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A New Parallel Segmentation Algorithm for Medical Image

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Abstract

In medical Image analysis, the parallel segmentation is the core technology. As one of the classical methods, regional growth algorithms have some problems: it is hard to confirm the feed points automatically. To solve this defect, a new parallel segmentation algorithm with regional growth and support vector machine (SVM) is proposed. SVMs have a good result in segmentation (classification) but a non-ideal convergence rate which is the advantage of regional growth method. So that, combining them and the idea of the algorithm is: classify by SVM to search the seed points, segment by regional growth method. A curvature flow filter is also used in this algorithm to reduce the noise. The experiments are performed on a parallel environment based on torque. The results show that the algorithm is faster than conventional algorithms and the results are better.

Keywords: *CT Image, Parallel Segmentation, Regional Growth, Support Vector Machine*

1. Introduction

The medical image segmentation that divides the image into meaningful sub regions is a key technology in the medical image processing and analyzing [1]. The development of image segmentation technology not only affects the progress in the medicine image processing, such as visualization, 3D reconstruction, different pattern medicine image registration and fusion, but also plays an extremely important role in the biomedical image analysis.

As far as innate character is concerned, the medical image is fuzzy [2], for there are many fuzzy factors in medical image, such as grey-scale, texture and region boundary and so on. Moreover, for the mass medical image data, we must consider the effectiveness and speed of segmentation simultaneously. Because of these medical image particularities, a universal suitable theory and method, which can be used as a perfect solution on the medical image segmentation question, is not exist.

Regional growth is a technique for image segmentation which starts at some known pixel points and extends to all neighboring pixels that are similar in gray level, color texture, or other properties in order to form a complete region. Easy to implement and run fast is the advantage of the algorithm, while requiring manual seed point selection is the shortcomings of the algorithm. SVM are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. A solo support vector machine is effective in segmentation, but the speed is slow.

In order to solve the problems of growth rules determination in conventional regional growth algorithm and speed up the support vector machine segmentation algorithm [3], we proposed a parallel image segmentation method combining support vector machine with regional growth in past work [4]. That method worked better and faster than conventional algorithm, but there are some drawbacks: the seed point's detection was not always exact in some case, and the algorithm complexity should be reduced to meet the need of some real-time computing. Therefore we amend the method, it includes four

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steps: firstly, from target and non-target area in an image whose segmentation result has been obtained, a certain numbers of sample points were selected for the support vector machine classification training. Secondly, select pixel points by granularity *N*, which means a pixel point every other *N* lines and *N* rows, and then use the trained support vector machines for discriminating whether these points and their 4 neighboring points belong to the target area. If so, the point recorded as a seed point. Thirdly, carry out the regional growth starting from those seed points, stopping with some gray values above or below the threshold. Finally, essential post-processing is done for the dealing with edge and noise points.

The remaining sections of this paper are structured as follows: Section 2 shows the main relevant works. In Section 3, we introduce the algorithm and its realization in detail. We carry out the experiments in Section 4. Finally, some concluding remarks are given in Section 5.

2. Relevant Works

2.1. Support Vector Machine

Support vector machine (SVM) algorithm is a machine learning technique based on statistics theory [5-7]. Compared with traditional machine learning techniques, this technique can overcome the dimensional disaster into a high dimensional features space as well as stronger generalization ability.

The support vector machine theory operates on a principle, called structural risk minimization, which aims to minimize the bound on the expected generalization error, so it has stronger generalization ability.

The enter samples x are mapped to the high-dimensional space H through the non-linear mapping $\Phi(x)$ in the process of pattern classification. Then these samples were linearly classified in mapping features space. In practice, SVM classification function can be expressed to the following: All printed material, including text, illustrations, and charts, must be kept within the parameters of the 8 15/16-inch (53.75 picas) column length and 5 15/16-inch (36 picas) column width. Please do not write or print outside of the column parameters. Margins are 1 5/16 of an inch on the sides (8 picas), 7/8 of an inch on the top (5.5 picas), and 1 3/16 of an inch on the bottom (7 picas).

