An Improved Watershed Segmentation Algorithm of Medical Tumor Image

Yuting Lu, Zhanjun Jiang*, Tao Zhou and Shengwen Fu
School of Electronics and Information Engineering, Lanzhou Jiao tong University, Lanzhou, China
*Corresponding author e-mail: 59444069@qq.com

Abstract. Aiming at the problem that the tumor is difficult to be accurately segmented due to noise and edge discontinuity in the chest breast MRI image, a medical image segmentation algorithm based on gradient edge detection and control marked watershed is proposed. Firstly, the mathematical morphology reconstruction filter is used to remove the small texture and noise of the MRI image of the breast tumor, and then the local minimum associated with the object is extracted from the low-frequency components of the gradient image, and they are formed into a binary marker image; The reconstructive technique is forced to be the local minimum of the original gradient image, the adaptive correction of the gradient image is realized, and finally the watershed segmentation is performed. The experimental results show that the algorithm can automatically and quickly extract the breast tumor region in the series of MRI images and realize the automatic segmentation of the region of interest in the medical image.

1. Introduction
With the increasing use of medical imaging techniques such as CT and MRI in medical diagnosis, pathology research, and surgical guidance, image segmentation has become a key technology for medical image processing and analysis. However, due to the ambiguity of the medical image itself and the complexity of the human anatomy, how to effectively extract the corresponding human tissue is still a hot research topic in the field of medical image processing [1]. Image segmentation based on watershed is a commonly used method in image segmentation, and it is also a good application in the field of medical image processing.

The watershed algorithm is a segmentation method based on topological theory and borrowing mathematical morphology. It has the advantages of fast calculation speed, precise positioning of image edges and single pixel width, closed and accurate regional boundaries [2]. However, it is sensitive to the detailed texture and noise of the image. Some important boundary lines in the image with low contrast are unstable, and the image is easy to be segmented with too small granularity. The over-segmentation phenomenon is more serious. In order to better solve the over-segmentation of the watershed segmentation algorithm, many experts and scholars have proposed various improvements to the algorithm, which can be roughly divided into two categories. One type is to preprocess the original image by using gradient image, noise removal and marking target area before the watershed segmentation, so as to reduce over-segmentation [3-5]. In [3], the application of morphological filtering...
based marker watershed in image segmentation of brain tumors is studied. It is a good solution to the problem that brain tumor images are difficult to be accurately segmented by noise and magnetic fields, but there are problems of weak edge extraction and inaccurate edge location.

In addition, the literature [4] proposed an improved H-minima improved watershed segmentation method. Aiming at the over-segmentation problem caused by the traditional watershed method, the algorithm can effectively suppress the over-segmentation and better segment the stacked cells, but it needs to be improved in segmentation accuracy and operational efficiency. In [5], the H-minima technique is used to obtain the mark and the fuzzy distance transform is used to divide the watershed. However, the algorithm still has a small number of pseudo-extremities, which affects the segmentation effect. The other type is the division of the watershed according to the similarity principle, using the corresponding combination criteria for regional merging, eliminating over-segmentation [6-7]. In [6], the similar regions are merged by inter-area neighbor propagation clustering. Although the noise is suppressed to some extent, there is still a small amount of over-segmentation. Literature [7] defines new similarity criteria by using edge information, fused grayscale distance, etc., to merge adjacent regions. However, the algorithm has a high time complexity and requires a certain amount of prior knowledge, and there is a small amount of over-segmentation.

In view of the advantages and disadvantages of watershed transformation and the characteristics of MRI images of thoracic tumors, in order to improve the image segmentation effect, the over-segmentation phenomenon can be well suppressed. Based on the existing research, this paper proposes a medical image segmentation algorithm based on gradient edge detection and control marker watershed. Firstly, the mathematical morphology reconstruction filter is used to remove the small texture and noise of the MRI image of the chest tumor, and then the local minimum associated with the object is extracted from the low frequency components of the gradient image, and they are formed into a binary mark image; the extracted mark is utilized. The morphological reconstruction technique is forced to be the local minimum of the original gradient image, and the adaptive correction of the gradient image is realized. Finally, the watershed segmentation is performed.

2. Improved watershed segmentation algorithm

2.1. Morphological reconstruction filter

Although the traditional pre-smoothing filter is easy to achieve better results in reducing noise and irregular details, it will lead to the loss of contour edge information, resulting in the positional shift of the region contour [8]. In the reconstruction filtering, for the characteristics of the MRI image of the chest tumor, while filtering and denoising the image, the edge contour information of the target can be well preserved. It also does not cause a positional shift of the contour of the area remaining in the reconstructed image.

