An Improved Algorithm for Medical Image Segmentation

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Abstract

The main objective of medical image segmentation is to extract and characterize anatomical structures with respect to some input features or expert knowledge. Traditional two-dimensional Otsu method for medical image segmentation is time–consuming computation and become an obstacle in real time application systems. This paper describes a way of medical image segmentation using optimized two-dimensional Otsu method based on improved genetic algorithm (GA). In proposed algorithm, the probability-ties of crossover are adaptively varied depending on the ranking value of individuals instead of fitness, and dyadic mutation operator was presented to take the place of the traditional one. The experimental results show that the new optimized method dramatically reduces the operating time in medical image segmentation while ensures the final image segmentation quality.

1. Introduction

Medical imaging application plays an indispensable role by automating or facilitating the delineation of anatomical structures. Medical image segmentation is a challenging task due to the various characteristics of the images, which lead to the complexity of segmentation. Threshold segmentation is wildly used in many fields because of its simplicity and efficiency.

Some scholars study some popular Threshold algorithms such as Maximum Entropy [1-3], Invariable Moment [3], Fuzzy Cluster [4] and Otsu [1], [3], [5]. Otsu algorithm manifests a more satisfactory performance in the image segmentation. It can well pledge the result [6]. However, medical images are often very noisy and the structures to be identified have large "internal" intensity variations. So it is inevitable to require an antinoise algorithm.

As an extension of Otsu algorithm, 2-D Otsu algorithm can present satisfactory result for the image whose histogram has not two peaks which represent objects and background, and have better effect to against noise performance than traditional Otsu algorithm [7-8]. However, because of the higher complexity of the algorithm itself, it is too time-consuming to apply for the real time image process. This paper presents an optimized method based on the 2-D Otsu algorithm using improved GA for medical image segmentation.

2. Two-dimensional Otsu Algorithm

The auto-adapted Threshold segmentation method based on 2-D Otsu was proposed by Liu Jianzhuang et al [9] who used the union histogram of the primitive image and the neighborhood of the smooth image [10]. The details are as follows:

A 2-D gray-level intensity image $f(x,y)$ can be represented in L gray levels, i.e., $0,1,2,\ldots,L-1$, where L is the number of distinct gray-levels. And the value of $g(x,y)$ is obtained from $f(x,y)$ by counting the average gray-level value of the neighborhood, ranging from 0 to $L-1$. At each pixel, the calculated transformation of $g(x,y)$ can be expressed as

$$g(x,y)=\frac{1}{l\times l}\sum_{i=(l-1)/2}^{(l-1)/2}\sum_{j=(l-1)/2}^{(l-1)/2}f(x+i,y+j) \tag{1}$$

l represents the width of square neighborhood of pixel $f(x,y)$. Generally, it takes odd number, but takes 5 in this paper.

The joint probability mass function in two-dimensional histogram is defined as:

$$p(i,j)=f(i,j)/M \tag{2}$$

Figure1 shows that A and D regions which far away from diagonal represent noisy and fringing field, C represents target sector and B represents background region.

978-0-7695-3334-6/08 $25.00 © 2008 IEEE
DOI 10.1109/WGEC.2008.116

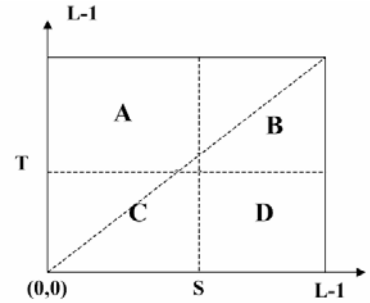


Fig. 1. Domain of 2-D histogram of image

Statistics are calculated for the two classes of intensity values (target and background) that are separated by a two-dimensional threshold, with two different probability mass functions. The two dimensional threshold denotes vector (S, T) that the gray-level of the pixel and the average gray-level of its neighborhood. The vector that maximizes the two-dimensional criterion function is the optimal threshold.

$$\omega_0 = \sum_{i=0}^{S-1}\sum_{j=0}^{T-1} p(i,j) = \omega_0(S,T) \tag{3}$$

$$\omega_1 = \sum_{i=S}^{L-1}\sum_{j=T}^{L-1} p(i,j) = \omega_1(S,T) \tag{4}$$

$$u_0 = (u_{0i}, u_{0j})^T = \left[\sum_{i=0}^{S-1}\sum_{j=0}^{T-1} i \times p(i,j)/\omega_0, \sum_{i=0}^{S-1}\sum_{j=0}^{T-1} j \times p(i,j)/\omega_0\right]^T \tag{5}$$

$$u_1 = (u_{1i}, u_{1j})^T = \left[\sum_{i=S}^{S-1}\sum_{j=T}^{T-1} i \times p(i,j)/\omega_1, \sum_{i=S}^{S-1}\sum_{j=T}^{T-1} j \times p(i,j)/\omega_1\right]^T \tag{6}$$

