Improvement of Grayscale Image 2D Maximum Entropy Threshold Segmentation Method

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Abstract: To increase the segmentation speed and efficiency, traditional 2D maximum entropy threshold segmentation method is improved. The improved segmentation method is called PSO-SDAIVE algorithm. In this new algorithm, the 2D gray histogram is changed and forms the 2D D－value attribute gray histogram. When computing image entropy, the spatial gray information of pixels is included in computation. The improved entropy is called spatial different attribute information value entropy (SDAIVE). Otherwise, Particle Swarm Optimization (PSO) algorithm is used to solve maximum of SDAIVE. The corresponding solution of SDAIVE maximum is taken as optimal image segmentation threshold. In experiment, segment different grayscale image and testify the algorithm performance. Experimental results show that PSO-SDAIVE algorithm can quickly and accurately obtain segmentation threshold. Compare with other segmentation method, the cost time of solving optimal threshold is short. Otherwise, this algorithm can better segment noise image.

Key Words: Grayscale Image Segmentation, 2D Histogram, Information Entropy, Gray Probability, PSO Algorithm

I. INTRODUCTION

Image segmentation is to separate pixels of image into some non-intersecting regions[1]. Image segmentation is a critical step in image processing. Grayscale image is a special image. The segmentation of grayscale image mainly utilizes pixel gray information. Threshold segmentation method is one of the most important methods in grayscale image segmentation. This method utilizes features of pixels. Threshold method utilizes gray value and gray probability. Other image information such as the spatial information is not utilized[2]. Segmentation results rely on the segmentation threshold value. Therefore it is very important to choose an optimal threshold value in grayscale segmentation.

In past years, many schemes have appeared in literature[3-6]. Many different selection criterions were proposed, such as Otsu method. They are one-dimension entropy method. Abutaleb proposed two-dimension entropy method in 1989[7]. When computing optimal threshold value, two-dimension entropy method needs cost more time than one-dimension entropy method.

In order to decrease the computation time and improve accuracy of segmentation threshold value, an improved 2D maximum entropy threshold segmentation method is proposed. This method narrows down the search space. Otherwise, PSO algorithm is used to solve the optimal segmentation threshold value. Improved 2D entropy is called spatial difference attribute information value entropy (SDAIVE). This improved 2D maximum entropy threshold segmentation method based on PSO is called PSO-SDAIVE algorithm.

II. IMPROVED GRAY HISTOGRAM

While segmentation image with 2D threshold segmentation method, associated 2D entropy need to be computed and obtains the optimal segmentation threshold value[8]. In traditional 2D gray histogram, the search space is large and the solution time of the optimal is long. In order to reduce the solution time and improve the search efficiency, using the feature of attribute histogram, gray histogram is improved in this paper.

A. The Improvement of Gray Histogram

In traditional 2D gray histogram, the horizontal axis denotes the gray-level value of pixel. It's range is from 0 to L-1; the vertical axis denotes the average gray-level value of pixel. It's range is also from 0 to L-1. f(m,n) denotes the gray-level value of pixel which locates at point (m,n).

This improved 2D gray histogram is called 2D D-value attribute gray histogram. In improved gray histogram, the horizontal axis of 2D D-value attribute gray histogram denotes gray value. The vertical axis denotes the D-value between gray value of pixels and average gray value of pixels. It denotes absolute value of the difference between $f(m,n)$ and $g(m,n)$.

The histogram with a given attribute is called attribute histogram. In this paper, the associated attribute conditions are set. Attribute conditions are $L_1 < f(m,n) < L_2$ and $|f(m,n) - g(m,n)| < \mu$. The attribute conditions restrict the range of search space. The average gray value is also in given range. Pixels which satisfy attribute conditions can be searched.

Figure1 shows the improved gray histogram and associated traditional gray histogram. According to attribute conditions, pixels in region G and region H are searched. A pair of value (s,w) represents the optimal threshold value. That is segmentation threshold value. Influences of noise points are reduced by using this improved gray histogram. Threshold method based on 2D D-value attribute gray histogram can decrease the computing quantity.

In the traditional 2D gray histogram, pixels in region G should satisfy the following conditions: $L_1 \leq f(m,n) \leq s$ and

$\max\{0, L_1 - w\} \le g(m,n) \le \min\{s + w, L - 1\}$.