Definition 1 Morphological reconstruction is defined as:

$$h_{k+1} = (h_k \oplus s_e) \cap f$$

Where: $h_{k+1}^{rec}(g, f)$ represents a morphological reconstruction of the mask image $g$ reconstructed by the marker image $f$, where: $s_e$ is the structural element that swells the marker image; $f$ is the original image as a mask; $h_k$ is the result image of the last iteration. $h_0$ is the initial iteration of the marker image $g$. Equation (1) is iterated to the end when $h_{k+1} = h_k$.

Since morphological open reconstruction can eliminate texture details and bright noise smaller than structural elements, morphological closed reconstruction can also eliminate texture details and dark noise smaller than structural elements and completely restore the target edge. However, using only morphological reconstruction or closed reconstruction can only remove one noise or detail in the image and can easily cause a shift in the position of the target contour. Therefore, by using the hybrid opening
and closing reconstruction operation, the texture details and the shading noise can be removed at the same time, and the image morphology reconstruction is used to maximize the boundary information while reducing the number of pseudo-minimum values.

Definition 2 Open operation reconstruction is defined as:

$$O^{rec}_{se}(f) = h^{rec}_{se}[ (f \Theta_{se}), f ]$$  (2)

Equation (2), $\Theta$ is a morphological corrosion operation.

Definition 3 the closed operation reconstruction is defined as:

$$C^{rec}_{se}(f) = \sim O^{rec}_{se}( \sim f )$$  (3)

Definition 4 the morphological opening and closing reconstruction operation based on the open and closed operations is defined as:

$$G^{rec}_{se} = C^{rec}_{se} [ O^{rec}_{se}(f), f ]$$  (4)

2.2. Markup extraction

Through the morphological reconstruction filtering of breast tumor MRI images, there are still some small value points that are not related to the target object in the image are not suppressed, resulting in a large number of meaningless regions in the segmentation results, which can be adopted by marker extraction. Solve it. Marker extraction is to reduce the large number of meaningless regions in the segmentation result by marking the minimum value of the target region in the gradient image and masking the extra minimum values before applying the watershed segmentation algorithm to the target image. In order to minimize the occurrence of over-segmentation problems, only the minimum value of the target area is allowed to be retained.

Therefore, the morphological-based extended minimum transform technique [9] proposed by Soille is used to solve the problem of regional minimum value labeling. The key issue of this technique is how to select the threshold $H$, which essentially removes the local minimum value whose depth is smaller than the threshold $H$ by setting the parameter threshold $H$. However, the advantage of the H-minima technique is that the threshold can be directly given. The disadvantage is that the threshold $H$ is fixed, the flexibility is poor, and the adaptation is single. In order to avoid the influence of artificial setting factors, the adaptive acquisition method can be used to select the threshold $H$. According to the characteristics of the MRI image of the breast tumor, when the marker of the reconstructed gradient image is extracted by using the H-minima transform, the threshold $H$ is automatically obtained by using the maximum inter-class variance algorithm, thereby extracting the target region where the breast tumor appears.

Step 1: Assuming that $H$ is a threshold, when the target image is divided, the target image is divided into two categories by the threshold $H$: the target class $C_0$ includes pixels within the gray scale of $\{0,1,\ldots,H\}$; and the background class $C_1$ includes pixels within the gray scale of $[H+1,H+2,\ldots,L-1]$.

Step 2: Find the intra-class variance or inter-class variance of the target class $C_0$ and the background class $C_1$.

Probability of occurrence of target class $C_0$:

$$w_0 = \sum_{i=0}^{H} P_i$$  (5)
Probability of occurrence of background class $C_1$:

$$W_1 = \sum_{i = H + 1}^{L-1} P_i$$  \hspace{1cm} (6)$$

Mean value of the target class $C_0$:

$$\mu_0 = \frac{\sum_{i=0}^{H} iP_i}{W_0}$$  \hspace{1cm} (7)$$

Mean value of background class $C_1$:

$$\mu_1 = \frac{\sum_{i=H+1}^{L-1} iP_i}{W_1}$$  \hspace{1cm} (8)$$

The variance of the target class $C_0$:

$$\sigma_0^2 = \frac{\sum_{i=0}^{H} [i - \mu_0]^2 P_i}{W_0}$$  \hspace{1cm} (9)$$

Variance of background class $C_1$:

$$\sigma_1^2 = \frac{\sum_{i=H+1}^{L-1} [i - \mu_1]^2 P_i}{W_1}$$  \hspace{1cm} (10)$$

The variance within the class is:

$$\sigma_w^2 = W_0 \sigma_0^2 + W_1 \sigma_1^2 = \sum_{i=0}^{H} [i - \mu_0]^2 P_i + \sum_{i=H+1}^{L-1} [i - \mu_1]^2 P_i$$  \hspace{1cm} (11)$$

