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An Image Segmentation Method by Multi-scale Local Thresholding Based on Class Uncertainty Theory *

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***Abstract*— Image segmentation is one of the most important core technologies in the field of image processing and computer vision, which has lots of applications specifically in medical image analysis. Due to medical imaging mechanism, medical images usually suffer from heavy noises, uneven intensity distribution and fuzzy boundaries between biological tissues. That makes classical segmentation methods based on global or local thresholding difficult to get accurate results. This paper proposes an image segmentation method by multi-scale local thresholding based on class uncertainty theory. Firstly, the original image is divided into a set of sub-regions with different scales by using a multi-layer pyramid structure. Secondly, the energy function with inequality constraints is constructed based on class uncertainty and region uniformity. Then by an iterative process, the optimal local threshold for each sub-region are calculated by an optimization algorithm for each layer until the final optimal threshold mask is determined for image segmentation. Experimental results verify that the proposed method can effectively eliminate the interferences caused by image noises, intensity unevenness and fuzzy boundaries, and preserve details of object structure while segmenting the object from the background. Segmentation results demonstrate the superior performance of the proposed method by comparison with supervised range-constrained thresholding methods (RCOtsu), classical global/local Otsu method, and the minimization of homogeneity- and uncertainty-based energy method (MHUE).**

***Index Terms*— image thresholding,class uncertainty,local threshold.**

I. Introduction

Image segmentation is one of the most important technologies in the field of digital image processing.In the field of medical imaging, accurate image segmentation is important for analyzing the anatomical structure of organs, determining the location of lesions, and subsequent diagnosis and treatment.The traditional image segmentation methods can be roughly divided into the following categories: (1) Edge-based image segmentation methods: such methods achieve segmentation by detecting the boundaries in the image. There are many commonly used gradient operators on extracting the edge of the image such as Sobel operator, Canny operator and so on. The advantage of such a method is that it can calculate fast and the edge can be quickly located. However, the methods anti-noise performance is poor, and it is difficult to ensure the continuity of the edge; (2) Region-based image segmentation methods: such methods utilize the local spatial information of the image to connect pixels with similar characteristics to achieve segmentation [1]. Such methods have a good segmentation effect for continuous uniform regions, but are sensitive to noise. In addition, the selection of seed point position often determines the image segmentation effect. (3) Edge- and region-based image segmentation methods: such methods have better effect on uniform connected images[2]. (4) Image segmentation methods based on function optimization: such as the Markov random field method and so on [3]. (5) Thresholding: such as the Otsu method, which uses the information of the image intensity histogram to select the optimal threshold[4]. (6) Image segmentation methods based on neural network: such methods import a large amount of image data into the neural network for training to achieve image segmentation. Such methods have excellent effects, but the processing speed is too slow to process real-time data [5].

Due to the complexity of the human body structure and the inevitable noise, field shift effect, local body effect, etc. in the imaging process of medical imaging equipment, there are problems in medical images, such as large noise, blurred

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boundaries, and uneven gray distribution [6], making the segmentation of medical images more difficult and complex, and because of which, traditional image segmentation methods are often difficult to achieve accurate segmentation of medical images. In recent years, a lot of relevant scholars have proposed many excellent methods to solve these problems. Ahmed et al. [7] proposed an improved fuzzy clustering algorithm, which has high accuracy for the segmentation of magnetic resonance imaging (MRI) images, but a large number of computation is required for each iteration , which is inefficient. Li et al. [8] proposed an improved cuckoo search optimization algorithm based on the maximum entropy multi-threshold segmentation method, which has better accuracy and efficiency than traditional methods and has better robustness. Zhang et al. [9] proposed an algorithm for automatically segmenting kidney tissue based on the active contour and graph cut energy minimization segmentation model. This method performs well on the overall segmentation of the kidney, but it has a poor effect on the internal division of the kidney. Yuan et al. [10] proposed a weighted target variance method based on Otsu, which weights a parameter equal to the cumulative probability of defects to the target variance of the variance between classes. The segmentation results of this method performs better than other threshold methods. Saha [11] proposed a classic Minimization of Homogeneity- and Uncertainty-based Energy (MHUE) method, which can overcome the problem of boundary blur in medical images effectively. Due to the global threshold, it has a poor performance when segmenting images with large noise or uneven gray scale distribution. Hu et al. [12] proposed a method based on supervised data to obtain a limited target gray frequency range and solve the optimal segmentation threshold. The method has high computational efficiency and can be widely applied to various computer vision problems such as character recognition and fingerprint recognition.

