contours implemented with level set techniques offer flexible topological adaptability to segment MRA images [6]. Topologically adaptable surfaces make classical deformable models more efficient in segmenting intracranial vasculature [1]. Fast segmentation of blood vessel surfaces was obtained by inflating a 3D balloon with fast marching methods [7].

The statistical methods can extract the vascular tree automatically, however, the accuracy depends on underlying probability models. The MRA images are multi modal in the sense that particular modes of the marginal probability distribution of signals are associated with regions-of-interest. To the best of our knowledge, the only adaptive statistical approaches for extracting blood vessels were proposed by Noble et al. [9-10]. The marginal distribution is modeled with a mixture of two Gaussian and one uniform or Rician components for the stationary CSF (cerebro spinal fluid) and bones, brain tissues, and arteries, respectively. The uniform component presumes the blood flow is strictly laminar. The mixture is identified with EM algorithm.

Blood vessels are extracted by hybrid approach which combines signal statistics and shape information. A recursive hybrid segmentation frame work [8] has been
proposed, which combines the Gibbs random field model, marching cubes and deformable models. Another hybrid segmentation [9] which employs the MRF (Markov random field) is present for the 3D MRA images. Before using the MRF model, Hassouna presented a mixture model for the volume intensity histogram.

In this paper, we present a new method by combining statistical method and MRF model for segmenting the 3D TOF-MRA images. The voxels of the volume data are classified as the background and blood vessels by the statistical model that fits the intensity distribution of the volume data. To get the more accurate vessel segmentation result, the MRF model is developed to describe the statistical dependence among the neighborhood voxels.

2. Statistical model for ROF-MRA data

2.1. Statistical model based on the intensity distribution

In [2], it was described that the histogram of the TOF-MRA volume data can be partitioned into three parts based on the intensity of the voxles. The lowest intensity region corresponds to cerebrospinal fluid (CSF), bone and the background air. The middle intensity region corresponds to brain tissues, including both the grey and white matter, and parts of the eyes. The third high intensity region corresponds to subcutaneous fat, and arteries. Now we adopted a statistical model for segmenting the TOF-MRA data before the MRF model. Since interested only in segmenting blood vessels, we assume that the MRA data consists of two major classes: background and vessels. The total probability density function of the statistical model is given as follows:

\[
f(x) = w_U p(x|U) + \sum_{i=1}^{3} w_{G_i} p(x|G_i),
\]

where \( p(x|U) \), \( p(x|G_1) \), and \( p(x|G_2) \) are the uniform and normal probability density function, the parameters \( w_U \), \( w_{G_1} \), and \( w_{G_2} \) are the class proportions whose sum is unity.

The probability density function to the uniform and normal distribution are:

\[
p(x|U) = \frac{1}{I},
\]

\[
p(x|G_i) = \frac{1}{\sqrt{2\pi}\sigma_{G_i}}\exp\left[-\frac{(x-\mu_{G_i})^2}{2\sigma_{G_i}^2}\right], \forall i \in [1,2],
\]

where \( I \) is the maximum intensity value of the volume data, \( \mu_{G_i} \) and \( \sigma_{G_i} \) are the mean and standard deviation respectively.

The voxels whose conditional probability from the uniform class is higher than the conditional probability of coming from either of the other two distributions are also those voxels above or below certain intensity thresholds. Therefore, voxel \( x_i \) is belong to the uniform class if

\[
w_U p(x_i|0) > w_{G_i} p(x_i|I), \forall i \in [1,2],
\]

\[
x_i > \mu_{G_i} + \sigma_{G_i} \sqrt{\frac{2}{n}} \cdot \ln \left( \frac{w_{G_i}}{w_U} \right) , \forall i \in [1,2],
\]

Before applying MAP segmentation, the parameters in the equation (1) should be estimated. These parameters are the proportion \( w_U \) and the mode \( I \) of the uniform distribution, and the proportion \( w_{G_i} \), the mean \( \mu_{G_i} \) and the variance \( \sigma_{G_i} \), \( i \in [1,2] \) of each Gaussian distribution. We will estimate these eight parameters using the expectation maximization (EM) algorithm.

2.2. Parameters estimation using EM algorithm

The EM algorithm is a common approach to find the maximum-likelihood estimate (MLE) of the parameters of a distribution from a given data set when the data is incomplete or has missing values. The mixture distribution parameter estimation is one of the most widely used applications of the EM algorithm.

In EM algorithm the parameters are iteratively estimated by updating initial parameter estimates under the contrast that the difference between the log-likelihoods of the mixture distribution is to be minimized.

In our experiment, the initial parameters as suggested by histogram \( h(x) \) analysis are estimated in Table 1.
Table 1. The initial parameters values

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w_{U}$</td>
<td>0.03, because the proportion of the vessels in the volume range from 1% to 5%.</td>
</tr>
<tr>
<td>$w_{G1}$</td>
<td>The area of $h(x)$ covered by the first initial normal distribution</td>
</tr>
<tr>
<td>$w_{G2}$</td>
<td>$1 - w_{U} - w_{G1}$</td>
</tr>
<tr>
<td>$I$</td>
<td>Maximum value of the volume data</td>
</tr>
<tr>
<td>$\mu_{G1}$</td>
<td>$I_{\text{peak1}}$, the value at maximum of the histogram $h(x)$</td>
</tr>
<tr>
<td>$\mu_{G2}$</td>
<td>$I_{\text{peak2}}$, the value which at second maximum of the histogram $h(x)$</td>
</tr>
<tr>
<td>$\sigma_{G1}^2$</td>
<td>Calculated using MLE from the samples in the region $[0, \mu_{G1}]$</td>
</tr>
<tr>
<td>$\sigma_{G2}^2$</td>
<td>Calculated using MLE from the samples in the region $[\mu_{G1}, \mu_{G2} + \Delta]$, where $\Delta = I_{\text{peak2}} - I_{\text{min}}$, $I_{\text{min}}$ is where the minimum value in the region $[I_{\text{peak1}}, I_{\text{peak2}}]$</td>
</tr>
</tbody>
</table>

