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A Novel Method for 3D-Segmentation of Vascular Images[1]

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Abstract: Constructing the accurate digital model of vessel networks is critical to vascular tissue engineering, in which the segmentation of vessel plays an important role. However, the existing segmentation methods are not able to achieve the goal of accurate segmentation of vessel networks. This paper presents the development of a method for vessel segmentation based on a data structure of octree and 3D region growing. Firstly, the volume data of vessel images are divided into different data groups according to the predetermined depth value of octree, and then the optimal slices sequence is defined by analyzing the octree's nodes which contain the vessel region. Then, the vessel segmentation is conducted from the vessels images of octree nodes based on 3D region growing. Finally, the treated data blocks are reset and the segmentation results of the whole volume data are obtained. By applying this method to the volume data of vascular images from MRA, accurate vessel segmentation results are achieved. This work would represent a significant advance for digital modeling of vessel networks.
Key Words: Vascular tissue engineering; Image segmentation; Region growing; Octree

1. INTRODUCTION

The mortality of human being due to vascular diseases has increased and been drawing considerable attention nowadays. Vascular tissue engineering provides a new approach for the cure of vascular disease (Vaz et al., 2005). Therefore, how to construct the vascular network matching human native tissue by the bionic fabricate has become a hot topic in the vascular tissue engineering. However, the construction of digital model of vascular network that exactly expresses the vascular shape and topology is the core of

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vascular tissue engineering. With the development of medical imaging technology, the resolution and signal noise ratio have been enhanced significantly, thus making it possible to reconstruct the digital model of vascular network from the medical images of human vascular tissue.

The current vascular segmentation methods were mainly developed for specific image model or some kinds of tissue. According to the dimension that segmentation algorithms work, the segmentation methods are divided into 2D methods (Passat et al., 2007; Socher et al., 2008) and 3D methods (Passat et al., 2004; Peters et al., 2008). Because the 2D segmentation does not take the continuity in the third dimension into account, the results are not always satisfied. Recently, different kinds of 3D segmentation algorithm are developed. Although most of them are effective for the segmentation of medical images, the time consumed is always an issue. Therefore, research on new methods for 3D segmentation with higher efficiency and accuracy is desirable.

The methods for 3D segmentation can be classified into two categories: model-based and region-based. The region growing algorithm (Mueller et al., 2004) is one of the region-based methods. Rose et al proposed an automated region growing method by taking the shape information into consideration (Rose et al., 2008) . The method was driven by statistical data computed from the evolving region and by a shape reference model. Robert et al developed an autonomous region-growing method which can generate seed locations internally with the help of pulse-coupled neural network (Rose et al., 2002). However, most of the previous methods only paid attention to the continuity of gray-level and neglected the special 'tubular' shape of vascular, even some method take the shape into consideration, the computation is very complex. Therefore, a novel method that takes both intensity information and geometrical information into consideration is proposed in this paper.

The original volume data of vascular images is divided successively by means of the octree method (Bras & Martins, 2010) , the region containing the blood vessel is extracted according to the gray threshold, then an 3D region growing method is used to extract the 'tubular' blood vessel. The algorithm is verified by the magnetic resonance angiography images of brain obtained by method of time of flight. The experimental results show that the algorithm can achieve better segmentation results. By applying this method to volume data of medical image, the digital model can be reconstructed accurately and can easily be used to compute the pore size and shape by the Boolean operation.

The paper is organized as follows. In Section 2 the method of vascular images segmentation based on octree structure is introduced and in Section 3 the segmentation results by means of the proposed method are presented, which is followed by the conclusions given in Section 4.

2. METHOD OF VASCULAR IMAGES SEGMENTATION

2.1 The partition of volume data based on octree structure

Octree is an important data structure in computer science, and has been widely applied in the analysis and comprehension of medical images. However, in the medical volume dataset, the regions of interest are only a small part of the whole volume data and always distribute continuously. Therefore, this distribution feature can be used to group the volume data, thus marking the interesting region and neglecting the unrelated region as well. As such, it becomes possible to reduce the processing time and storage space in the process of segmentation.

The volume data from the medical devices is divided firstly based on the octree structure, and then the sub-dataset are classified and the regions which contain the vessel segments are marked. Only the nodes of octree containing the vessel segments are processed. In this way, the workload is significantly reduced. The octree structure is designed as below:

```
Struct OctreeNode
{
int m_depth;
COctree * m_parent;
```

```
int m_Width;
int m_Height;
int m_Level;
int m_MaxGray;
int m_MinGray;
COctree *m_pOctreeNodes[8];
};
```

where the member variable *m_depth* is used to save the depth value of current node; *m_parent* is the pointer which points to the parent node; *m_Width*, *m_Height*, *m_Level* are used to save the resolution of current node, respectively; *m_MaxGray* and *m_MinGray* are used to save the maximal and minimal gray level of current node, respectively; and the pointer array *m_pOctreeNodes* points to the eight child nodes, respectively.

