A Saliency Measure Constraint Multi-level Immersion Watershed transformation for Medical Image Segmentation

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***Abstract*—Watershed transformation, comes from mathematical morphology is a powerful tool for image segmentation. Level-by-level immersion simulation is one of the most popular approach for implementing watershed which typically needs additional preprocessing or postprocessing techniques to suppress the oversegmetnation. In this paper, we propose a novel framework that allows the immersion implemented in a multi-level scheme, within which oversegmentation can be reduced effectively during the immersion process. Experiment results demonstrate the superior performance of the Saliency measure based dynamic multilevel immersion watershed framework for the task of white matter and grey matter extraction in MRI brain segmentation.**

I. Introduction

Medical image segmentation algorithms, which used for delineate anatomical structures and other region of interest are key component in assisting and automating diagnosis and treatment planning, and play a vital role in various biomedical image applications.

Numerous segementation algorithms and techniques have been proposed[1]. Among these algorithms, the watershed transformation is a powerful one and has been widely used medical image processing [2], particularly in medical image segmentation[3], due to several advantages it possess: simple, intuitive, fast and can be paralleled, and most importantly, it produce complete division of the image into separate regions, thus avoiding edge joining.

Typically, two types of approach for implementing the watershed transformation are the rainfall simulation [4] and the immersion simulation [5]. The former is is a top-down scheme, with no limitation to the precision of segmentation, while the later is more efficient and suitable for practical implementation in digital spaces.

The important drawbacks of watershed transformation is oversegmentation. Plenty of algorithms have been proposed to overcome it which can be categorized as two types: prepossing and postprocessing. Preprocessing is usually based on choosing seed points, or finding marker image before watershed transformation to guarantee that each marker point growing into one region. Unfortunately, finding markers can itself be problematic.Postprocessing mainly consist in various region merge algorithms after watersed transformation, which focus on merging some of the basin by removing irrelevant watershed. However it is difficult to define proper criteria for all the objects in the image.

In this paper, we make two main contributions. First, a difference function is introduced to measure the saliency of watershed lines. Secondly, we present a framework that allows the immersion based watershed transformation to be implemented in a multi-level scheme, in which unsalient watershed lines can be supreesed during the immersion process. The significant improvement within this framework is that oversegmentation can always be reduced dramatically, while preserving the border of objects.

We now briefly summarize the contents of the paper. In the following section, we present the saliency measure constrained multi-level framework for immersion based watershed and some of the implementation details. In the section III, we introduce three kinds of proposed difference functions In section IV,We show our experiments on grey matter and white matter delineation in 2D brain MRI,compare the proposed framework with the traditional level-by-level framework, analyze the key parameters, and discuss the limitation. In section VI, we make concluding remarks and give direction for the future research.

I. Multilevel Watershed Framework

A. Level-by-Level Immersion Watershed

In the traditional immersion based watershed, pixels are immersed level by level in the immersing process, and pixels of each level being immersed are defined by the threshold set function T_h ,

$$T_h = \{ p \in D \mid I(p) \le h \} \quad (1)$$

And the watershed transformation process can be defined as the following recursion:

First, we define the initial catchment basin set $X_{h\min}$ at each $h = h_{\min}$ as:

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$$X_{h_{\min}} = \{p \in D \mid I(p) = h_{\min}\} = T_{h_{\min}} \quad (2)$$

Then, we define the catchment basins set X_h at each level by recursion as:

$$X_{h+1} = MIN_{h+1} \cup IZ_{T_{k+1}}(X_h), \quad h \in [h_{\min}, h_{\max}) \quad (3)$$

Where $h_{\min}$ and $h_{\max}$ are the minimum and maximum value in the image; X_h is the union of basins at level h ; MIN_{h+1} denotes the union of all the regional minimum at the level h; $IZ_A(B)$ is the union of the geodesic influence zones of the connected components of B: $IZ_A(B) = \bigcup_{i=1}^{k} iz_A(B_i, B)$,Where the geodesic Influence zone $iz_A(B_i, B)$ is defined as : $iz_A(B_i, B) = \{p \in A \mid d_A(p, B_i) < d_A(p, B \setminus B_i)\}$.

Finally, we define the watershed $Wshed(f)$ of f as the complement of $X_{h_{\max}}$ in D:

$$Wshed(f) = D \setminus X_{h_{\max}} \quad (4)$$

B. Multi-Level Immersion Watershed based on saliency measure

Level by level immersion scheme utilize the information of neighbor pixel to label watershed line, this type of highly localized information is adequate in some situations, but has found to be very sensitive to image noise. Therefore we propose a multi-level immersion scheme to take into consideration the information within a larger extent.