This paper proposes a method based on class uncertainty theory to solve the optimal multi-scale local threshold and realize image segmentation. The basic idea is to define a set of multi-scale sub-regions on the original image based on the pyramid-based hierarchical structure, and use the classical class uncertainty method to obtain the global optimal threshold, which is used as the initial estimate of threshold of each sub-region in the first layer. Then, based on the global gray distribution statistical rule, a constrained energy function is constructed for each sub-region of each layer, and the optimal threshold of each sub-region is solved layer-by-layer through the iterative process until the average class uncertainty measure of all sub-region is less than a predefined value. Finally, the algorithm solves a mask of the same size as the original image, and contains the optimal local segmentation threshold for each multi-scale sub-region. Compared with other classical thresholdings, the experimental results show that the segmentation effect of our method is obviously better than other methods.

II. Theories and methods

The method proposed in our paper is a thresholding method for image segmentation, which is to define objects in images by selecting an appropriate threshold. In theory, this type of method works when the grayscale distribution of the foreground and background respectively meets a certain statistical distribution law. In the field of medical image analysis, one of the characteristics of medical imaging equipment imaging is that the gray scale distribution of specific human tissue images will satisfy certain statistical laws, so threshold selection methods are widely used in this situation. The most representative threshold selection method is the MHUE method proposed by Saha in 2001 [11], which is a global method. This method is effective when dealing with the images with fuzzy boundaries, for its comprehensive consideration of the effects of class uncertainty and region uniformity. Fig.1 shows the class uncertainty graph and the result of the method using the global optimal threshold. However, this method has a poor effect when dealing with images with large noise or uneven local gray distribution, especially in the case of subject details. There is a big difference of class uncertainty and Region Homogeneity between the local area and the global image, so the global optimal threshold may be not optimal in some local area. Fig.2 shows a case of mis-segmentation. For the selected image local region, the global optimal threshold given by MHUE is equal to 118. It is obvious that the segmentation result incorrectly preserves noise and some redundant structure. Actually, the local optimal threshold at this time should be slightly lower, setting it as a value of 110 will obtain a significantly improved result. So using the local optimal threshold can result in better segmentation. Based on the class uncertainty theory proposed by Saha [11], our paper proposes an image segmentation method for solving multi-scale local optimal thresholds, and determines the local region location, size and its optimal threshold. The flow chart is shown in Fig.3.

A. *The multi-scale local region space is constructed and the optimal local threshold is solved layer by layer*

1) Construct multi-scale local region space: We propose a pyramid-type region block iterative algorithm In our paper. We can get a set of multi-scale sub-regions after the iterative process. By using the local optimal threshold of each sub-region, the segmentation of local image, where the gray scale distribution is imbalance, is more accurate than using the global threshold. Also, the continuity in the local region is better than the local threshold segmentation method such as Otsu.The specific multi-scale local region space construction method is as follows.