Firstly, the whole volume dataset is regarded as the root node of octree, and the value is assigned to the member variables. For the specific characters of root node, *m_parent* is set to NULL, and *m_depth* is set to 0. Meanwhile, the three dimension values of resolution are assigned to the variable *m_Width*, *m_Height* , *m_Level*, and then the dataset is traversed to get the maximal and minimal gray level and assigned to the variable *m_MaxGray* and *m_MinGray*. The depth value of octree partition needs to be set according to the resolution of dataset, and then the dataset is grouped according to the depth value set before. Each node in accordance with the location, which will facilitate the merge of nodes finally, is numbered. The location of each node is shown in Fig. 1. In each step, the node structure is established and the corresponding values are assigned to the node, which facilitate subsequent traverse the dataset and get the node containing the vessel.

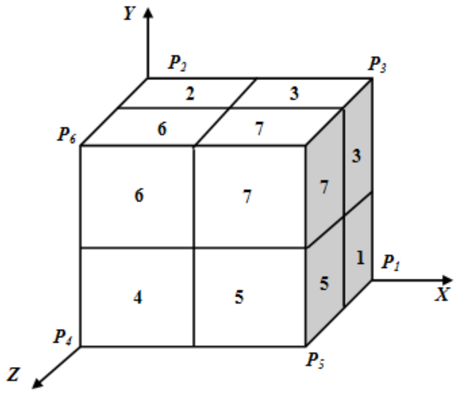


Fig. 1: Illustration of octree nodes distribution

Table 1: The statistics results of the number of nodes produced by different volume data segmentation

Volume dataset	No. of columns	No. of rows	No. of Images	Bits of each pixel(bits)	No. of child nodes	No. of nodes not contain of vessel segments
1	416	512	112	10	8	2
					64	13
					512	31
2	256	320	128	8	8	1
					64	12
					512	29
3	512	512	512	12	8	2
					64	14
					512	33

After the partition of the volume dataset, many smaller datasets in space can be obtained. For example, for a volume dataset whose dimension is $512 \times 512 \times 512$, the child node's dimension is only $32 \times 32 \times 32$ if the depth value is set to 5. Therefore, after the partition based on octree, the workload is reduced. Besides, by browsing the dataset being partitioned, those datasets that do not contain vessel tissue can be removed, so the efficiency of vessel segmentation can be enhanced. On the other hand, as the dimension of dataset decreases, the complexity of vessel trend is also reduced. Therefore, the slice sequence which makes the vessel's trend perpendicular to the slice plane can be selected by analyzing the smaller datasets and the accuracy of vessel segmentation can be improved. However, when the depth value is oversize, the nodes produced by segmentation will increase, thus increasing the complexity and human intervention during the vessel segmentation. In conclusion, an optimal depth value should be selected when grouping different volume data. By applying the group method based on the octree structure, the correspondence between the depth value and the number of nodes which do not contain the vessel can be obtained, as shown in Table 1. From this table, it can be concluded that the depth value set to 3 is optimal. On one hand, if the number of nodes decreases, the human intervention becomes less too. On the other hand, if the depth value is set to 3, the dimension of child nodes is about 128, which is suitable for vessel segmentation based on region growing.

2.2 Region-Growing Algorithm

The principle of region-growing method is to take the pixel with the similar characterization together to produce several continuous sub-regions. The region-growing method selects a series of seed points in the image firstly, and combines the pixels which have the similar gray level to the sub-regions, and sets the new combined pixel as the new seed points to execute similar process until the region is not growing. The main feature of region-growing method is its easy implementation and suitable for small tissues and regions such as the cancerous region. The main difficulty of region-growing method is to determine the consistency criterion, which has a direct influence on the accuracy of segmentation results. One drawback of region-growing method is the need to select the seed points and the other is that the method likely produces some regions containing holes due to the presence of noise. Given the fact that the goal is to obtain the accurate digital model of vessel networks, human intervention is necessary for adopting the region-growing method by properly selecting the seed points.

For the vessel networks, some vessel segments may not be perpendicular to the slices, and even parallel to the slice due to the complex vessel' trend. As shown in Fig 2, the continuous image is in the *xy* plane, and the region marked by the green circles is the interesting vessel segments. From Fig. 2, we can find that the vessel segments are approximately parallel with the *xy* plane. However, vessel segmentation always adopts the criterion which supposes the vessel contour is similar to circle. Therefore, if the region-growing method is directly applied to the volume data similar to Fig 2, the result may not be accurate. Considering the impact of vessel' trend, each segmentation node is analyzed and the vessel's trend which goes along the slice sequence is defined, which will be benefit to determine the growing criterion.