Pixels in region H should satisfy $s + 1 \le f(m,n) \le L_2$ and $\max\{0, s + 1 - w\} \le g(m,n) \le \min\{L_2 + w, L - 1\}$.
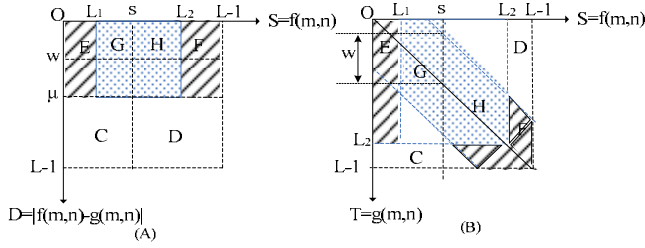

FIGURE Ⅰ THE PLAN OF IMPROVED AND TRADITIONAL GRAY HISTOGRAM

B. Parametric Spatial Average Gray

Every neighboring pixel plays different role in computation of average gray. When compute average gray, The influence of neighboring pixel is same or set the control neighboring weight constant 'a'. If parameter 'a' is too big, the edge of region occurs the overly smoothness. If parameter 'a' is too small, the spatial information can't be adequately utilized and the segmentation results have huge error. The average gray of pixel which locates point (m,n) is computed by formula 1. The size of window is 3×3 [9].

$$g(m,n) = \left\lfloor \frac{1}{9} \sum_{i=-1}^{1} \sum_{j=-1}^{1} f(m+i, n+j) \right\rfloor \quad (1)$$

In order to better utilize the spatial information and avoid the overly smoothness, set a dependent parameter α and improve the computation formula of average gray. The value of α is between 0 and 1. α denotes the influence degree of neighboring pixels to average gray. Suppose pixel x is a neighboring pixel of y which locates at point (m,n). While neighboring pixel x locates the region inside or region edge, they have different influence to the computation of pixel average gray. If neighboring pixel x locates the region inside, x influences the classification of pixel y. If neighboring pixel x locates the region outer, x can't influence the classification of pixel which locates at point (m,n).

Because the size window is 3×3, every pixel has 8 neighboring pixels. In this paper, establish a α value criterion. If $|f(m,n) - f(m+i, n+j)| < t$, then α value is 1, else α is 0. Dependent parameter α of every neighboring pixel is put in array A. There are nine dependent parameters. Every neighboring pixel has a dependent parameter associated with a pixel point. The improvement of average gray not only utilizes the pixel spatial information, but also adequately considers the influence of neighboring pixels. Therefore, more accurate average gray can be obtained and is called parametric spatial average gray. The computing formula of parametric spatial average gray is shown as formula 2.

$$g(m,n) = \left\lfloor \frac{1}{9} \sum_{i=-1}^{1} \sum_{j=-1}^{1} A(k) f(m+i, n+j) \right\rfloor \quad k = 1, 2 \cdots\cdots 9 \ (2)$$

III. SPATIAL DIFFERENCE ATTRIBUTE INFORMATION VALUE ENTROPY

In general, image segmentation with entropy only utilizes the grayscale information of image. Average gray is spatial information of pixels. In order to better utilize the gray information and spatial information of grayscale images, computation method of 2D entropy is improved in this paper. When computes 2D entropy, spatial information of pixel substitutes for gray probability.

A. Computation of 2D Entropy

Suppose m_i denotes the number of pixels which gray value is i. The gray probability is defined by formula 3. f_{ij} denotes the number of pixels which gray value is i and average gray value is j.

$$M = \sum_{i=0}^{L-1} m_i, \quad p_{ij} = f_{ij} \Big/ M \quad i, j = 0, 1, \cdots, L - 1 \quad (3)$$

Suppose s is a gray value of pixel. t is an average gray value of pixel. To a pair of value (s,t), the computation of information entropy is defined by formula 4.

$$\phi(s,t) = \ln\left(\sum_{i=0}^{s} \sum_{j=0}^{t} p_{ij}\right) - \frac{\left(\sum_{i=0}^{s} \sum_{j=0}^{t} p_{ij} \ln p_{ij}\right)}{\sum_{i=0}^{s} \sum_{j=0}^{t} p_{ij}}$$

$$+ \ln\left(\sum_{i=s+1}^{L-1} \sum_{j=t+1}^{L-1} p_{ij}\right) - \frac{\left(\sum_{i=s+1}^{L-1} \sum_{j=t+1}^{L-1} p_{ij} \ln p_{ij}\right)}{\sum_{i=s+1}^{L-1} \sum_{j=t+1}^{L-1} p_{ij}} \quad (4)$$