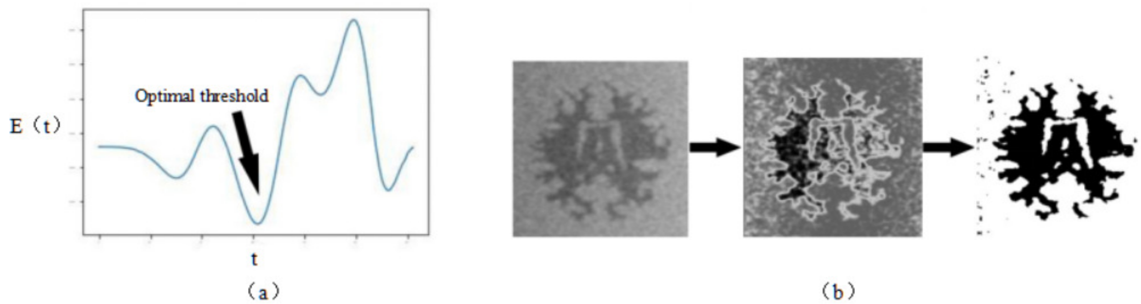


Fig. 1: (a) The distribution map of energy function E(t) for the image.(b) From left to right: Original image, class uncertainty map and segmentation result under global optimal threshold.

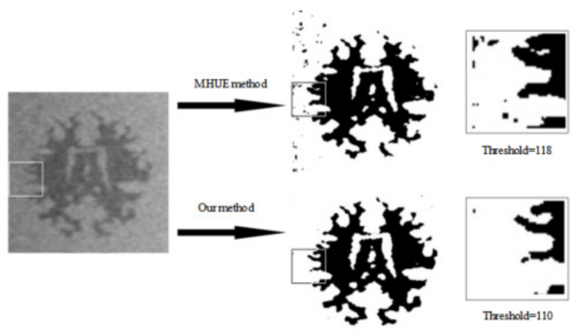


Fig. 2: Comparison of image segmentation results.

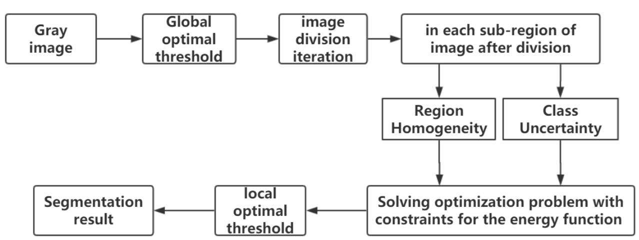


Fig. 3: Flow chart of the proposed algorithm.

Firstly, we divide the input image S into four rectangular sub-regions S_{ij} overlapping each other, where $j = 1, 2, 3, 4$ and i represents the layers of iterated ($i = 1$ here); j represents 4 rectangular sub-area numbers in each layer. Then we calculate the local optimal t_{1j} and the average class uncertainty H_{1j} for each S_{1j} ,where $j = 1, 2, 3, 4$. If H_{1j} is greater than the predetermined value H_α, then we divide S_{1j} into four sub-region S_{2j}, where $j = 1, 2, 3, 4$ continue doing so until average class uncertainty H_{ij} of every single S_{ij} is less than or equal to the predetermined value H_α or the layer i=5. In this way, we construct a multi-scale local region space and obtain the local optimal threshold t_{ij} for each S_{ij}. The process is shown in Fig.4.

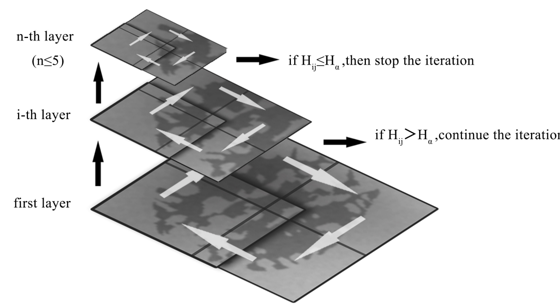


Fig. 4: Schematic diagram of the process for image division.

2) The optimal local threshold is solved layer by layer: We assume that S is a square with a side length of a, then S_{1j} is a square with a side length of 0.6a. In this way, each layer S_{ij} will be divided into four rectangles $S_{(i+1)j}$ with an area of 0.36 times S_{ij}. The purpose of constructing the overlapping region in the division process is to make the average value of the adjacent sub-regions as the optimal threshold of the overlapping region after calculating the local optimal threshold t_{ij} of each sub-region S_{ij}, so as to ensure that the segmentation region has better continuity.