Due to the continuity in the 3D volume data, the proposed method expands the region-growing method to the 3-dimensional space. Therefore, the 26 neighborhoods around the current nodes of seed point are judged, which can fully take the space continuity into account. However, when the region-growing method is expanded to 3-dimensional space, the calculation amount will increase tremendously. Therefore, the 3D region growing method is proposed to combine with the group method based on the octree structure.

This new method was developed bases on the following considerations. The dataset resolution dropped a lot after the segmentation based on the octree structure, so a smaller threshold range can be set, which will reduce the rupture of the vessel. The other consideration is that the priority of region growing can be specified owing to the vessel's "tubular shape", which specify the growing sequence in the current slice firstly, and then grows in the neighbor slices. The method is outlined below.

Step 1: Select the seed point in the location where the vessel diameter is bigger in the current child node of the octree.
Step 2: Set the threshold range as the growing criterion.
Step 3: If (the 8 neighbors in the current slice satisfy the growing criterion)
    S<-voxel   //*S* is the aggregate containing the voxel satisfies the growing criterion
    If (the 18 neighbors in the adjacent slices satisfy the growing criterion)
    S<-voxel   //*S* is the aggregate containing the voxel satisfies the growing criterion
Step 4: Repeat the step 3 until no voxels satisfy the growing criterion

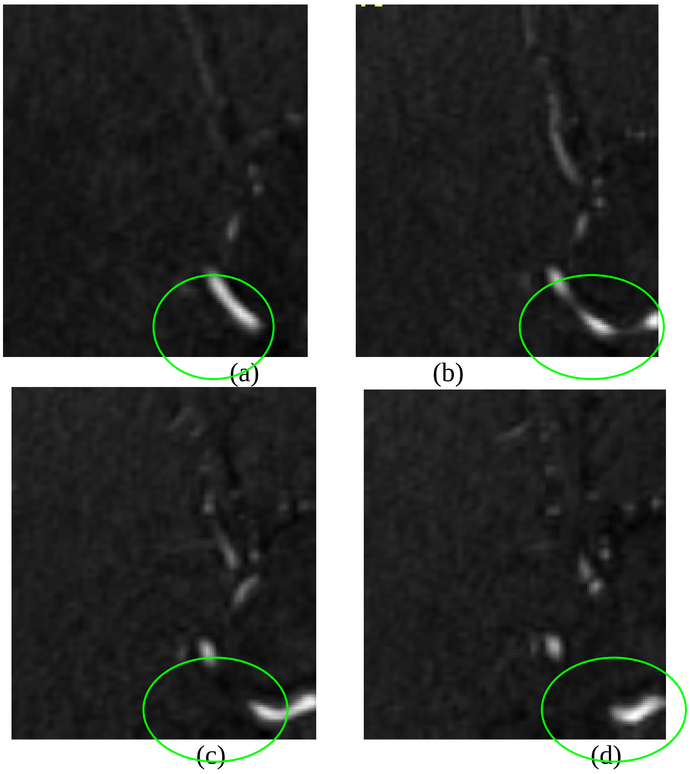


Fig. 2: Illustration of special intersects case for vessel and slice

After the completion of the vessel segmentation of each octree node, the method combines the octree nodes according to the nodes' coding order and the relation of father-child nodes, and displays the segmentation result of the whole volume data. The flow diagram of the method is shown in Fig 3.