For this purpose, we redefine the threshold function as:

$$T'_h = \begin{cases} \{p \in D \mid I(p) - Diff(I(p), h) \le h\}, & Diff(I, h) < thres \\ \{p \in D \mid I(p) \le h\}, & else \end{cases} \quad (5)$$

In this new definition, the pixels being immersed at each level are extended to include both pixels with intensity h and those unsalient watershed line points at higher level. Here $Diff(p,h)$ is used to measure the relative saliency of pixel p to current immersion level h, and if the $Diff$ value is under the specific threshold $thres$, then the pixel p will be regarded as unsalient.

With this new definition T'_k, definition of the traditional level-by-level watershed transformation process can then be redefined as multi-level immersion watershed transformation process as following recursion:

First, the initial image $I_\alpha(p, h_{\min})$ can be obtained at the initial level by following recursion:

$$\begin{aligned} & I_0(p, h_{\min}) = I(p), \qquad p \in D \\ & I_{i+1}(p, h_{\min}) = I(p, h_{\min}) - Diff(p, h_{\min}) \\ & where \quad i = 1, 2, 3 \ldots \alpha \quad and\ p \in IMI(N_G, \quad h_{\min}) \end{aligned} \quad (6)$$

And we get initial catchment basins set $X_{h\min}$ on the obtained initial image $I_\alpha(p,h)$ at level $h = h_{\min}$

$$X_{h_{\min}} = \{p \in D \mid I_\alpha(p, h_{\min}) = h_{\min}\} = T_{h_{\min}} \quad (7)$$

Then, the image $I_\alpha(p,h)$ can be obtained at each immersing level h by following recursion:

$$\begin{aligned} & I_0(p, h+1) = I_\alpha(p, h) \\ & I_{i+1}(p, h+1) = I_i(p, h+1) - Diff(p, h+1), \quad i = 1, 2, 3, \ldots \alpha \\ & where \quad p \in IMI(N_G, h+1) \\ & \qquad IMI(N_G, h) = \{q \mid q \in N_G(p), p \notin T_h \text{ and } I(q) = h \end{aligned} \quad (8)$$

$N_G(p)$ is the set of neighbor pixels of pixel p

And we get catchment basins set X_h on the obtained image $I_\alpha(p,h)$, at each level $h = h_{\max}$:

$$X_{h+1} = \mathrm{MIN}_{h+1} \cup IZ_{T_{h+1}}(X_h), \quad h \in [h_{\min}, h_{\max}) \quad (9)$$

Where $h_{\min}$ and $h_{\max}$ are the minimum and maximum value in the image; and α stands for the iterative times.

Finally, we can get the watershed $Wshed(f)$ of f is the complement of $X_{h_{\max}}$ in D:

$$Wshed(f) = D \setminus X_{h_{\max}} \quad (10)$$

C. Criteria of Designing Difference Function

In our multi-level framework, the difference function can be versatile enough to be designed using any saliency measurement. However, the proper saliency measurement varies from images to images. Here we give out two guidelines for designing the difference function.

Criterion1. The saliency measurement should guarantee of decreasing the number of watershed regions.

Criterion2. The near neighbor pixels are more important to saliency measurement than the far ones.

II. VARIOUS DIFF FUNCTION DESIGNS

In this section, we introduce three specific *Diff* functions.We present these functions as examples of how immersion watershed can be improved by implemented in a saliency constrained multi-level immersion scheme.

A. Multilevel function1: Maximum Difference Constrained

$$Diff(p,h) = \max_{q \in N_G(p) \text{ and } I(p,h) \ge I(q,h)} \{I(p,h) - I(q,h)\} \quad (11)$$

Here the difference function is defined as the maximum difference between the intensity of p and its neighbor pixels whose intensity is less than h.

B. Multilevel function2: Minimum Difference Constrained

$$Diff(p,h) = \min_{q \in N_G(p) \text{ and } I(p,h) \ge I(q,h)} \{I(p,h) - I(q,h)\} \quad (12)$$

Here the difference function is defined as the minimum difference between the intensity of p and and its neighbor pixels whose level is less than h.

C. Multilevel function3:Mean Difference Constrained

$$\begin{aligned} & Diff(p,h) = \sum_{q \in \{p, N_G(p)\} \text{ and } I(p,h) \ge I(q,h)} (I(p,h) - I(q,h)) / n \\ & where \quad n = \| q \in \{p, N_G(p)\} \text{ and } I(p,h) \ge I(q,h) \| \end{aligned} \quad (13)$$

Here the difference function is defined as the difference between intensity of p and the average intensity of its neighbor pixels whose level is less than h.