When calculating the local optimal threshold of the four sub-regions of each layer, we first calculate the global optimal threshold of the image based on the MHUE method, and add the following restrictions t_α on the local optimal threshold d-ifference of the adjacent sub-regions. Set the global threshold as the starting point, search for the local optimal threshold t_{1j} for each sub-area of the first layer S_{1j}.

$$\max_j (t_{1j}) - \min_j (t_{1j}) \leq t_\alpha, j = 1, 2, 3, 4 \quad (1)$$

By analogy, when searching for the local optimal threshold of the 4 sub-regions of the $i + 1$th layer, the optimal threshold t_{ij} of the image S_{ij} of the previous layer is the search starting point, and the constraint is imported as shown in formula (1).

Algorithm 1 Image division algorithm.

Input: S:image to be divided
Output: $Mask$: a 4*i array
i=0
while $H(t_{ij})>H_\alpha$ && i<5 **do**
  $i=i+1$
  divide S_{ij} into four sub-regions: S_{i1}, S_{i2}, S_{i3}, S_{i4}
  solving following optimazation problem with constraint:
  $minE_i(t)$
  $s.t. \max_j(t_{ij})-\min_j(t_{ij})\le t_\alpha, j=1,2,3,4; i=1,2...n;$
  obtain local optimal thresholds: t_{i1}, t_{i2}, t_{i3}, t_{i4}
  for $j=1, j\le 4, j++$ **do**
    if $H(t_{ij})>T_\alpha$ **then**
      break
    else
      $Mask_{ij}=t_{ij}$
    end if
  end for
end while

When the search is done, we assume that the gray value of the pixels in each sub-area satisfies the gray distribution law of the global image, and thus the average class uncertainty H_{ij} of each sub-area S_{ij} under its local optimal threshold t_{ij} can be calculated. The expression is as follows :

$$H_{ij}=\frac{\sum_{s\in S_i} H_{t_{ij}}(g_s)}{|S_{ij}|} \tag{2}$$

$H_{t_j}(g_s)$ is the class uncertainty when the gray level of the pixel s is g_S. $|s_{ij}|$ is the number of pixels in the image S_{ij}.

After obtaining t_{ij}, we set the average value of the local optimal threshold of the adjacent sub-regions as the threshold of the overlapping regions. Finally, we obtain a mask of the same size as the original image. The pseudo code of the algorithm in this paper is shown in Algorithm 1.

B. The optimal threshold of multi-scale local area is solved based on the theory of quasi-uncertainty

1) Measurement of class uncertainty and regional uniformity: Let S denotes the set of all pixels in the input image, s denotes a single pixel in the image, its gray value is g_s. Also, θ represent the probability of a pixel in the image belongs to the object. Similarly, $1-\theta$ represent the probability of a pixel belongs to the background. Then, the probability that a pixel with intensity value g belongs to the object or the background can be expressed as:

$$\begin{aligned} P_{\mathrm{o}}(g_s=g)=P(f(s)=g|s\in F_o)\\ P_{\mathrm{b}}(g_s=g)=P(f(s)=g|s\in F_b)\end{aligned} \tag{3}$$

Where F_o is the set of pixels of object and F_b is the set of pixels of background. As [11] and [13] proposed, when the intensity value of a pixel in the image is g, the class uncertainty that the pixel belongs to the object or background is the entropy of its posterior probability, and thus the class uncertainty Ht (when the intensity value gs of the pixel s is g) is obtained under the threshold value t can be expressed as

$$\begin{aligned} H_t(g_s=g)=-\tfrac{\theta(t)P_{o,t}(g)}{P_t(g)}\log\tfrac{\theta(t)P_{o,t}(g)}{P_t(g)}\\ -\tfrac{(1-\theta(t))P_{b,t}(g)}{P_t(g)}\log\tfrac{(1-\theta(t))P_{b,t}(g)}{P_t(g)}\end{aligned} \tag{4}$$

