REGION GROWING SEGMENTATION OF CT-IMAGE BY THE ANALYSIS OF 3D LOCAL NEIGHBORHOOD

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New approach of matter segmentation in medical images is proposed. The main idea is rely on region growing method and additional constraints on inclusion of neighbor voxels. Additional constraints is based on analysis of 3D local neighborhood which is include only those voxels that satisfy the user specified thresholds on first and second derivatives. The paper will describe the implementation of widely used region growing algorithms in open-source.

Introduction

The growth of technologies favors creating much powerful medical equipment like Computed tomography (CT), Magnetic resonance tomography (MRT) and Positron emission tomography (PET). Current multislice CT scanners can configure up to 256 or even 512 detectors in an array. The resolution and quality of obtained images reaches remarkable values. Consider a standard chest CT image exam, which covers between 300 and 400 mm generating from 150 to 200 2-mm slices and up to 600 to 800 0.5-mm slices, depending on the slice thickness, or data sizes from 75 MB up to 400 MB. A whole body CT scan for screening can produce up to 2500 images or 1250 MB (1.25 GB) of data, with each image being 512×512×2 bytes [1]. With such a detailed data sets, the quality of image processing algorithms plays a significant part in clinical diagnostics but sometimes it is reached to the prejudice of performance.

There is no universal algorithm for segmentation of every medical image. Each imaging system has its own specific limitations. For example, in MR imaging (MRI) one has to take care of bias field noise (intensity in-homogeneities in the RF field). Of course, some methods are more general as compared to specialized algorithms and can be applied to a wider range of data [2].

One of the fastest semi-automatic segmentation methods is region-growing approach. The main idea is to grow region starting from seed pixel by comparing neighborhood pixel intensity with current. In the simplest case, a matter is in choosing of pixel, scanning of neighbors to find close values and merge it into new region. Common criterion for region homogeneity is based on estimation of maximal difference of current pixel's intensity and average intensity of new region. However, this clause will work if estimation of mean intensity is reliable only, so the size of region should not be small.

Among methods for region growing next are marked out: centroid connection (a priori information based on seed points), "merge-and-split" (growing of initially chosen homogeneous regions), "watershed" (based on gradient of intensity of image), deformable templates (based on template matching, which may change under function of internal energy). In addition, D.J. Withey and Z.J. Koles have provided a brief survey of three generations of medical image segmentation techniques [3].

1. Region growing in segmentation software

Region growing algorithms was implemented in many libraries and frameworks including open, commercial and academic sources. In some cases, it is better to use their highly tested and fast frameworks. The most popular and freely available medical imaging and processing frameworks are VTK and ITK. The main objective of VTK is data visualization but it still covers many image-processing algorithms (http://vtk.org). ITK provides developers with an extensive suite of software tools for image analysis and employs algorithms for registering and segmenting multidimensional data (http://itk.org/). Connected Threshold Image Filter, Neighborhood Connected Image Filter, Confidence Connected Image Filter are frequently used region growing ITK filters.

Connected Threshold Image Filter. This filter uses the flood fill iterator. Most of the algorithmic complexity of a region growing method comes from visiting neighboring pixels. The flood fill iterator assumes this responsibility and greatly simplifies the implementation of the region-growing algorithm. Thus, the algorithm is left to establish a criterion to decide whether a particular pixel should be included in the current region or not.

The criterion used by the Connected Threshold Image Filter is based on an interval of intensity values provided by the user (fig. 1). Values of lower and upper threshold should be provided. The region-growing algorithm includes those pixels whose intensities are inside the interval $I(X) \in [lower, upper]$.