If the threshold is located at the pair (S, T), then ω_0 and ω_1 are respectively the probabilities of C0 class and C1 class occurrence, and u_0 and u_1 are respectively the class mean levels.

$$u_z = (u_{zi}, u_{zj})^T = \left[\sum_{i=S}^{S-1}\sum_{j=T}^{T-1} i \times p(i,j)/\omega_1, \sum_{i=S}^{S-1}\sum_{j=T}^{T-1} j \times p(i,j)/\omega_1\right]^T \tag{7}$$

u_z is the total mean of the image $f(i,j)$.

In many situations, because it is reasonable to suppose that $p(i,j) \approx 0$ in both A and D regions, the off-diagonal probabilities in the two-dimensional histogram are negligible value. Therefore it is obvious.

$$\begin{cases} \omega_0 + \omega_1 \approx 1 \\ u_z \approx \omega_0 \times u_0 + \omega_1 \times u_1 \end{cases} \tag{8}$$

The variance between the two classes is given by the following:

$$\sigma(S,T) = \omega_0\left[(u_0 - u_z)(u_0 - u_z)^T\right] + \omega_1\left[(u_1 - u_z)(u_1 - u_z)^T\right] \tag{9}$$

The trace of $\sigma(S,T)$ is used to express the variance between the two classes:

$$\begin{aligned} tr\sigma(S,T) &= \omega_0\left[(u_{0i} - u_{zi})^2 + (u_{0j} - u_{zj})^2\right] \\ &+ \omega_1\left[(u_{1i} - u_{zi})^2 + (u_{1j} - u_{zj})^2\right] \\ &= \left[(\omega_0 \times u_{zi} - u_{0i})^2 + (\omega_0 \times u_{zj} - u_{0j})^2\right] \div \left[\omega_0(1-\omega_0)\right] \end{aligned} \tag{10}$$

The optimal Threshold vector (S_max, T_max) can be written as:

$$\begin{aligned} FitV &= tr\sigma(S\_max, T\_max) \\ &= \max_{0 \le S,T \le L-1}\left(\{tr\sigma(S,T)\}\right) \end{aligned} \tag{11}$$

The 2-D Otsu needs to iterate every Threshold vector, thus, the computation complexity is very large. The computation order of complexity is about $O(L^4)$, so that it is difficult to apply [8].

3. Optimized 2-D Otsu method using Improved GA

GA [11-12] is not only an efficient and parallel searching algorithm, but also a random probability searching technology based on natural selecting and genetics principle. And it is capable of adaptive searching space for optimal solution [13].

GA has many merits, such as the robustness strong and the randomicity. GA is especially suit to search the optimal solution in a question. Combined improved GA with 2-D Otsu algorithm is applied in the segmentation of the medical image. The segmentation speed and precision are greatly enhanced.

The optimized 2-D Otsu algorithm is based on the auto- adapted improved GA, and composed of the following steps:

Chromosome coding: The chromosome is the Two-dimensional vector that the gray-level of the image pixel and the average gray-level of its neighborhood. Because the gray-level of the image pixel and the average gray-level of its neighborhood both are from 0 to 255, each element is built from a 16 length binary string, the first 8 bit express the gray-level of image pixel , and the second 8 bit express the average level of its neighborhood.

Initial population: The initial population is randomly chosen in the range form 0 to 255. To keep an appropriate balanced distribution, random selection is usually preferred. Selecting correct population size is an important aspect. Small population size may obliterate suitable solutions while big population size will add the algorithm execution time and waste computational resources. There should be a trade off between population size and the mentioned factors [14].

The designation of fitness function: This factor illuminates the extent of influence which the element has on the final solution and estimate the satisfaction percentage of the result. Because the GA is used to seek the optimal solution of the formula (10), the fitness function takes the formula (10). Each element has a fitness value associated with it. Elements with highest fitness value will be selected as the optimized solution in the last generation.

Selection: The process of selection is that calculates the sum S of all individual fitness, randomly products number K between 0 and S, then starts to accumulate the fitness from the first individual until the accumulation value is bigger than this random number K.