And $P_{o,t}(g)$ and $P_{b,t}(g)$ can be expressed as:

$$p_{o,t}(g_s=g)=\frac{1}{\sqrt{2\pi}\sigma_o(t)}e^{-\frac{(g-m_0(t))^2}{2\sigma_o(t)^2}} \tag{5}$$

$$p_{b,t}(g_s=g)=\frac{1}{\sqrt{2\pi}\sigma_b(t)}e^{-\frac{(g-m_b(t))^2}{2\sigma_b(t)^2}} \tag{6}$$

Where $m_o(t)$ and $m_b(t)$ are the means of the pixel intensities belonging to the object and background respectively. $\sigma_o(t)$ and $\sigma_b(t)$ denote the standard deviations of the pixel intensities belonging to object and background.

The region homogeneity $\mu(s)$ of the pixel s can be expressed as follow:

$$\mu(s)=1-G_\tau(s) \tag{7}$$

The expression of $G_\tau(s)$ is as follow:

$$G_\tau(s)=\frac{G(s)-G_{\min}}{G_{\max}-G_{\min}}, G(s)=\sqrt{G_x^2+G_y^2} \tag{8}$$

Where G_x, G_y are calculated by Sobel operator, $G_{\min}$, $G_{\max}$ are the minimum and the maximum value of the $G(s)$. Region homogeneity reflects the connectivity between the pixel gray levels, and the larger the value, the stronger the connectivity between the pixel gray levels.

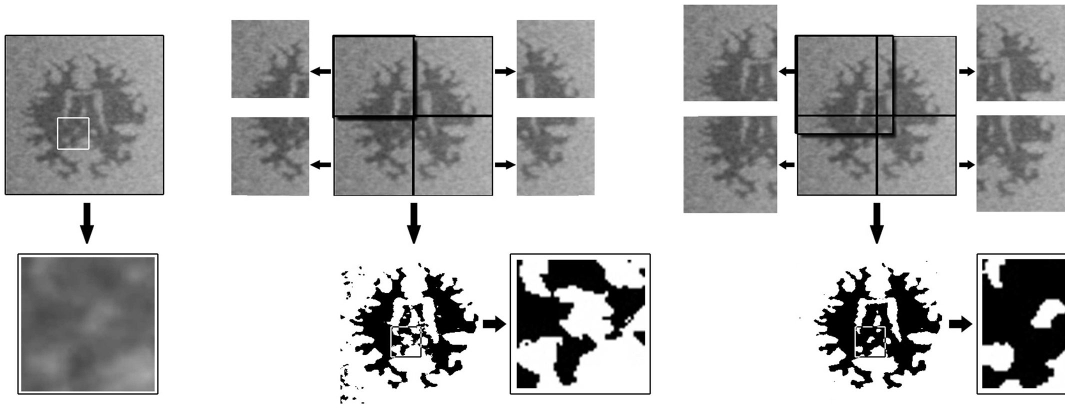
2) Construction of energy function and optimization problem solving: We construct the following energy function for each sub-region after iterations that the image S has been devided into several sub-region S_{ij}.

$$E_i(t)=\sum_{j=1}^{4}\sum_{s\in S_{i,j}} H_{t_{i,j}}(g)\mu(s)+\left(1-H_{t_{i,j}}(g)\right)(1-\mu(s)) \tag{9}$$

Where i is the number of layers of iterative, j is the number of four sub-region of each layer, and S_{ij} is the $j-th$ image of the $i-th$ layer in the iterative process of image division . $H_{t_i}(g)$ is the class uncertainty of pixel s with intensity value g under the threshold t_{ij}, and μ represent the region homogeneity of the image.

In this energy function, the class uncertainty interacts with the region homogeneity. When the class uncertainty and the region homogeneity are both small or large, the value of the energy function will be larger. The smallest energy value may be obtained with a large region homogeneity and a small class uncertainty. Therefore, in the iterative process, the threshold at which the energy function of each layer is the smallest is the local optimal threshold for the layer.