The update equations of parameters in the statistical model are given as follows:

$$
\mu_{G}^{k+1} = \frac{\sum_{i=1}^{N} p^k(G_i | x_i) x_i}{\sum_{i=1}^{N} p^k(G_i | x_i)}, \quad (6)
$$

$$
(\sigma_{G}^{k+1})^2 = \frac{\sum_{i=1}^{N} p^k(G_i | x_i) (x_i - \mu_{G}^{k+1})^2}{\sum_{i=1}^{N} p^k(G_i | x_i)}, \quad (7)
$$

$$
w_{U}^{k+1} = \frac{1}{N} \sum_{i=1}^{N} p^k(G_i | x_i), \quad w_{G1}^{k+1} = \frac{1}{N} \sum_{i=1}^{N} p^k(U | x_i), \quad (8)
$$

where $N$ is the number of volume data, and $x_i$ is the intensity of voxel $i$. The term $p^k(G_i | x_i)$ and $p^k(U | x_i)$ can be rewritten as follows:

$$
p^k(G_i | x_i) = \frac{w_{G_i} p^k(x_i | G_i)}{w_{U} p^k(x_i | U) + \sum_{i=0}^{C} w_{G_i} p^k(x_i | G_i)},
$$

$$
p^k(U | x_i) = \frac{w_{U} p^k(x_i | U)}{w_{U} p^k(x_i | U) + \sum_{i=0}^{C} w_{G_i} p^k(x_i | G_i)}. \quad (9)
$$

For the 3D volume data, the steps of the statistical model are as follows and the histogram curve fitting result are shown in Figure 2.

Step1: Initial the parameters of the model as suggested in the Table 1.

Step2: Apply the EM algorithm to update the parameters according to Eqn. (6)-(9).

3. 3D MRF model for refined segmentation

Although the statistical model based on the voxels intensity can provide a good fit to the volume histogram as shown in the Figure 2, some voxels may be still misclassified because the classification is based entirely on the voxels intensity. For examples, the high intensity noise maybe as blood vessels, and some vessels voxels will be taken for the background. So we present the MRF model for the refined segmentation on the basis of context information.

3.1 MRF-based segmentation

Markov random field is a $n$ dimensional random process defined on a discrete lattice. Assume that $S$ is set based on the voxels lattice, Let $R = \{R_q | q = 1, 2, ..., Q\}$ is the observed random data, and $X = \{X_{s} | s = 1, 2, ..., C_{s}\}$ is a label field, $X_{s}$ is the region labels provided in the statistical models. $C_{s}$ is the number of the classes. In our experiment, the major problem is to find the accurate estimate of the true class label $x$. We use MAP (maximum a posteriori) method to find the estimate $\hat{x}$ that maximizes the posteriori distribution $p(x | r)$.

$$
\hat{x} = \arg \max_{x} p(r | x) p(x), \quad (10)
$$

where the function $p(r | x)$ is a conditional distribution of the volume data. The function $p(x)$ is given by the Hammersley-Clifford Theorem [10], i.e.,

$$
p(x) = \frac{e^{U(x)}}{Z},
$$

where $Z = \sum_{x} e^{U(x)}$ is called partition function, and the energy function $U(x)$ is defined as $U(x) = \sum_{x \in C} V_{c}(x)$, where
$V_c(x)$ is the potential energy function.

3.2 Model of spatial segmentation based on MRF

Applying 2D MRF to the slice will diminish the vessels with small and middle size in the volume data [9]. So we extend the second order neighborhood clique $c$ of pair-wise interaction and restrict 26 neighborhood voxels around $s$. The 3D MRF model is shown in Figure 2. In the structures, the Multi-Level Logistic Model [11] is applied to define the energy function for the equation (11). The potential energy function $V_c(x_i)$ is defined as the following equation (12):

$$V_c(x_i,x_j) = \begin{cases} 
\beta & (x_i = x_j) \\
-\beta & (x_i \neq x_j) 
\end{cases}.$$  (12)

After updating model parameters, ICM (Iterated conditional modes) algorithm is used to estimate the true label of the voxels.

4. Result

In the experiment, we applied the vessel segmentation method to the 3D TOF-MRA data. The MRA data have 96 slices, and every slice has 256×320 pixels of 16 bit precision. Slice thickness is 0.9mm and the pixels size is 0.63×0.63mm$^2$. Our implementing program is on the Matlab IDE, and the running time is about 15s using 2core with 2G RAM computer.

The result of volume histogram fitting is shown in Figure 3. The Absolute Error between the histogram and fitting curve is 0.0213. According to the equation (5), we get the initial segmentation label sets for the 3D MRF model. After the processing of MRF, the blood vessels segmentation is shown in Figure 4(b), and the range of vessels diameters are from 3 to 11.

5. Conclusion

In this paper, we present mixture model for the blood vessel segmentation of the 3D TOF-MRA data. We built the model by considering both the intensity of the voxels and the context information among the volume voxels. The segmentation result shows a good performance for our method.

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References