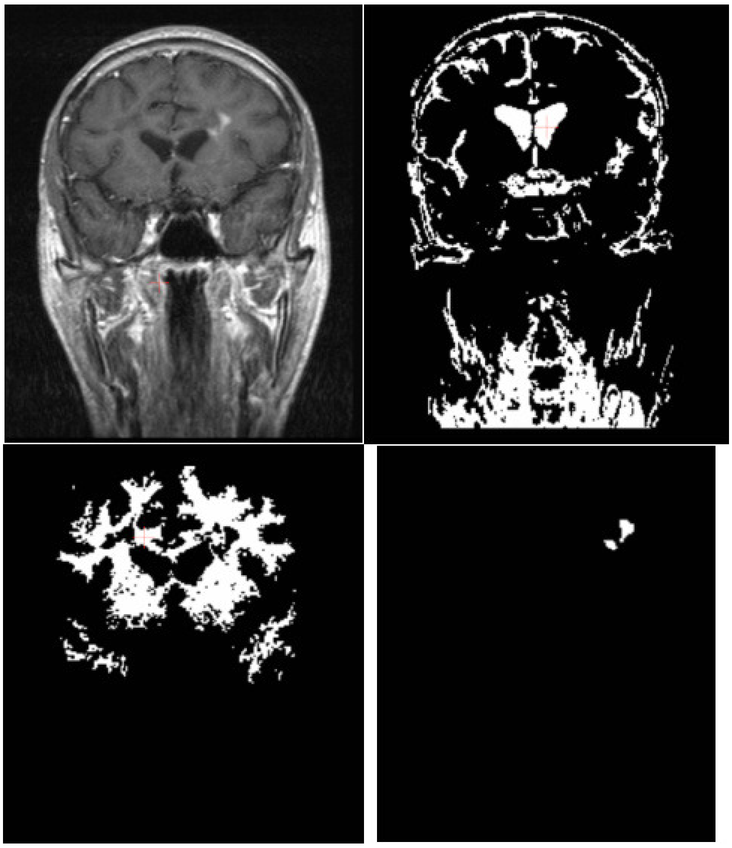

Fig. 11. Results of Connected Threshold Image Filter

Similar algorithm is implemented in VTK, vtkImageThresholdConnectivity class provides such functionality. Output results of ITK and VTK segmentation are identical, so in this case preferable to use VTK filter when the visualization part is made by VTK and not to spend memory and CPU time to converting pipeline from VTK to ITK and vice versa (table 1).

Table 1

Parameters used for segmenting some brain structures

Structure	Seed Index	Lower	Upper	Output Image (fig. 1)
White matter	(128, 208, 18)	633,00	826,20	Down left
Ventricle	(198, 146, 18)	154,00	440,20	Up right
White spot	(174, 210, 18)	973,00	6648,20	Down right

Neighborhood Connected Image Filter. This filter is a close variant of the Connected Threshold Image Filter. On one hand, the Connected Threshold Image Filter accepts a pixel in the region if its intensity is in the interval defined by two user-provided threshold values. The Neighborhood Connected Image Filter, on the other hand, will only accept a pixel if all its neighbors have intensities that fit in the interval. The size of the neighborhood to be considered around each pixel is defined by a user-provided integer radius.

The reason for considering the neighborhood intensities instead of only the current pixel intensity is that small structures are less likely to be accepted in the region. The operation of this filter is equivalent to applying the Connected Threshold Image Filter followed by mathematical morphology erosion using a structuring element of the same shape as the neighborhood provided to the Neighborhood Connected Image Filter.

Confidence Connected Image Filter. The criterion used by the Confidence Connected Image Filter is based on simple statistics of the current region. First, the algorithm computes the mean and standard deviation of intensity values for all the pixels currently included in the region. A user-provided factor is used to multiply the standard deviation and define a range around the mean. Neighbor pixels whose intensity values fall inside the range are accepted and included in the region. When no more neighbor pixels are found that satisfy the criterion, the algorithm is considered to have finished its first iteration. At that point, the mean and standard deviation of the intensity levels are recomputed using all the pixels currently included in the region. This mean and standard deviation defines a new intensity range that is used to visit current region neighbors and evaluate whether their intensity falls inside the range. This iterative process is repeated until no more pixels are added or the maximum number of iterations is reached.

The following equation illustrates the inclusion criterion used by this filter: $I(X) \in [m - f\sigma, m + f\sigma]$.

