

Left Ventricle MR image segmentation Based on Locally Weighted Entropy Geodesic Active Contour model

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Abstract: In this paper, an improved Geometric Active Contour model is presented. This model introduced a window function to research the mean information of each pixel's neighbor region, and constructed a novel signed pressure force function based on the entropy to drive the contour towards the boundary. In order to improve the efficiency and stability of the algorithm, this paper adopts two valued level set method to realize the segmentation process. The experimental results show that this method can obtain satisfied result even when the images have intensity inhomogeneity and weak edges.

Key words: GAC model; signed pressure force function; Local information entropy; Image segmentation

1 Introduction

Generally speaking, active contour models (ACM) [1] are usually classified into two types: edges-based models [2] and region-based methods [3]. The edges-based models can well segment the target boundary with strong edges, but fail to segment the image with weak boundaries and noise. The region-based models utilize the grey mean or variance can well overcome the influence of weak boundaries or noise. However, these models are sensitive to intensity inhomogeneous, thus it can not well segment images with bias field.

Li et al. [4] proposed the local binary fitting (LBF) model, which utilizes the local image information can well segment objects with intensity inhomogeneity, but fail to segment the images with weak boundaries and noise. Zhang et al proposed a novel region-based GAC model in paper [5] can well segment the images with noise and weak boundaries. This model assumed the grey information of image is homogeneous, so it can not well segment the images with bias field.

From the research, most medical images local grey information presented gauss distribution and local statistical information can well describe the grey information distribution of the image. This paper can segment the medical images with bias field or weak boundaries and noise better by constructs a novel signed pressure force function based on local entropy information.

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2 Background

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Geodesic active contour (GAC) model is put forward by V. Caselles et al. [2] in 1997, and the energy functional of this model is defined as follows:

(1)

Where L is the length of contour C , ∇I is the gradient of image I , λ is the edge stopping function and s is the arc length unit of image. The level set evolution equation corresponding to formula (1) as follows:

(2)

Where div is divergence operator, μ is a constant. λ is the edge-stopping function that decreasing with the image gradient values

increase.

Generally, medical images often exist weak edges and noise. The GAC model only relies on the gradient information of images and cannot segment the target boundary well, which leads to the evolution contours over the weak boundaries or fall into the local optimal.

$$E(f) = - \int p(I(y)) \quad (1)$$

3 GAC based on Local Information Entropy model

3.1 Image information entropy

For the image, $I(x, y)$, the information of the pixel (x, y) is:

$$- \log_2 p(I(x, y)) \quad (3)$$

Where $G(x, y)$ is a Gaussian distribution function in the local region, $w(x, y)$ is a window function which centered at the pixel point (x, y) . The information entropy [6] can achieve the maximum when the grey distribution is uniform.

3.2 Signed Pressure Force function based on Local Information Entropy

Zhang et al. proposed a region-based GAC (RGAC) [5] model, which constructs a signed pressure force ($F(x, y)$) function replace of the GAC model. The definition of $F(x, y)$ as follows:

$$\frac{\sum_{i=1}^n |f_i - g_i|}{2} \quad (4)$$

Where \max indicates the absolute maximum of grey difference, \bar{f} grey mean

$$1 - \frac{\sum_{i=1}^n |f_i - \bar{f}|}{\sum_{i=1}^n |f_i - g_i|} \quad 2 - \frac{\sum_{i=1}^n |g_i - \bar{g}|}{\sum_{i=1}^n |f_i - g_i|} \quad (5)$$

and \bar{g} respectively defined as follows:

$$\bar{f} = \frac{\sum_{i=1}^n f_i}{n}$$

$$\bar{g} = \frac{\sum_{i=1}^n g_i}{n}$$

$$\bar{f} = \frac{\sum_{i=1}^n f_i}{n}$$

Because of the RGAC model still rely on intensity homogeneity, and medical image usually include the bias field, so this model cannot to segment the object boundary well.

This paper introduced window function to research the grey distribution of local image and introduced the image information entropy into to construct a novel drive force function which defined as follows:

P

background region and target region, P is the whole image region, posterior probability of background and target regions. According to literature [7], Where μ_b and μ_t we can know:

Where μ_b and μ_t respectively present grey mean of background and target is window function, σ_b and σ_t respectively present Gaussian function of background and target regions and they respectively computed the regions:

$$\int_{-1}^1 I(y) dy \quad \int_{-1}^1 f_b dy$$

respectively present image information of

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□

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$$P_m(I(y)) = \exp\left\{-\frac{1}{2} \frac{I(y) - f_m}{\sigma_m}\right\} \quad (6)$$