In addition, local thresholding such as Otsu method ignores the connection between adjacent local regions, resulting in the uncontinuity in the result of the image segmentation. To



(a) (b) (c)

Fig. 5: Comparison diagram of Image segmentation strategy. (a)The original image. (b)Segmentation result of Local Otsu method. (c)Segmentation result of the proposed method

solve this problem, we adopt two strategies to ensure the continuity between adjacent sub-regions.

Introducing the constraint that the difference between the thresholds of the four adjacent sub-regions is less than a certain threshold t_α, and obtaining the local optimal threshold of each sub-region by solving the following optimization problem with constraints.

$$\begin{aligned} &\min\nolimits_t E_i(t) \\ &\text{s.t. max } (t_j) - \min\nolimits_j (t_{ij}) \leq t_\alpha, j = 1,2,3,4; i = 1,2\ldots n \end{aligned} \tag{10}$$

When dividing the image into four sub-regions, there is a overlap between adjacent sub-regions (as shown in the upper right corner of Fig.5. On one hand, this strategy can make the calculation of the local optimal threshold of adjacent sub-regions fully consider the influence of gray-scale changes in overlapping boundary regions, thus ensuring that the lcoal optimal threshold of adjacent sub-regions obtained by optimization calculation will not be much different. On the other hand, since the threshold of the overlapping portion is taken as the average value of the local optimal thresholds of the adjacent sub-regions, the value considers the influence of the adjacent two sub-regions at the same time, thereby further the continuity of the segmentation result.

Fig.5 shows the effect of different image dividing strategies on the segmentation results. Consider the overlapping part of the sub-area. It is obvious that the simple division strategy of the Ostu's local method may cause the incontinuity of the boundary of the sub-regions, but our method guarantees the continuity of the object of the sub-region's boundary.

In conclusion, when searching for the local optimal threshold, by adding the limitation of the difference between the local optimal threshold of adjecent sub-regions and making the adjecent sub-regions overlapped with each other at the boundary, we can obtain close local optimal threshold for the four adjecent sub-regions. In this way, the segementation result is not only continuous, but also retains more accurate details.

III. Experiment Results

In order to demonstrate the effectiveness and robustness of the proposed method, we design two sets of experiments to segment testing images.We select two testing images, one is the brain slice model image P_1(from BrainWeb dataset, $https://brainweb.bic.mni.mcgill.ca/brainweb/$) and the other one is the rice image P_2, as are shown in Fig.6. The experimental design is based on Visual Studio 2013 and OpenCV3.1. The hardware platform is Intel(R) Core(TM) i7-6700 CPU @ 3.40GHz 3.41GHz and memory is 16G.

Local Otsu method, MHUE and RCOtsu method are also applied on the testing images to compare with the proposed method. For local Otsu method, the block size is 55 and the parameter c is set to 15. For RCOtsu method, refer to [12], we can obtain the value of parameter r_{low} is 38 and r_{high} is 87. For the proposed method in this paper, the parameters H_α and t_a affect the number of iteration layers in different regions, we obtained the optimal parameter value in the experiment. Finally,we set the multi-scale space iteration termination condition H_α to 0.1 , and set the difference between the thresholds of adjacent regions at the same scale to be no more than 5, which means $t_a = 5$.

In order to quantitatively evaluate the accuracy of segmentation algorithm, this paper uses misclassification error (ME) to measure the efficiency of segmentation. The function is as follows:

$$ME = 1 - \frac{|B_G \cap B_T| + |F_G \cap F_T|}{|B_G| + |F_G|} \tag{11}$$

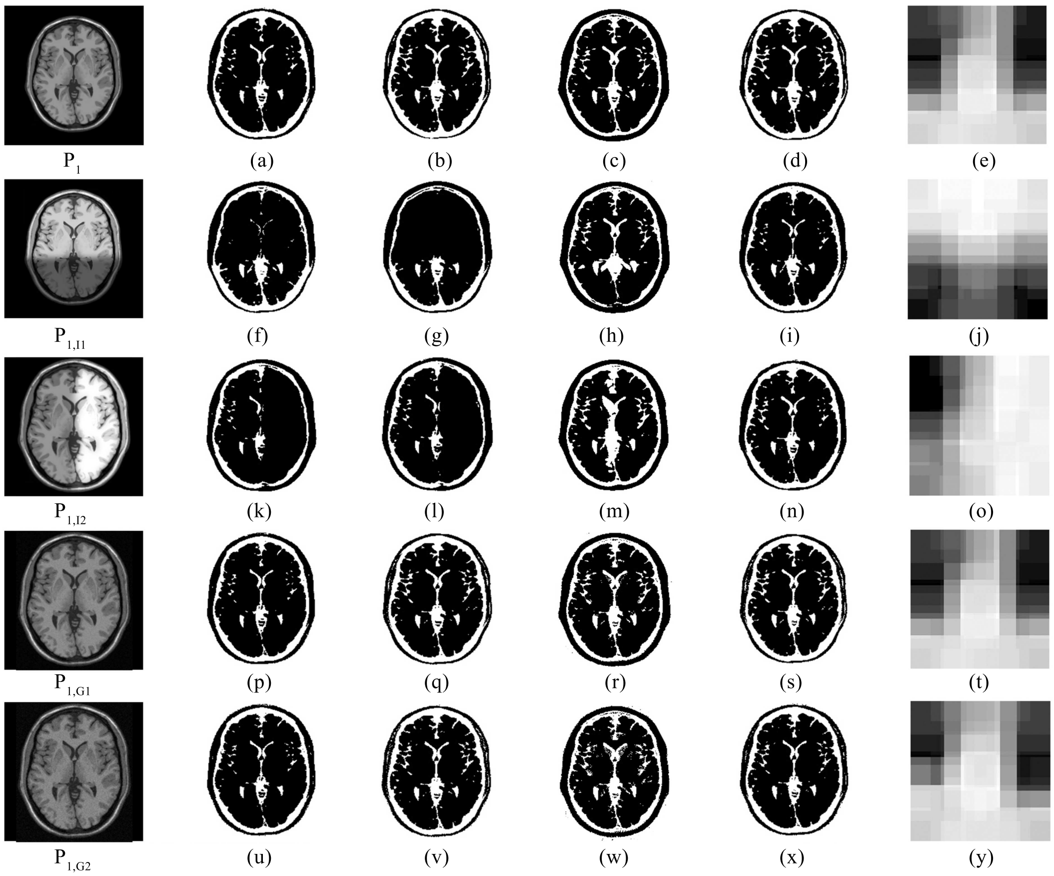


Fig. 7: The first column from left: P1: Origin image. $P_{1,I1}$, $P_{1,I2}$: Images under uneven local intensity distributions. $P_{1,G1}$, $P_{1,G2}$:Noisy Images with $\sigma = 0.1$,$\sigma = 0.3$, respectively. The second column to the sixth column from left: Segmentation results by RCOtsu method((a),(f),(k),(p),(u)), MHUE((b),(g),(l),(q),(v)), Local Otsu method((c),(h),(m),(r),(w)),the proposed method((d),(i),(n),(s),(x)) and the normalized masks((e),(j),(o),(t),(y)),respectively.

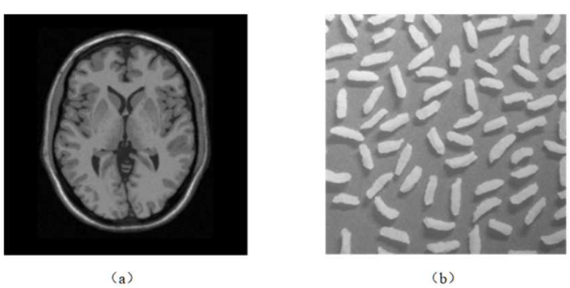


Fig. 6: The test images for experiments, (a) Origin image P1, (b) Origin image P2.