Where m and σ are the mean and standard deviation of the region intensities, f is a factor defined by the user, I is the image and X is the position of the particular neighbor pixel being considered for inclusion in the region.

2. Region growing segmentation based on the analysis of 3D local neighborhood

The main idea of introduced method rely on region growing method and constraints of inclusion of neighbor voxels. The analysis of 3D local neighborhood gives us two additional constraints.
The first stage is visiting neighborhood voxels starting from the seeds.
The second stage is to apply the constraints on neighboring voxels to the current. Neighbor voxel would be included to the current region if

1. $I(x, y) \in [lower, upper]$, where I(x,y) – intensity of neighbor voxel, **lower and upper** – user specified thresholds.
2. $I'(x, y) \in [lower, upper]$, where $I'(x, y) = \left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2$ – the gradient magnitude of intensity of neighbor voxel, **lower and upper** – user specified thresholds.
3. $I''(x, y) \in [lower, upper]$, where $I''(x, y) = \left|\frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}\right|$ – the Laplacian absolute value of intensity of neighbor voxel, **lower and upper** – user specified thresholds.

Algorithm is similar to Connected Threshold Image Filter with additional derivatives terms. It is remarkable that the computing of gradient would increase the computation time only by the constant value. Scheme of algorithm is on fig. 2.

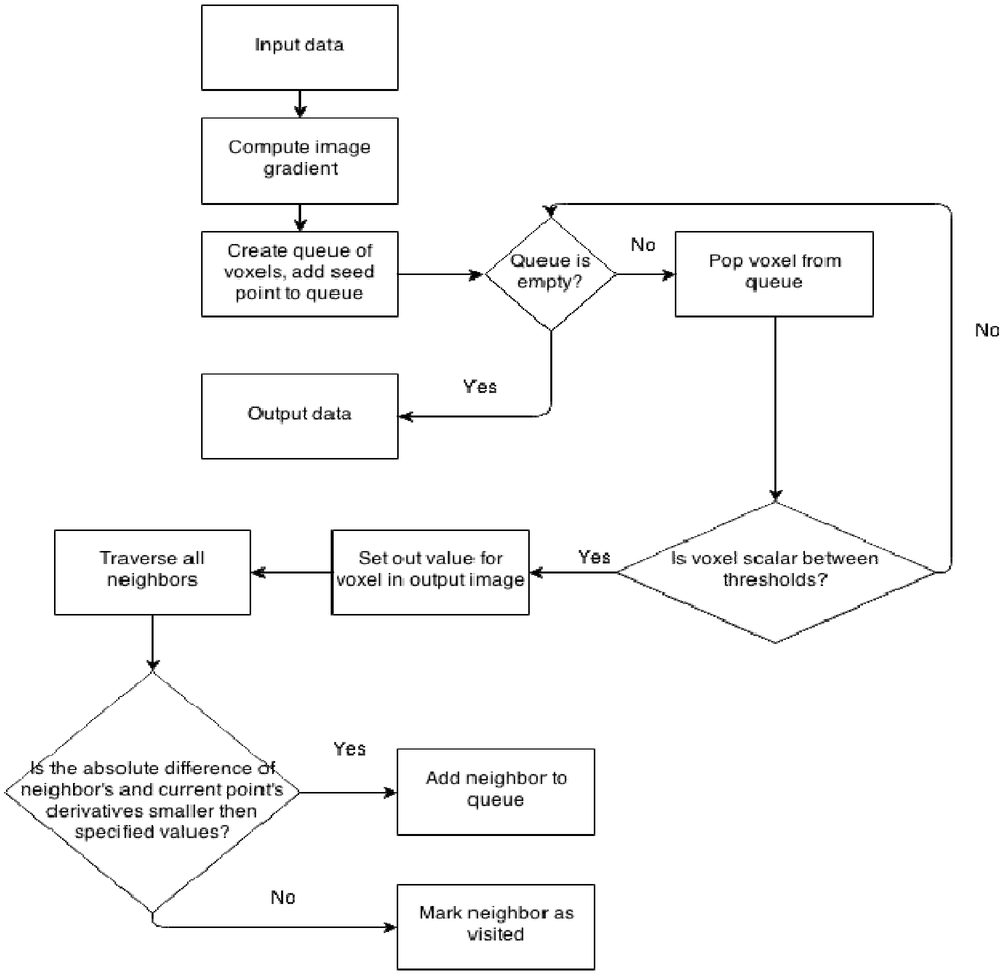

Fig. 12. Region growing segmentation based on the analysis of 3d local neighborhood