(7)

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□

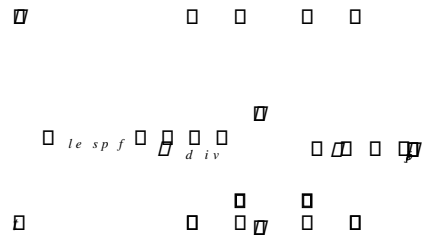
$$\int_{-1}^1 \frac{1}{\sigma_m} \exp\left\{-\frac{1}{2} \frac{I(y) - f_m}{\sigma_m}\right\} dy \quad (8)$$

Where: σ_b and σ_m respectively present variance of background and target regions.

$$\sigma_b = \int_{-1}^1 (I(y) - f_b)^2 H(y) dy$$

$$\sigma_m = \int_{-1}^1 (I(y) - f_m)^2 (1 - H(y)) dy$$

$$\int_{-1}^1 (I(y) - f_b)^2 H(y) dy = \int_{-1}^1 (I(y) - f_m)^2 (1 - H(y)) dy \quad (9)$$



In local region, grey changes present Gaussian distribution according literature [7]. Take a point v in contour, suppose Ω is a local region which is controlled by window function w and centered at point v . Ω_{in} and Ω_{out} respectively present background and object regions that the image region divided into inside and external by the contour line. If $\mu_{in} < \mu_{out}$, v get a smaller value and μ_{out} get a bigger value, then $\mu_{in} < \mu_{out}$. This situation can drive evolution curves shrinkage to object boundary. In contrast, if $\mu_{in} > \mu_{out}$, it can drive evolution curves expansion to object boundary. As we can know, the grey information in local region satisfies Gaussian distribution, thus the maximum posterior probability of inside and external regions is 1 when the contours approach to object boundary. Moreover, we can know that $\mu_{in} < \mu_{out}$ and $\mu_{out} > \mu_{in}$, therefore $\mu_{in} < \mu_{out}$ and the contour line will stopping evolution at the object boundary. From the formula (6), the range of variation of function μ is $[-1, 1]$ satisfies definition of function based on the above discussion.

Take μ instead of μ in the RGAC model; get the corresponding gradient descent flow equations as follows:

$$(10)$$

Because of grey values in local region of medical images changes slowly, the

derivative of ϕ approach to 0, writing as $\phi = \phi_0 + \epsilon$. Simultaneously,

$\phi = \phi_0 + \epsilon$

" $\phi = \phi_0 + \epsilon$

$\phi = \phi_0 + \epsilon$

$\phi = \phi_0 + \epsilon$

$\phi = \phi_0 + \epsilon$

, and \mathbf{F} can be used to approach ϕ in this paper. This paper through utilize Gauss filter instead of curvature regularization. From the above discussion, formula (10) can be written brief as:

$$\begin{matrix} a \\ 0 \end{matrix} \quad \begin{matrix} v \\ 0 \end{matrix} \quad (11)$$

a

4 Experimental Results and Analysis

Figure 1 is the segmentation of left ventricle MR image. Figure 1(a)-(b) is the original image with initial curve and the true segmentation result. Figure 1(c) is the segmentation result of C-V model. This model can not well segment the images with bias field or weak boundaries. Figure 1(d) is the result of GAC model which iterate 600 times. This model can only precede single direction evolution. Figure 1(e) is the result of RGAC model which iterate 100 times. This model can easy occur over-segmentation. Figure 1(f)-(g) respectively presents the result of LBF and LGD model which iterate 100 and 200 times. The parameter of them is $\lambda = 100$,

and kernel parameter $\sigma=15$. Both of them can well segment images with bias field, but fail to segment noise image. Figure 1(h) is segmentation result of this paper method iterate 100 times with parameter $\sigma=15$ and . This method can well segment the images with bias field and weak boundaries.

