Medical Image Segmentation With Wavelet Transform and Information Fusion

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ABSTRACT

A novel method providing a supervised processing of medical image for segmentation is presented. This method was based on a pyramid-structured wavelet-transform and improved watershed transform algorithm. The method contains three consecutive stages: image segmentation based on multi-resolution watershed transform, region projection and mergence with extracted multi-future information, edge refinement based on fuzzy information fusion. In the processing, both texture and gray variation information are used inside the tissue regions, and only gradation information is used near the edges of regions. Experimental results for the proposed algorithm indicate feasibility and reliability for certain medical images segmentation.

Keywords: Image segmentation; Watershed image segmentation; Wavelet transform; Multi-resolution image analysis; MR image;

1. INTRODUCTION

Magnetic resonace (MR) and Computerized Tomography (CT) image segmentation allows the visualization of individual anatomical structures in three-dimensional (3D), which facilitated analysis of pathology for diagnosis, surgery and treatment planning [1-2]. During recent years, a lot of segmentation approaches have been investigated in literatures. However, as the basis of visualization, medical image segmentation still faces many technical problems. According to literatures [3-7]， common segmentation methods are classified as statistics based method, informatics based method and fuzzy clustering method. But many methods are not fast enough or need intensive user interaction. Furthermore, a common problem these methods encountering is hard to discriminate pathological tissue regions from normal tissues, due to noise, blurred object edges, and artifacts in MR images.

In this paper, taking the segmentation of MR brain images as an example, we discuss the approach of segmenting and label meaningful areas from medical images. After a survey, we find out that this kind of image has some obvious features:

1. Different area has its own texture features that denote different tissue types (head, the brain white matter, the brain gray matter).
2. The same area often contains two tissue matters, the object and the boundary.
3. Parts of a tissue adhere to each other, with various degree of intensity. So the brinks, corners and bodies of the objects are difficult to discriminate precisely.

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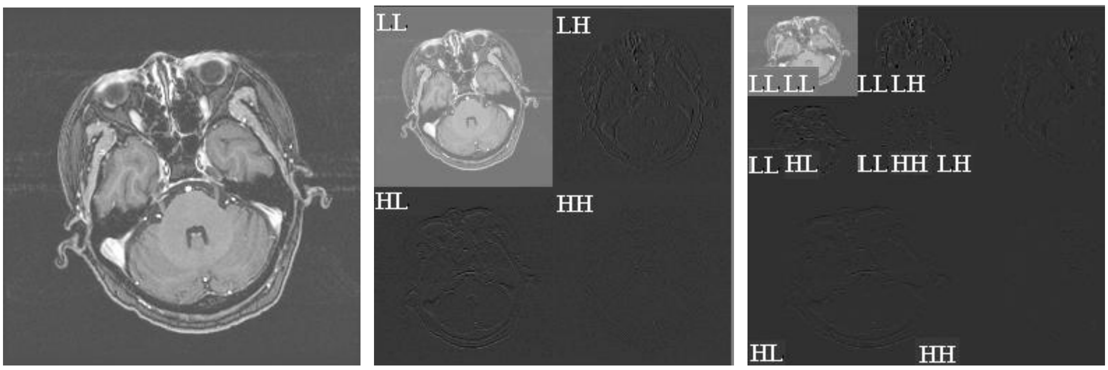
Under this situation, segmentation algorithm only using gray scale information does not work effectively consequentially. To solve the problem, we present a novel method combining multi-resolution Watershed algorithm and region merging using texture features. The method is an improved Watershed algorithm in essence. An important assumption in the method is that there is sufficient feature information in pathological areas in MR image, so we can make use of gray variation information near edges of the region and both gradation and texture information inside the region. Experimental results show that the presented method can accomplish supervised segmentation and automatic labeling of the segmented result efficiently.

This paper is divided into three parts. The first part gives an overview of our method. The second part discusses the three steps, segmentation, the region mergence and the edge refinement, of the method in details. The third part is experimental results and conclusion.