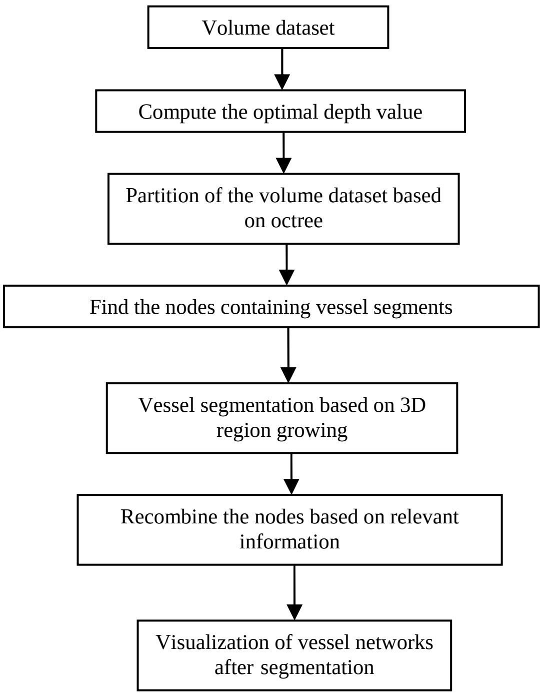
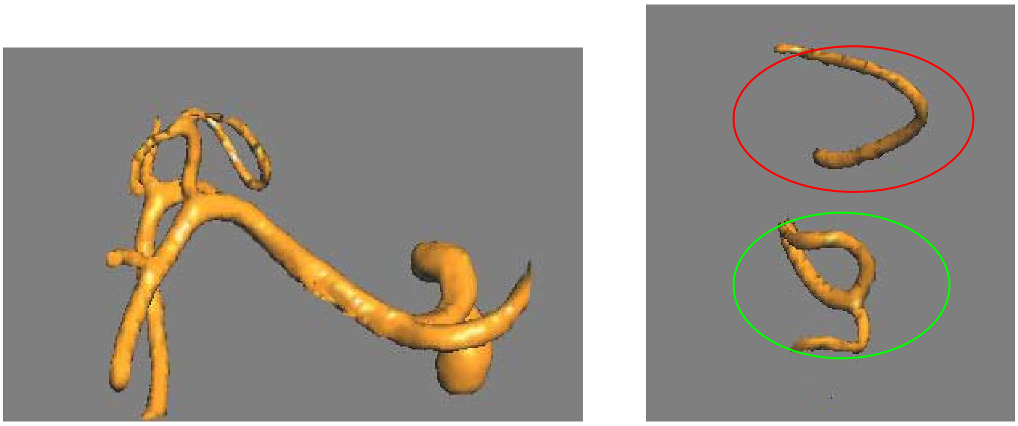


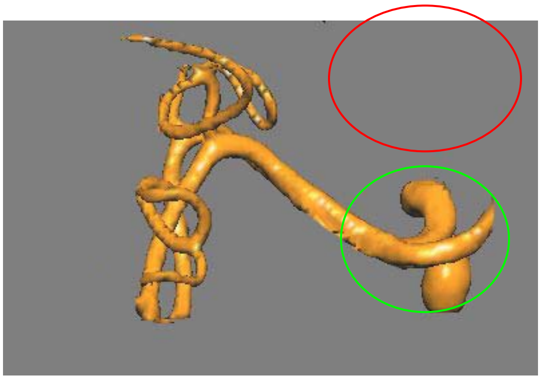
Fig. 3: Flow diagram of vessel segmentation method

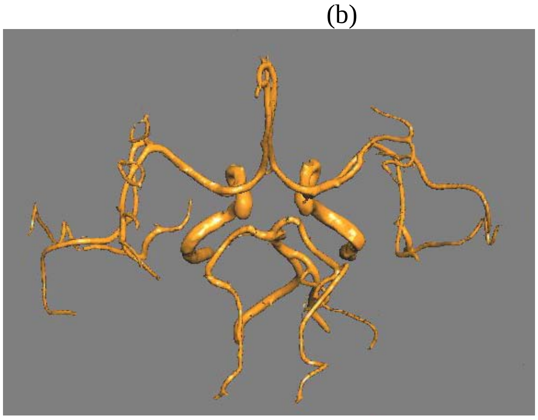
3. SEGMENTATION EXAMPLE

For the octree nodes after the vessel segmentation, the nodes were re-combined according to the coherence of nodes and the segmentation results of the whole volume dataset was composed. This makes it possible to improve the digital model of the vessel networks and biological manufacturing. Fig 4 shows the result of vessel dataset after segmentation based on March Cube algorithm. All the nodes were re-combined according to the relation of octree nodes of the vessel volume dataset. The volume data of Fig 4(c) is composed of 4(a) and 4(b), i.e. the regions in the Fig 4(c) surround by red circle and green circle are composed of Fig 4(a) and 4(b). Fig 5 shows the segmented vessel network from image dataset of part of human brain.



(a) (b)





(c)

Fig.4: Display result of vessel segment of part of human brain

Fig. 5: Segmentation result of volume dataset after recombination

4. CONCLUSIONS

The accurate segmentation of vessel network is critical to the vessel tissue engineering and plays an important role in the re-construction of vessel structure and topology. The presented method which groups the whole volume dataset based on the octree structure can not only remove the irrelevant tissue, but also achieve a better segmentation sequence by analyzing the trend of vessel segment in the child nodes. By re-combining the whole nodes after vessel segmentation, the segmentation result of the whole vessel networks is obtained. Compared with other vessel segmentation method, the proposed method can reduce the workload and improve the segmentation speed and accuracy in the case of ensuring the topology of vessel networks.

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