B_G and F_G are the ground truth sets of background and foreground respectively, while B_T and F_T are the ground truth sets of background and foreground respectively.

Due to the importance of gray matter and white matter in the diagnosis and treatment of brain diseases, the target of the experiment is to divide gray matter and white matter into foreground, and to divide cerebrospinal fluid, skull and scalp into background. Fig.7 shows segmentation results of P_1 with different Gaussian noises and under different local uneven intensity distributions. As Fig.7 shows,for the original image P_1, MHUE and the proposed method both achieve fine results. For $P_{1,I1}$ and $P_{1,I2}$, RCOtsu method and MHUE have a poor performance for them because of the characteristic of global thresholding.Compared between the results of local Otsu method and the proposed method,our method has a better performance. For $P_{1,G1}$ and $P_{1,G2}$, the proposed method is also superior to other methods in terms of accurate structural details.

TABLE I shows the misclassification error values of different methods for P_1, $P_{1,I1}$, $P_{1,I2}$, $P_{1,G1}$ and $P_{1,G2}$.Smaller value indicates berrer performance.It can be found that the proposed method has the best performance among the four methods for each image. It follows that the result demon-

TABLE I: Misclassification Error Of Different Methods

Error	RCOtsu	MHUE	Local Otsu	This method
P_1	0.0143	0.0327	0.0254	0.0126
$P_{1,I1}$	0.0697	0.0634	0.0429	0.0309
$P_{1,I2}$	0.0514	0.0482	0.0357	0.0181
$P_{1,G1}$	0.0213	0.0217	0.0351	0.0115
$P_{1,G2}$	0.0220	0.0229	0.0362	0.0122

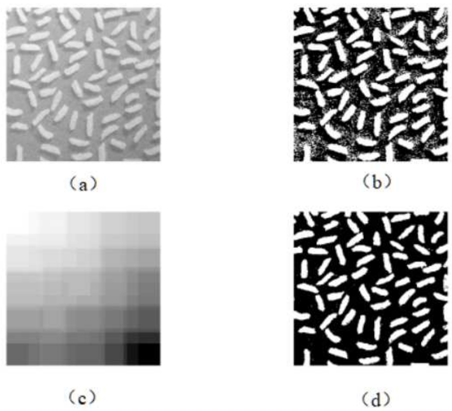


Fig. 8: Segmentation results of P_2. (a) P_2 with Gaussian noise $\sigma = 0.3$.(b) Segmentation result of Local Otsu method. (c)Normalized mask.(d) Segmentation result of the proposed algorithm.

strates the effectiveness and robustness of our method.

To furtherly demonstrate the performance of the proposed method,we use the above-mentioned methods to segment P_2 with different Gaussian noises.Segmentation results of RCOtsu method and MHUE always exist misclassification errors, so only results of local Otsu method and our method are shown in Fig.8. It can be seen that the segmentation result of local Otsu performs well for the whole rice, but it retains many noisy points locally. The segmentation result of our method is more clearly and accurately. The experimental result of Fig.8 shows that, compared with other local threshold methods, our method has a better performance in anti-noise.

IV. Conclusion

To solve classic problems in medical image analysis, this paper proposed an image segmentation method by multi-scale local thresholding based on class uncertainty theory. Compared with the classic thresholdings such as RCOtsu method, Local Otsu method and MHUE, the proposed method has better performance, and can better overcome noises and local uneven intensity distributions, which reflects the advantages of the local thresholding. What's more, compared with the classical local Otsu method, the segmentation result of the proposed method is better in local continuity and stronger in anti-noise ability.On the other hand, because the method adopts a multi-layer block iterative optimization strategy, the computational cost is relatively high, the proposed method takes several times longer than traditional methods, so there is a large room for improvement. In addition, finding a better intensity-scale distribution model will help to further improve the segmentation accuracy.

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