Crossover: This article uses two points crossover. Two crossover points are stochastically selected in the individual string (a point is located the first 8 bit, another is located the latter 8 bit), then individual partial strings which is behind the crossover points of stochastically match individuals exchange, and operate according to crossover probability pc. The selection of pc is as follows:

$$\begin{cases} pc = \dfrac{k'}{m'} & 0 \le k' \le m \\ pc = 1.0 & m < k' \le n-1 \end{cases} \qquad (12)$$

m is the current population, n is the serial number of individual whose fitness value is most adjacent with the average fitness value. k' is serial number of individual whose fitness value is the max in the two crossover individuals [15].

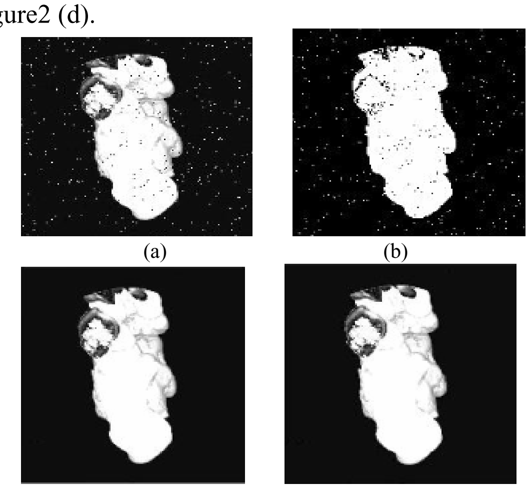
Mutation: Mutation is usually considered as a complementary operator. Its main purpose is to broaden the search space because using crossover alone may drive our results to one direction. In order to strengthen the ability and the speed which is the algorithm seek the optimized solution and avoid the precocious phenomenon of the algorithm, this article uses the dual mutation operator means to execute the mutation to the currently population. Two individuals of the currently population are randomly drew out. They are separately operated with XOR and XNOR to produce the new sun-generation individual.

The inactive judgment: To terminate a GA's execution, one of the ways is to end the execution after a fixed amount of iterations. Another approach is to end the algorithm when the best fitness value of the elements in the population has reached a specific peak. This article uses the strategy that combine them, namely the termination condition is to achieve the max number of the evolving generation G or the absolute dispersion is small as ε between the average fitness value of current population and the fitness average of previous population.

Partial search: In the practical application, the optimal solution is possibly the suboptimal solution. Generally the error is about 10%. In order to guarantee the acquisition of the optimal solution, the undulate threshold e=25 is established. Based on the suboptimal threshold (S, T) which is searched by improved GA, a calculation of 2-D Otsu is done to obtain the optimal threshold and it is decoded into the gray-level.

4. Experiment Results

To evaluate the practical performance of the proposed method, the algorithm has been implemented in Matlab7.0 under window XP system; experiments were done to the ankle of ct image. Figure2 (a) was typical the ankle of ct image. Figure2 (a) showed the image was disturbed by noise. The optimal threshold by the Otsu method was 44 and the corresponding segmentation image was shown in Figure2 (b). The optimal threshold by 2-D Otsu method was 41 and the corresponding segmentation image was shown in Figure2 (c). And the optimal threshold by optimized 2-D Otsu method was 41 and the corresponding segmentation image was shown in Figure2 (d).



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

Fig.2. (a) Original image (b) Reconstructed image using Otsu (c) Reconstructed image using 2-D Otsu (d) Reconstructed using Optimized 2-D Otsu Method

The experimentation results showed, although Otsu algorithm was not produced satisfactory results on noisy image, it was simplicity of implementation. The 2-D Otsu algorithm produced satisfactory results on the image. The main reason was it considered the neighborhood information of the pixel. But the algorithm was 'Time consumed'. This paper's algorithm did not have too much distinct differences in the segmentation effect as compared to 2-D Otsu algorithm, but the running time was about a half of the 2-D Otsu algorithm, because the modified GA made the 2-D Otsu algorithm optimized. To sum up, the result of the ankle image proved that the paper's method could clearly extract ankle bone from the background in noisy CT image.

5. Conclusions

This paper proposed an optimal 2-D Otsu algorithm to search the optimal threshold for medical image segmentation. It used the modified GA to optimize 2-D Otsu algorithm. Its crossover probability gained auto-adapted according to the population situation, and its mutation used the dual mutation operator's method, in order to quicken the speed of seeking the optimal solution and prevent partially optimization. Meanwhile, the experimental results indicated that the optimized 2-D Otsu method could achieve a good segmentation quality, furthermore improved the computational efficiency by 46.34% as compare to 2-D Otsu method. Using optimized 2-D Otsu method to segment the medical image obtained a better antinoise performance and effect than other methods. And the medical images could supply powerful proof for early disease detection.

6. Acknowledgements

This project was supported by the Guangxi Science foundation under grant No. 0640169.

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