2. FRAMEWORK OF OUR METHOD

Watershed transform is one of the basic segmentation techniques. It is based on mathematical morphology. A major problem in the conventional watershed segmentation algorithm is the severe over-segmentation due to large number of local minima and various background noises. Hence, it is not applied in our method directly. We develop a multi-resolution watershed algorithm using wavelet transform. By this algorithm, over-segmentation and noise problems are gravely reduced as the watershed operation is carried out on the low-pass filtered low-resolution images, meanwhile, depending on the novel image projection and reconstruction algorithm, it can be possible that reducing noises and preserving details at same time.



(a) (b) (c)

Fig.1. Wavelet transform at each scale: (a) original image, (b) one-scale wavelet transform, (c) two-scale wavelet transform

As a multi-resolution analysis tool, wavelet transform provides a precise uniform framework to analyze and formulate signals under multi-resolution. We choose the Haar wavelet transform, considering it can be quickly processed and easy recovered to original resolution. And we use Mallat's pyramid algorithm. Fig.1.illustrates the Wavelet transform. The original image can be decomposed into its wavelet coefficients to provide a smaller resolution image using the pyramid algorithm. Fig.1 shows the hierarchical structure. Ideal wavelet transform is 2 or 3 level. Approaches on wavelet have been investigated in so many literatures that verbose repeats do not needed here. Fig.2 is the main flow chat. First, the lowest subband I_L is segmented into over-segment regions. Then these labeled regions are projected to the next scale by inverse wavelet transform. Finally, after regions mergence and edge refinement, we get the segmentation result at resolution I_{L-1}. This procedure will repeat until full-resolution result obtained.

In the same tissue area, sub-regions of different location have some approximately consistent gray variation and texture feature. Therefore, a region mergence rule based multi-features information is build up by this fact. As far as the blurred boundaries problem is concerned, an edge refinement algorithm is used to solve it. In the human vision system, it is the optical receivers distributed on the retina surface in human eyes that form our vision. The optical receivers divide into two kinds: Pyramidal body and rod-shaped body. The pyramidal body is very sensitive to the color, so it can recognize images in details. And the rod-shaped body is used to produce the whole shapes in the field of vision. Therefore, in human vision system, the contour of observed object always formed in advance, and then more details are distinguished subsequently, judging by psychological parameters such as contrast, texture, shape, structure and color. The edge refinement algorithm simulated the human vision system. We regard the object contour from the pre-segmentation result as the aggregating center and get new edges of the object after data fusing.

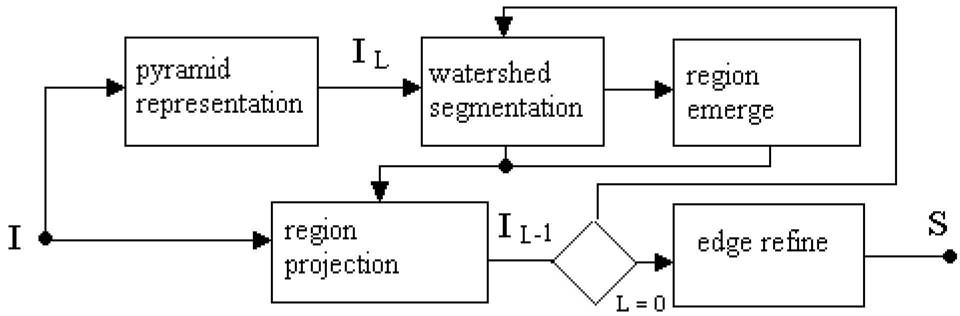


Fig.2. Outline of the method presented.

3. IMAGE SEGMENTATION

Watershed algorithm[8] considers the morphological gradient of the image as a geodesic topographic surface and define the numerical value of each pixel as the elevation at this point. Also local minima of each region and influence zones are called catchment basin, and the boundaries of catchment basins which correspond larger gradient value is named watershed lines. The procedure of the watershed lines merging can be simulated by a flooding procession. Imaging that we pierce each minimum of topographic surface and we plunge this surface into a lake with at a constant speed. The water overflowing the holes floods the surface. During the flooding, two or more floods coming from different minima may merge. So we build a dam on the points of the surface where the floods. At the end of process, only the dams emerge. These dams form the water lines, which are shown in Fig.3.