$$f_{\mathrm{SVM}}(x) = w^T \Phi(x) + b \tag{1}$$

Where w and b are the smallest in the training set of samples. Generalization of the function in structural risk as follows:

$$J(w,\xi) = \frac{1}{2} w^2 + C \sum_{i=1}^{N} \xi_i \tag{2}$$

$$s.t.\ y_i f_{SVM}(x) \geq 1 - \xi_i, \xi_i \geq 0\ (i = 1, 2, \cdots, N)$$

Where the positive parameters C are chosen in accordance with specific issues and the slack variables $\xi_i \geq 0$, $i = 1, \cdots, N$. Generalization of risk is a compromise between (1) risk of experience (error of the second training) and the complexity of model (first). Parameter c can control the degree of compromise, which can avoid over-fitting, that is, the ability of classification to avoid deterioration. The training samples (x_i, y_i) as support vector meet $y_i f_{SVM}(x_i \leq 1)$. It can substitute kernel function $K(x,z) \equiv \varphi(x) T \varphi(z)$ into the decision-making function (2) and has the following:

$$f_{SVM}(x) = \sum_{i=1}^{N} a_i K(x, s_i) \tag{3}$$

Where s_i ($i = 1, 2, \cdots, N$) denotes the support vector.

It can directly be the decision-making function from function (3) using of kernel function $K(\cdot,\cdot)$ without considering the potential mapping $\varphi(\cdot)$ [8,9].

It used the Gaussian Radial Basis Function (RBF) as kernel function in this paper:

$$K(x,z) = \exp(-\| x - z \|^2 / 2\sigma^2) \tag{4}$$

Where σ ($\sigma \geq 0$) can control the width of nuclear.

2.2. Image Segmentation based on Region Growing Method

The region growing algorithms, the basic idea of which based on region growing method integrates similar pixel points into a region, have proven to be an effective approach for image segmentation. Typically, region growing is to start from a seed region which is considered to be inside the object to be segmented [10]. The pixels neighboring this region are evaluated to determine whether they should also be considered part of the object. If so, they are added to the region and the process continues as long as new pixels are added to the region.

Based on the nature of questions, region growing algorithms vary depending on the criteria used to decide whether a pixel should be included in the region or not, the type connectivity used to determine neighbors, and the strategy used to visit neighboring pixels. Furthermore, some kind of restrictive criterions were defined to finish the region growing automatic. Grays and texture information of sub-regions in different space position are similar in contents and changes generally, so we can select the appropriate features to describe the differences in these regions. Before region growing, a curvature flow filter is used to reduce the noise and get a result with sharp and smoothing boundaries.

3. Method and Realization

This paper introduces an image segmentation method based on SVM and region growing. This method selects the feature vectors corresponding sample point to train the SVM. Secondly, feed point is computing features and classified. The concrete processes are as follows:

(1) Selecting and marking of sample points in target area and the non-target area;

(2) Selecting a small region of each sample point to extract the features to consist training samples of the support vector machines;

(3) Training the support vector machine with obtained training sample;

(4) Detecting seed points in segmented image with trained support vector machine.

3.1. Combined Support Vector Machine and Regional Growth

Last using an inverse two-dimensional discrete fast Fourier transform. Obtained the set of discrete coefficients $C^D(j,l,k)$ .This paper proposed a combined support vector machines and the region grow method diagram shown in Figure 1.

The method is divided into four steps:

(1) Training classifier with selected sample: Select the certain amount support vector machines sorter's training sample from target area and non-target area of the known segmentation result's image and trains support vector machines;

(2) Seed point selection: Pixels of every *N*th column of Nth row and their 4 neighboring points will be checked by the trained SVM whether they belong to the target area, where N is a certain granularity. Then the pixels in the target marked as the seed points.

(3) Denoise filter: a curvature driven image de-noising filter is used to reduce the noise and it also contributes to a sharp and smoothing segmentation result.

(4) Region growing: region growing starts from these seed points, using the gray level threshold value to decide which points should be consider as the target area;