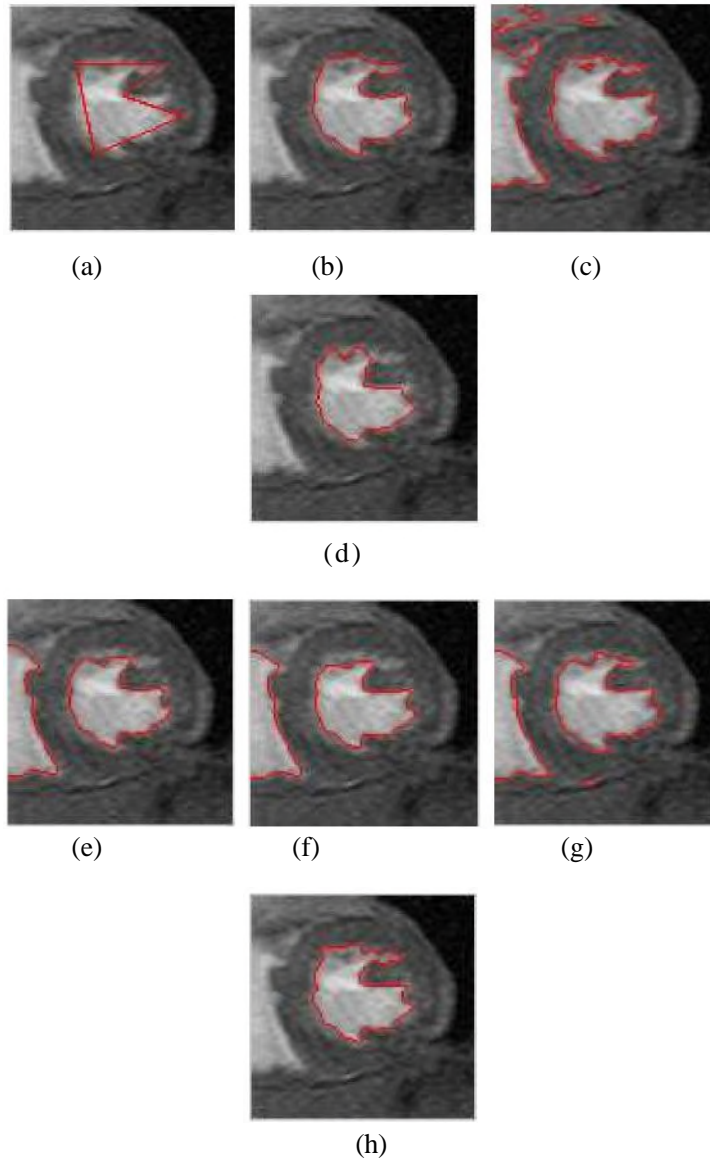


Fig.1. The segmentation result of left ventricle magnetic resonance (MR) image. Figure 1(a)-(b) respectively present original image with initial curve and accurate segmentation result. Figure 1(d)-(h) respectively present segmentation result of C-V model, GAC model, RGAC model, LBF model, LGD model and this paper method.

In order to better respond or compare segmentation accuracy and segmentation efficiency of each model, we utilize 20 groups left ventricle MR images for experiment segmentation test. The size of image is , and utilize the Jaccard Similarity (JS) index [8].

As shown in Figure 2 and 3, the segmentation accuracy of this paper method is more than 90%. The C-V model can not well segment the images with bias field. The GAC model can easily produces boundary leakage. The RGAC model fails to segment the images with bias field. Due to lots of convolution operation, the segmentation efficiency of LBF and LGD model is lower. This paper method can well segment the images with bias field. Due to this method adopt window function to computer, the average iteration time no more than 3 seconds and iteration times less than 200 times. This situation is still in reasonable range.

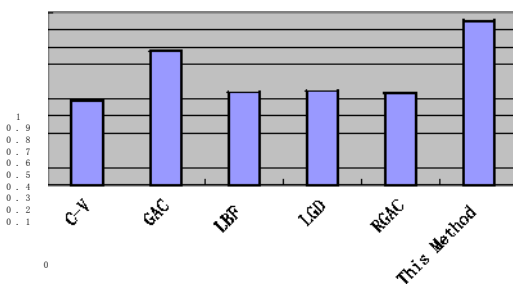
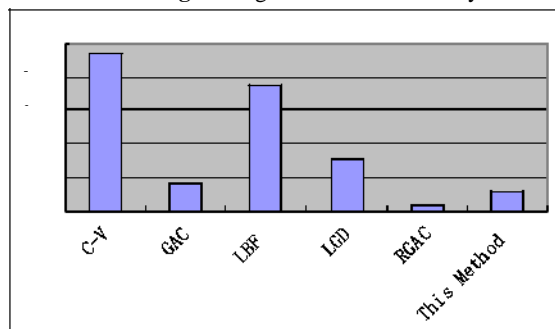


Fig. 2. Segmentation Accuracy

Fig. 3. Segmentation Efficiency



5 Conclusions

This paper proposed an improved GAC model for the images with noise, bias field and weak boundaries. This paper model utilizes the window function to investigate the grey information of local region, while introduce the local information entropy to describe the distribution of the grey information. Compared with GAC model, this method can achieve the high segmentation accuracy. Compared with C-V and RGAC model, this method can well segment the images with bias field. And compared with LBF and LGD model, this method has more choice of kernel parameters.

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