It is assumed that the lowest-resolution image has been segmented through the watershed algorithm, after creating the pyramid image using a wavelet transform. The following points should be pay attention to:

1. The verges of most regions are ambiguous and gray variation is not intense, so watershed transform should be applied on the gray level image instead of the gradient image.
2. The amount of over-segment regions utterly depends on the flooding criterion.
3. The extent-prior search algorithm assures that pixels joining process is isotropic.

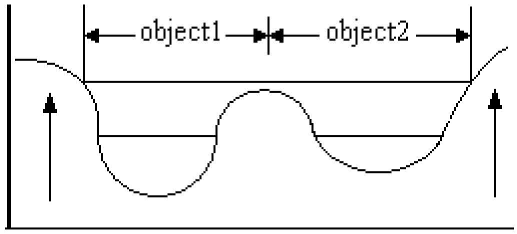


Fig. 3. Watershed algorithm

Thus we replace the conventional watershed algorithm with one based pixel jointing. The improved algorithm just only needs three scans for one image [9]. It even needn't to form the watershed lines but work directly on neighbor domains of pixels. In the 1st scan, if pixel p has any joint pixel points of smaller gray values, it is to be labeled as $l_{\arg}$. If not, this pixel point is the local minimum, labeled as $l_{\min}$. Since the minimum has no neighbors with bigger gradient, point p and its neighbors with the same gray value are classified into the same region. The scan result is recorded in $l(p)$。In the 2nd scan, compute the minimum in every region. We pick out the minimal point by using searching function $find(l, p)$, and label the minimum of the region with the coordinate values of minimal point. In the 3rd scan, all pixels in each region will be denoted with the label of local minimal point. The image segmentation completes.

4. REGION MERGING

Thanks to abundant texture information in brain MRI images, the target regions are not always distinguished mutually by their average luminance values, but very possibly by the texture information described with smoothness, sparseness, period and quasi-period. Therefore we make effectively use of this texture information. Firstly the labeled segmented image is projected to the original image by simple geometry mapping[10], and then pick-up the features information in the original pixel image before regions mergence. The reason that region merging algorithm works in pixel domain instead of wavelet coefficient domain is to avoid losing partial textures details caused by wavelet transformation. The merging rules are as follows:

1. Average gray value of the region G_{th}.
2. The area of the catchment basin S_{th}. Owing to noises or details in the object surface, there exist a lot of catchment basins. The operation of aggregating small basins into their big neighbors can be done to make the result of segmentation more organized.
3. The gray level co-occurrence matrix (GLCM) has been widely used to descript the space correlation and distribution of gray information in images [11]. According to GLCM, we defined an examination rule based on the texture consistency A and the contrast C, and the definition is:

$$W_{A,C} = \sum_{q1}\sum_{q2} |q1 - q2| p(q1, q2) \sqrt{|q1 - q| \times |q2 - q|} \tag{1}$$

Where $p(q1, q2)$ is the co-occurrence matrix P which takes value. $p(q1, q2)$ represents the joint distribution gray gradation of the corresponding position operator. $\sum_{q1}\sum_{q2}|q1-q2|p(q1,q2)$ represents the texture contrast in corresponding position. But considering the differences of texture quasi-periods of the image, we only add a weighting to the contrast value, when only taking the neighbor position operator into account. Also the weighting is related with the error between each operator's position and the mean of gray in object region. This rule can reflect well the similitude and contrast of the textures in an entire region. Texture threshold value:

$T_{th} = W_{A,C}$.

R_n represents the over-segmented region after watershed transform, where n is the number of over-segmented region. A set of statistical characteristics of each region are represented by $SF_{i,j}\,(i \in n,\, j \in m)$, where m is the number of the characteristics. The number is decided by the image's features, for example, for an image in strong contrast, we can add the average boundary gray value into the characteristics set. In this paper, we used three characteristics, $SF_{i,1}, SF_{i,2}, SF_{i,3}$, respectively represents the average gray gradation G_{th}, the region area size S_{th}, and the texture features T_{th}. The basic thought of merging algorithm is: If the difference of statistical characteristics between two regions does not surpass the given criterion, the verdict is that these two regions are of the same segmentation region. First obtains statistical characteristic information of the regions, and then calculates the regions' the characteristic vector mean value $\overline{F_i}$.