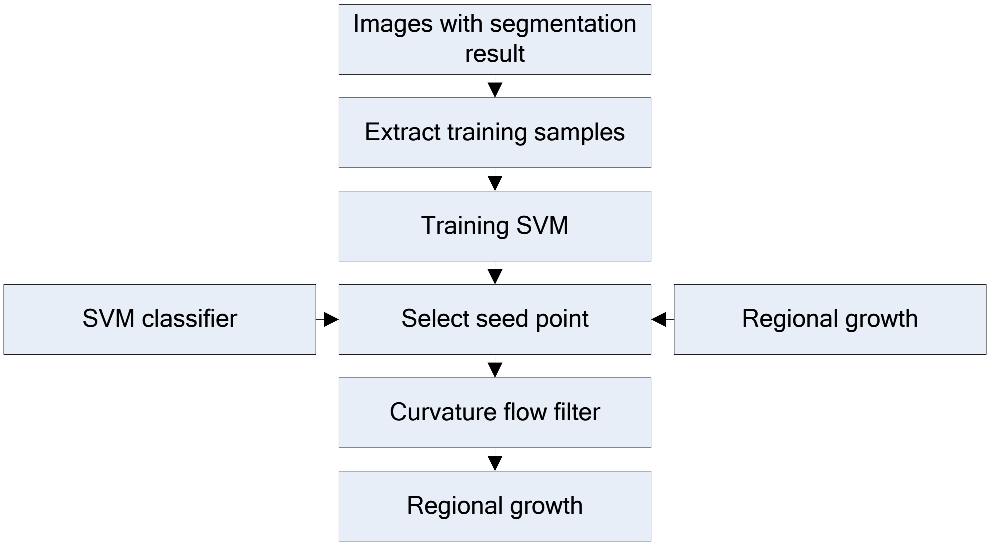

Figure 1. Diagram of Combined Support Vector Machines and the Region Grow Method

The method has the following advantages:

(1) The simple method using support vector image segmentation requires classification of all points in image, but the proposed method only needs part of points, which is faster than the former.

(2) Contrasted with the classics region growth algorithm, the interaction of manual seed point selection is avoided. In this proposed method, the seed selection automatically searches by using support vector machines.

(3) After training the support vector machines by a known segmentation result image, division of similar image can realize automatically.

3.2. Parallel Image Segmentation based on Torque

For there is not relativity between images but between pixels and their neighborhoods in every images, we can segment different images in different nodes at the same time. We realize the parallel segmentation algorithm by Master-Slave model under the torque environment. Here is the main execution sequence: first, according to the numbers of images and the load of nodes, node 0 will send the image which should be segmented to the others then gets ready to receive the result. Meanwhile, after receiving the images, other nodes will segment images following the segmentation algorithm this paper proposed then send them back. The process above repeated until all the images were segmented. Figure 2 shows the flow chart.

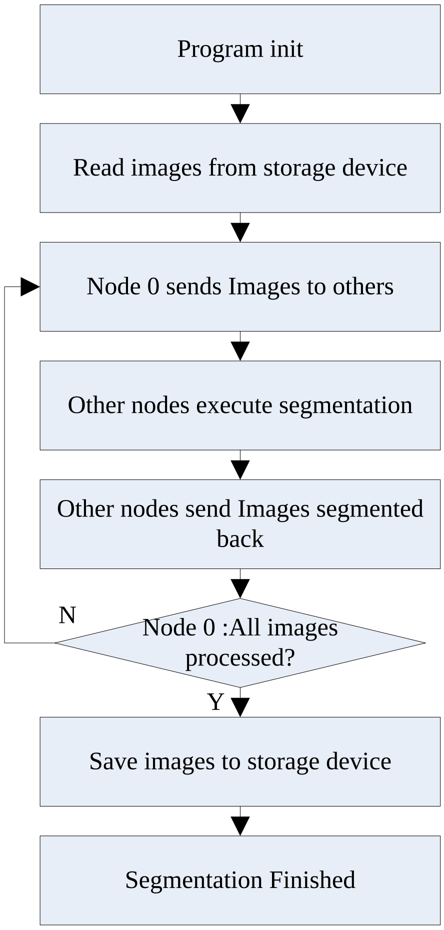

Figure 2. The Flow Chart of Parallel Segmentation

4. Experiments and Result

This experiment use 512×512×40 chest CT images which has been segmented the lung essence and 512×512×740 chest CT images that waited for the segmentation. We use 8 pc with AMD Athlon64 4800 as the hardware platform of the computer nodes. The software platform is Ubuntu 10.4, torque 3.0 and mpich2. Our parallel program is running on the platform to achieve the proposed algorithm.

Typically, the main indicators of performance evaluation of parallel algorithm are speedup and efficiency. Speedup is defined for each number of nodes n as the ratio of the elapsed time when executing on a single node and efficiency is a concept closely related to speedup ratio, defined as the quotient of speedup and the numbers of nodes. We used a different number of nodes, repeat 10 times the implementation of the program, and finally we get the average value shown in Figure 3 and 4. The segmentation result is shown in Figure 5 and 6.