Conclusion

Region growing approach could be used with Energy functions, Bayesian functions, wavelets and fractals, and Neural net and may be performed in several ways starting from simple pixel-wise growing to models similar to active contours and "Snakes". However, variety region growing methods either do not use a number of important local characteristics or work slowly. Therefore, new analysis should be introduced. One of new approaches is to analyze global and local information of image.

In medical images segmentation we often could know some image characteristics of region of interest. The first and second derivatives of each point could be computed using Sobel or Laplace filters. Analysis of these characteristics gives us more accuracy and quality of segmentation. The idea is not to add pixels which absolute difference between derivatives of current and neighbor pixel is larger than specified value (table 2).

Table 2

Proposed method

Structure	Seed Index	Lower	Upper	First derivative	Second derivative	Output Image (fig. 3)
White matter	(128, 208, 18)	633,00	826,20	105,00	102,00	Down left
Ventricle	(198, 146, 18)	154,00	440,20	111,00	90,00	Up right
White spot	(174, 210, 18)	973,00	6648,20	164,00	180,00	Down right

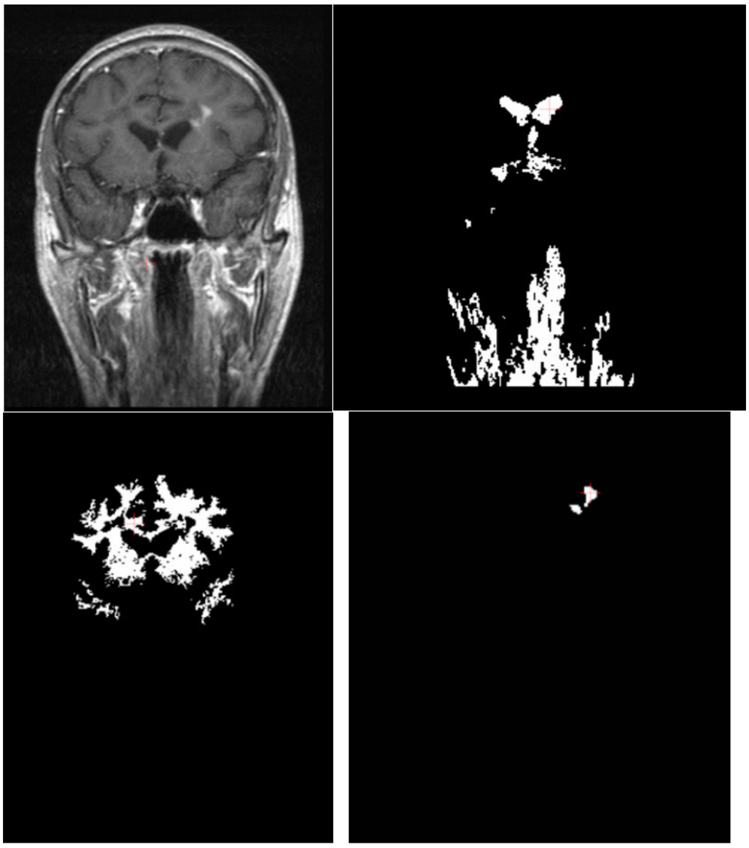

Fig. 13. Segmentation results for the region-growing algorithm with derivatives analysis

Comparing results of Connected Threshold Image Filter segmentation (fig. 1) and Region growing segmentation based on the analysis of 3D local neighborhood (fig. 3) we can admit that proposed method has higher accuracy.

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