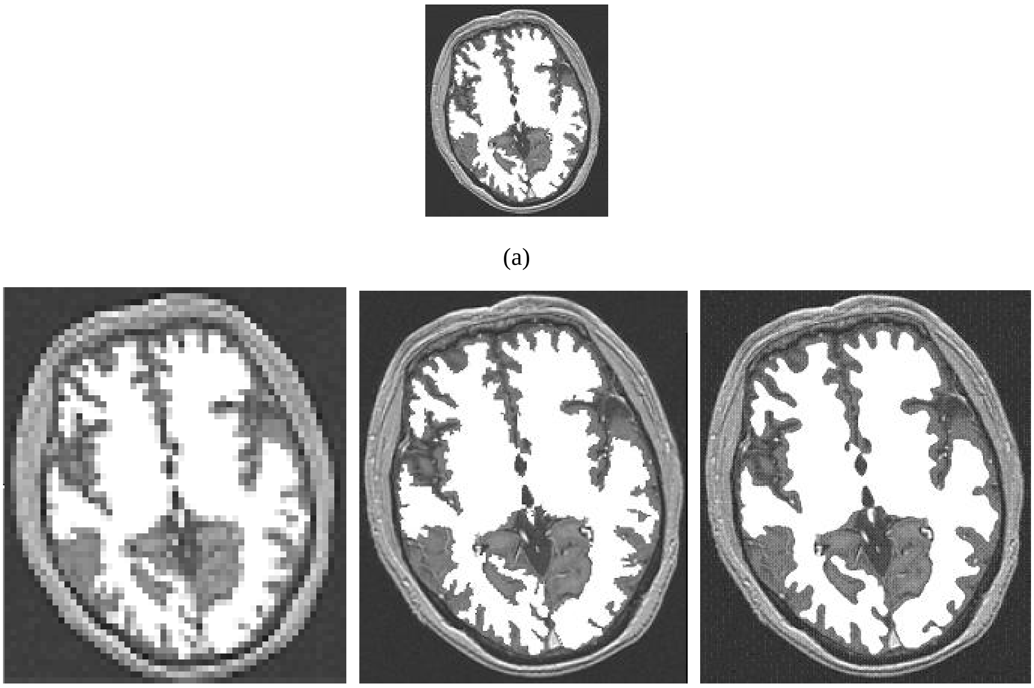
$$\overline{F_i} = \frac{1}{m}\sum_{j=0}^{m} | SF_{i,j} | \tag{2}$$

Where i is the region serial number for computation. Computing the average changing altitude of the statistical characteristic values in neighboring regions: $\Delta\overline{F} = \overline{F_i} - \overline{F_{i-1}}$. The initial threshold value is set to be T. Carry on the region merging by judging the value $\Delta\overline{F}$. If the error value $\Delta\overline{F}$ between two joint regions is smaller than the threshold value T, the mergence happens.

5. REGION PROJECTION AND EDGE REFINEMENT

The medicine image essentially has the fuzziness, including the gradation ambiguity and the geometry fuzziness. But the projection simply based on the coordinate transformation will lose the partial images details, and causes the problem so called mosaic effect. Given the gray gradation information preponderant in the verges of regions, we apply the boundary gradation information model to describe the spatial relations between fuzzy small regions and the entire region, and describe the information of the model with fuzzy logic. Finally fuses these fragments with the information fusion technology.