III. EXPRIMENTS AND RESULTSS

In order to demonstrate the strengths and limitations of the proposed saliency constraint multilevel immersion watershed approach, it was tested on a challenging application: white matter and grey matter extraction from brain MRI. In this case, we use the standard 2D Brain MRI Image from McConnell Brain Imaging Center, with size of 334 * 400 pixels.

We first compare the proposed scheme with the traditional level-by-level scheme to show its superiority in reducing the oversegmentation and its speed property. We then continue with a study of the effects of using different difference function and saliency threshold to the accuracy of white matter and grey matter extraction.

A. Criteria for performance evaluation

In order to accurately assess the performance of different watershed segmentation method, we first give out some criteria for evaluation:

1) Oversegmentation

Oversegmentation occurs when more than one segment is produced for a given semantic object in the image, we use the region numbers (RN) and oversegmentation degree (OV) as two criteria for evaluating the oversegmentation:

$$OVD(g) = \frac{1}{|C|}\sum_{i=1}^{|C|}\frac{|S_i|}{|R_i|} \qquad (14)$$

where g is a given image, $|C|$ is the number of the classes, $|S_i|$ is the number of segmented regions which contain at least one pixel of the class C_i, and $|R_i|$ is the number of reference regions for the class C_i.

2) Accuracy

Here the accuracy of segmentation is evaluated by the sensitivity of segmentation, which is defined as:

$$SEN = \frac{TP}{TP+FN} \qquad (15)$$

where TP, TN, FP, FN stands for then number of pixels that labeled true positive ,true negative, false positive, and false negative

B. Steps for white matter and grey matter extraction

The whole process for white matter and grey matter extraction is perfomed as the steps shown in the Fig.1

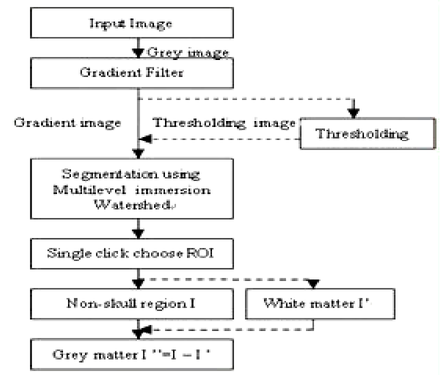
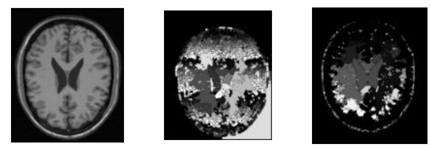


Fig. 1. Flow chart for the whole process of white matter and grey matter extraction in 2D brain MRI

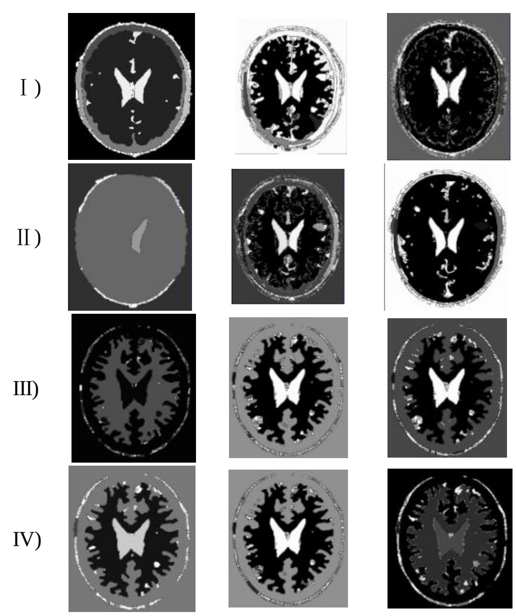
C. Results and Performance



(a) (b) (c)

Fig.2. 2D brain MRI and Segmentation result using level-by-level watershed. (a),(b),(c) shows the original image, result of level-by-level watershed on gradient image, result of level-by-level watershed on thresholding image respectively

1) Initial segmentation with Multilevel watershed



(a) (b) (c)

Fig. 3. Segmentation result for 2D brain MRI using multi-level watershed. Column (a),(b),(c) show the result of multilevel function1, multilevel function2, multilevel function3 respectively. In each column, row I), II) show the result of performing algorithms on gradient image with saliency threshold=3, and saliency threshold=5, and row III), IV) show the result of performing algorithms on thresholding image with saliency threshold=3, and saliency threshold=5, respectively.