The variance between classes is:

$$\sigma_k^2 = W_0 (\mu_1 - \mu_0)^2 + W_1 (\mu_1 - \mu_0)^2 = W_0 W_1 (\mu_1 - \mu_0)^2$$  \hspace{1cm} (12)$$

The overall variance is:
\[
\sigma_f^2 = \sigma_k^2 + \sigma_w^2
\]  

(13)

Step 3: Find the optimal threshold. With the method of sorting search, the threshold is the optimal threshold when \( \sigma_w^2 \) obtains its minimum or \( \sigma_k^2 \) obtains its maximum.

\[
H = \arg \min_{0 \leq H < L} \{ \sigma_w^2 \} 
\]

(14)

Or

\[
H = \arg \max_{0 \leq H < L} \{ \sigma_k^2 \} 
\]

(15)

2.3. Mark-based watershed transformation

In order to prevent the occurrence of meaningless minima, the threshold \( H \) is obtained by using the Otsu algorithm mentioned above, and then the gradient reconstructed image \( G_{\text{rec}} \) is extracted using the extended minimum transform technique to force the marker to appear at a minimum value.

In order to ensure that the local minimum occurs only at the marked position and deletes other local minimum regions, after acquiring the local minimum value marker image associated with the target region, by using the minim imposition technique proposed by Soille [10], to modify the gradient image so that other pixel values are consistent as needed. Its operation is:

\[
G_{\text{mark}} = \text{imimpose} \min \{ G_{\text{rec}}^{\text{se}}, C_1 : C_0 \} 
\]

(16)

Where: \( \text{imimpose} \min (\ ) \) represents the forced minimum operation proposed by Soille, \( G_{\text{mark}} \) indicates the modified gradient image.

The watershed segmentation is performed on the gradient image \( G_{\text{mark}} \) after the minimum value forced minimum operation, and the watershed segmentation operation is:

\[
G_{\text{ws}} = \text{watershed} \left( G_{\text{mark}} \right) 
\]

(17)

Where: \( \text{watershed} (\ ) \) represents the watershed transformation; for the marking completion, the image of the corresponding target area can be obtained according to the marker value \( G_{\text{ws}} \).

3. Experimental results and analysis

In order to verify the segmentation performance of the proposed method, two clinical MRI images (MRI1, MRI2) of breast tumor changes were selected, and experimental comparisons were made from the aspects of regional contour location and segmentation accuracy, as shown in Fig. 1, Fig. 2. The spatial resolution of the MRI series image is that the breast tumor region is automatically extracted from the MRI series image by the above method. (a) is the original picture in the MRI series image, (c) is the morphological reconstruction filtering operation picture of the original picture, in order to eliminate the dark details and noise of the gradient image, (g) in order to extract the maximum mark area after the watershed transformation, Basically, the extraction of breast tumor areas can be completed, but the edge contour extraction is still unstable, and further research is needed. (a) (b) is image grayscale, (c) (d) is image binarization, (e) (f) is image gradient edge, and (g) segmentation result flag.
Figure 1. MRI1 segmentation results
By comparing the images of two breast tumor images, the breast tumors of the breast can be clearly observed. Since the traditional watershed algorithm does not filter the target image, but directly performs the watershed transformation after calculating the gradient, there is a serious over-segmentation, and pre-processing is needed to control the over-segmentation [11]. In order to avoid the influence of background pixels on the threshold calculation and the threshold deviation, this paper focuses on the threshold selection in adaptive extended minimum value transformation, and proposes the use of...
gradient image non-zero local minimum value. The method of the largest inter-class variance method of points to adaptively obtain the tag value.

4. Conclusion
In order to achieve effective segmentation of breast tumors, a medical image segmentation algorithm based on gradient edge detection and control marker watershed is proposed. According to the characteristics of MRI images of breast tumors, for the comprehensive consideration of smooth denoising and retaining target information, the original image is firstly reconstructed and filtered by morphological opening and closing, and then the local minimum associated with the object is extracted from the low frequency components of the gradient image. According to the characteristics of MRI images of breast tumors, for the comprehensive consideration of smooth denoising and retaining target information, the original image is firstly reconstructed and filtered by morphological opening and closing. Then extract the local minimums associated with the objects from the low-frequency components of the gradient image and form them into a binary marker image. The extracted mark is forced by the morphological reconstruction technique as the local minimum of the original gradient image, the adaptive correction of the gradient image is realized, and finally the watershed segmentation is performed. Compared with the standard watershed and some improved methods, this method can be used to extract breast tumor regions when applied to the segmentation of breast mammary MRI images. However, there are still problems in the extraction and segmentation accuracy of breast tumor regions in the experimental results. How to improve the accuracy and robustness of the algorithm needs further study.

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