By an inverse wavelet transformation and the coordinate transformation, the labeled result of the low-resolution image segmentation is projected to the next level. For the boundaries of the small over-segmented regions are the potential result of segmentation that we want, assuming the boundaries of the final segmentation result is certainly to be located at the region boundaries obtained by the over-segmentation, and we apply the watershed transformation once more, but on the original image. Then enough small regions are obtained. Defines a structure S to represent the sum aggregate of the small regions r, using equation: $s = \bigcup_{i=1}^{n} r_i$. The problem of edge refinement is equal to finding out a method that distributes these small regions into the respective structure they belongs to, where the structures refer to the pre-segmented regions. In order to describe the mapping from small regions to a structure, we define membership function: $F: R \times S \to [0,1]$, where $F(r,s)$ represents the degree of membership that small regions belong to the structure. Fig.4. is the comparison of different projection and refinement methods.



(a)

(b) (c) (d)

Fig.4. Results of projection: (a) segmented image, (b) direct projection, (c) our projection, (d) edge refined image using our projection.

5.1. Gray information model

The gray gradation information of a structure is got from the gradation histograms of segmentation samples. The gray gradation f then is obtained from the gaussian function approximately,

$$G(f \mid \mu, \sigma) = \exp[-(f-\mu)^2 / (2\sigma^2)] / (2\pi\sigma^2)^{1/2} \tag{3}$$

Fits the gradation histogram of the structure s with the gaussian function, then we can obtain mean μ and the variance σ of the structure. Meanwhile, we can obtain fuzzy membership degree that small region r subordinates to the structure.

$$F(r,s) = G(\mu \mid \mu, \sigma_s) = \exp[(\mu_r - \mu_s)^2 / (2\sigma_s^2)] / (2\pi\sigma_s^2)^{1/2} \tag{4}$$

Where μ_r in the formula is the average gradation of small region r.

5.2. Edge information fusion

$S_L(p)$ is the labeled segmentation result, and $S_L(p)'$ is the result of projection of $S_L(p)$ by converse wavelet transformation . We apply a watershed transform on the pixel image $I_{L-1}(p)$ of next-level resolution to obtain the water line image $B_{L-1}(p)$. The algorithm steps is described as follows:

1. Firstly project the labeled image $S_L(p)'$ to $B_{L-1}(p)$, and take the segmented tissue regions as the structures. Then set the fusion threshold value and the distance threshold value in advance.
2. In the $B_{L-1}(p)$, compute the membership values of all the small regions r around the structure s . If both the fusion criterion and the distance criterion are meet at the same time, we add the region r to the structure s . This process will not complete until all small regions near the structure are assessed.
3. Finally get the labels from the corresponding positions in $S_L(p)'$ and assign these labels to $B_{L-1}(p)$. Add the new labels s which are got from the edge to $B_{L-1}(p)$, then we obtain the segmentation result $S_{L-1}(p)$.