TABLE I
OVERSEGMENTATION AND TIME COMPLEXITY

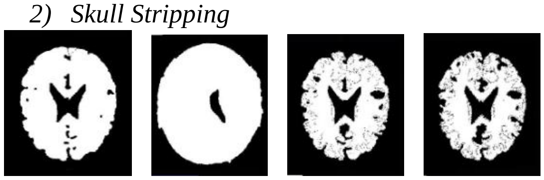
preprocess	Watershed scheme	RN	OVD	TC
Gra	Level-by-level	1379	257	562
Gra	Multi func1, thres=3	532	68	2215
Gra	Multi func1, thres=5	515	52	3619
Gra+Thr	Multi func1, thres=3	921	60	466
Gra+Thr	Multi func1, thres=5	456	48	456
Gra	Multi func2, thres=3	89	6	1092
Gra	Multi func2, thres=5	30	2	2153
Gra +Thr	Multi func2, thres=3	211	25	734
Gra+Thr	Multi func2, thres=5	128	15	764
Gra	Multi func3, thres=3	129	11	1419
Gra	Multi func3, thres=5	68	5	2231
Gra+ Thr	Multi func3, thres=3	280	37	733
Gra+ Thr	Multi func3, thres=5	213	24	749

Gra=Gradient fileter; Thr=Thresholding with low level =108 and high level = 163; RN = Region Number; OVD = OVersegmentation Degree; TC=Time Complexity (ms) , In each watershed transformation, we check 8-connection in the neighbourhood

Fig. 4. The table show the corresponding performance of suppressing oversegmentation of the leve-by-level watershed, multilevel watershed function1, multilevel watershed function2, and multilevel watershed function3

This experiment shows that compared with the traditional level by level scheme, the proposed method can reduce the oversegmentation while preserve the important feature.Multi function 2 out perform the other two functions in reducing both RN and OVD criteria, indicating its superiority in both reducing the oversegmentation and preserving the important feature. While Multi function 1 only show superiority in reducing the RN, and multi function 3 only show superiority in reducing OVD

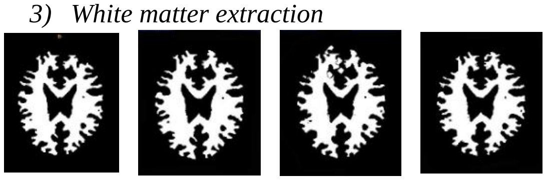
2) Skull Stripping



(a) (b) (c) (d)

Fig. 5. Skull stripping result for 2D brain MRI. (a),(b),(c) (d)shows the result by choosing ROI on column(a)(c) and row(Ⅰ)(Ⅱ) in Fig.3.

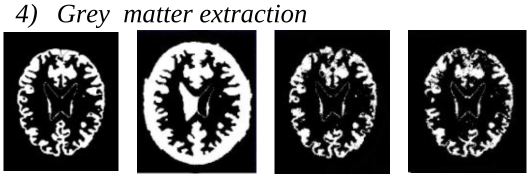
3) White matter extraction



(a) (b) (c) (d)

Fig. 6. White matter extraction result for 2D brain MRI. (a),(b),(c) (d)shows the result by choosing ROI on the result by choosing ROI on column(a)(c) and row(Ⅰ)(Ⅱ) in Fig.3.

4) Grey matter extraction



(a) (b) (c) (d)

Fig. 7. Grey matter extraction result for 2D brain MRI. (a),(b),(c) (d)shows the result by subtracting white matter in choosing ROI on column(a)(c) and row(Ⅰ)(Ⅱ) in Fig.3.

TABLE II
ACCURACY

preprocess	Multilevel Function 2		Multilevel Function 3	
	Thres = 3	Thres = 5	Thres = 3	Thres = 5
GM	93.28%	36.74%	92.19%	34.21%
WM	85.21%	69.78%	84.84%	57.36%
BR	97.57%	14.23%	94.18%	11.29%

ACCURACY = TP/(TP+FP); TP=True Positive; FP=False Positive

Fig. 8. The table show the corresponding accuracy of segmentation using multilevel function 2 and multilevel function 3

This experimentation shows two points: First, multilevel function 2 always achieve higher accuracy for segmentation. Secondly, comparatively lower saliency threshold lead to higher segmentation accuracy and the vice versa.

The explanation for the effect of using different saliency threshold is that higher salient threshold will place stricter constraint on potential watershed line point, however a n excess higher threshold will suppress some of the real boundary points.

IV. CONCLUSIONS

In this paper, we present a new saliency measurement constraint multilevel immersion scheme for implementing the immersion watershed transformation which show significant superiority to the traditional level-by level scheme. First, unlike the traditional level-by-level immersion scheme, the proposed multi level immersion scheme can reduce the oversegmentation significantly by taking information in a lager scale into consideration. Secondly, the imposed saliency measurement constrain guarantee the accuracy of the segmentation result by preserving the important feature in the image. Furthermore, within our scheme, the saliency measurement is flexible and easy to design according to different images.

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