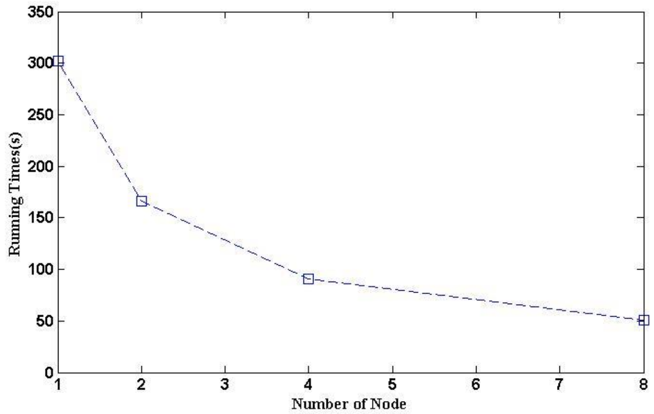

Figure 3. Execution Time with Different Number of Nodes

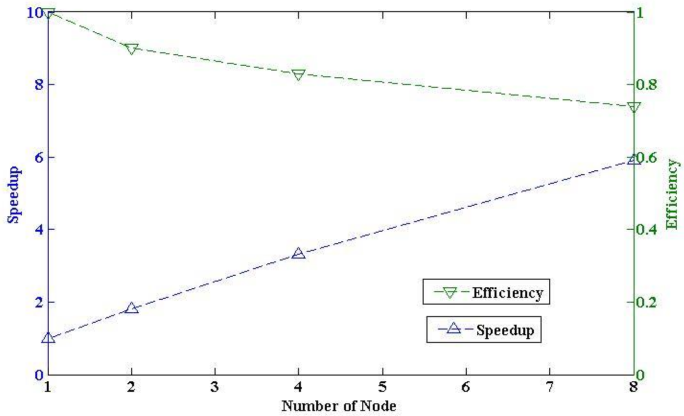

Figure 4. Efficiency and Speedup with Different Number of Nodes

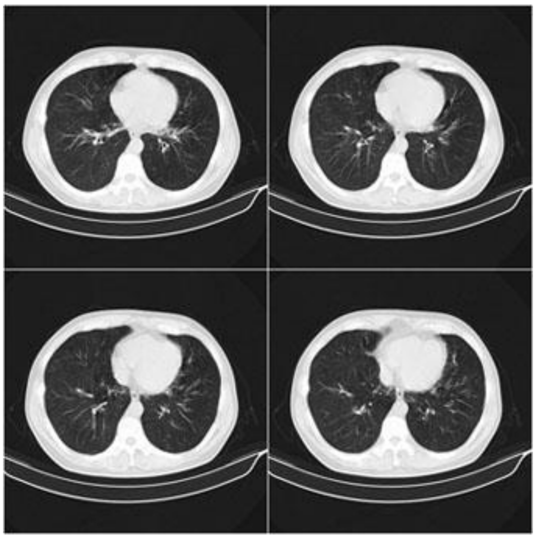

Figure 5. The Original Images

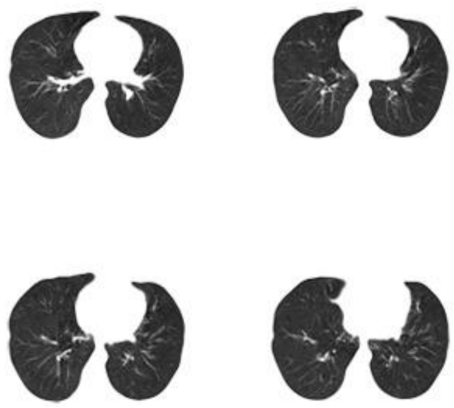

Figure 6. The Results of Segmentation

From the results we can analyze that, as the number of node increases, the execution time is leveled off, the speedup is improved smoothly, and the efficiency always maintains in a higher level. More intuitively, the segmentation results of CT images by this algorithm are satisfactory.

4. Conclusions

This paper proposed a new method of image parallel segmentation combining support vector machine with regional growth, this method selects sample from the known segmentation result image, trained support vector machines is used for searching seed point, avoiding the manual seed selection. Compared with solo support vector machines segmentation, this method reduces the distinguishing times, speed up the segmentation. Parallelization of the algorithm in torque environment further speeds up the segmentation. The method this paper proposed has a well application prospect in image segmentation domain.

Acknowledgements

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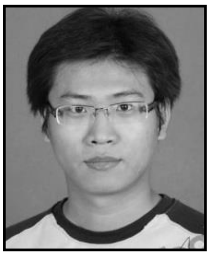

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