6. EXPERIMENTAL RESULTS

6.1. Medical image processing and analyzing system

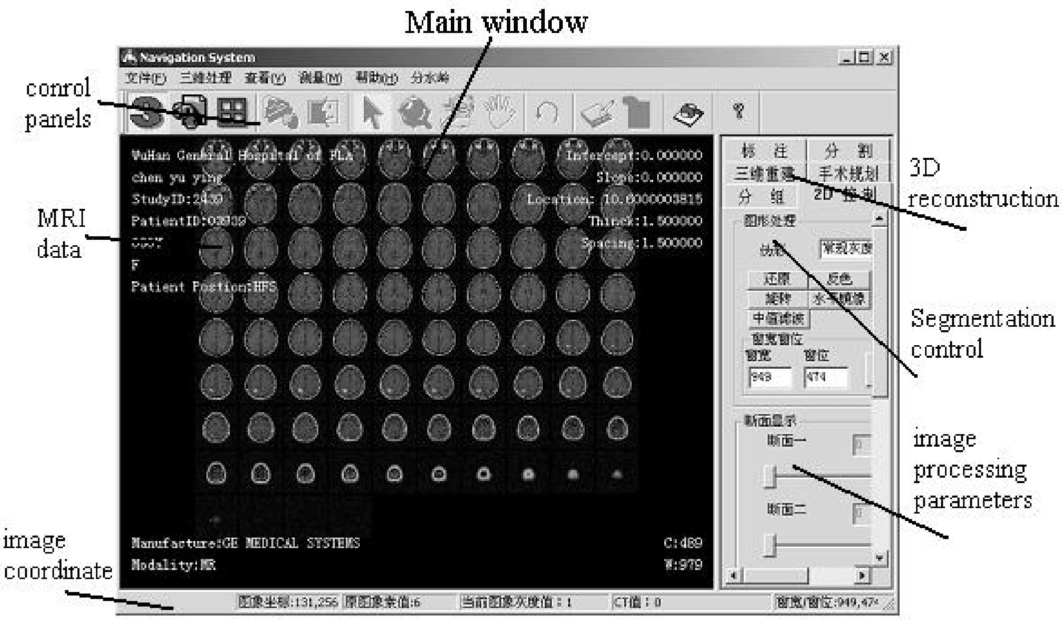
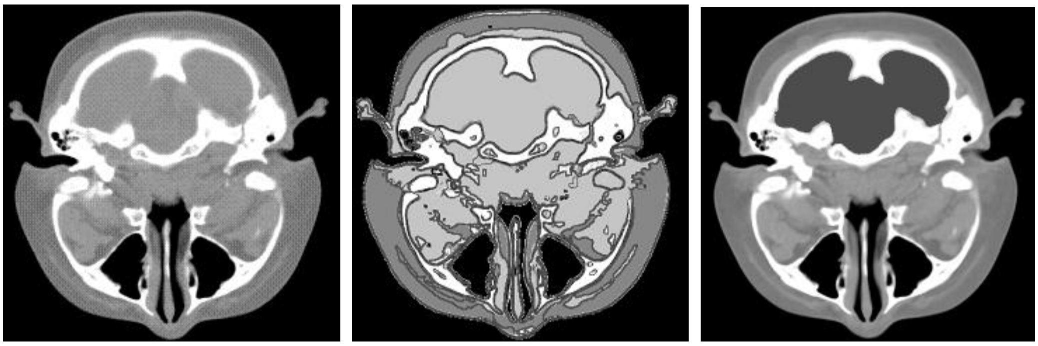


Fig. 5. A medical image procession system using our segmentation method

Fig. 5. is a snapshot of the medicine image processing and analyzing system, with each function unit indicated. The object file of this system is CT, MR and other medicine image datum saving as DICOM format. The basic functions include the image segmentation, the image labeling, the image processing, 3D reconstruction of visualization, the surgery planning function and so on. Among them, the image segmentation and the automatically labeling module have used the algorithms presented in this paper. During processing a medical image, first the system load the image data,

automatically carrying on the image edge searching based on the histogram statistics algorithm, then the user may choose some sub-image, and clicks the mouse on the locations of the tissue areas to be segmented. After adjusting parameters, segmenting and labeling steps, user obtains the final outcome.

6.2. Segmentation results



(a) (b) (c)

Fig.6. The segmentation of the brain MR image: (a) original image, (b) over-segmentation, (c) final segmentation.

We carried on the segmentation experiment by using the medicine image processing and analyzing system above. Fig.6. is segmentation results of a group of brain MR images. The experimental results indicate that, this algorithm presented in this paper can effectively carry on the segmentation to most medical images, in particular to images with obvious texture features and blur boundaries. At the same time, the application of the algorithm has short running time and high efficiency, superior by far to the conventional fuzzy aggregation based region growth algorithm.

7. CONCLUSION

Most of the segmentation methods for medical images, especially for MR brain images, encounter problems brought by noise, blurred object edges, and artifacts. The proposed method in this paper combines Watershed transform and wavelet transform, providing an adaptive multi-level processing of multi-resolution medical images for segmentation. The region merging based texture features and gray gradation information makes the more accurate merging processing, and more reasonable result. The edge refinement based fuzzy information fusion optimizes the blurred segmentation edges. As shown above, the method is robust and efficient, as it works in a low-resolution image and makes full use of the multi-feature information that the image contains. Many a few experimental result shows that the method provides supervised segmentation of images into meaningful classes: CSF, white matter, gray matter, blood, thalamus, ventricles and so on. It can be applied in volumetric labeling and quantification analysis in longitudinal studies.

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