B. Spatial Information Function

According to gray value i and average gray value j, spatial information function is defined. Pixel spatial information value is defined by formula 5. O denotes other spatial gray information. g_i denotes weight value factor of every gray information.

$$I(i,j) = I_{ij} = \left(g_1(i+1)^2 + g_2(j+1)^2 + g_3 O\right) p_{ij}$$
$$g_1 + g_2 + g_3 = 1, 0 \le g_1 \le 1, 0 \le g_2 \le 1, 0 \le g_3 \le 1 \quad (5)$$

In this paper, gray value and average gray are considered. Suppose weights of gray and average gray are same. Therefore, spatial information function formula is simplified as formula 6.

$$I(i,j) = I_{ij} = \left(\frac{(i+1)^2 + (j+1)^2}{2}\right) p_{ij} \quad (6)$$

Refer the 2D D-value attribute gray histogram and compute the information value entropy. When computing image 2D entropy, pixel spatial information value substitutes for gray probability. This entropy is called spatial difference attribute information value entropy (SDAIVE). This improved method is called SDAIVE method.

C. Implementation of SDAIVE

Suppose threshold value pair (s,w), that is said, the gray value is s, and the gray D-value is w. According to figure 2, the range of gray value and the range of gray D-value are confirmed. In computation, the gray value range of object is from L_1 to s. The gray value range of background is from $s+1$ to L_2. The computation formula is formula 7.

$$\psi(s,w) = H'(O) + H'(B)$$
$$= \ln\left(\sum_{i=L_1}^{s}\sum_{j=L_1-w}^{w+s} I_{ij} \times \sum_{i=s+1}^{L_2}\sum_{j=s+1-w}^{w+L_2} I_{ij}\right) \quad (7)$$
$$- \frac{\left(\sum_{i=L_1}^{s}\sum_{j=L_1-w}^{w+s} I_{ij}\ln I_{ij}\right)}{\sum_{i=L_1}^{s}\sum_{j=L_1-w}^{w+s} I_{ij}} - \frac{\left(\sum_{i=s+1}^{L_2}\sum_{j=s+1-w}^{w+L_2} I_{ij}\ln I_{ij}\right)}{\sum_{i=s+1}^{L_2}\sum_{j=s+1-w}^{w+L_2} I_{ij}}$$

Formula 8 defines the maximum function. In this paper, the maximum of SDAIVE is taken as the selection criterion of threshold value.

$$(s,w)^* = Arg\ \underset{L_1<s<L_2,\,0<w<u}{Max}\ (\psi(s,w)) \quad (8)$$

Solve the maximum of SDAIVE with some optimize algorithm and obtain the optimal segmentation threshold value of image. Then segment image with the optimal threshold value $(s,w)^*$.

In this paper, PSO algorithm is used to solve the SDAIVE maximum. Therefore, the new method is called PSO-SDAIVE algorithm. Function SDAIVE(s,w) is defined with Matlab. In this function, the computations of I_{ij} and p_{ij} are defined.

IV. PSO-SDAIVE ALGORITHM

Particle Swarm Optimization(PSO) algorithm was jointly proposed by the American sociologist and psychologist of James Kennedy and electrical engineer Russell Eberhart in 1995. The basic idea of PSO algorithm was inspired by researching results of behavior about bird groups and makes use of a biological communities model which was proposed by biologist Frank Heppner.

A. The Brief of PSO Algorithm

PSO algorithm is a Swarm Intelligence Algorithm. It takes particle as individual and flights with a certain speed in the search space. These particles haven't quality and volume. According to the flying experience of individuals and groups, particles can dynamically adjust the flying speed.

Implementation of PSO algorithm is simple and easy. Since 1995, researchers have proposed different algorithm models in many fields. PSO algorithm was analyzed and designed in different respects.

Kenney constructed simple PSO model. Eberhart constructed PSO model with inertia weight factor. YuhuiShi and Clerc constructed PSO model with the shrinkage factor. These models were based on the simulation ideas of PSO. Through a large number of experiments, the significance and roles of different control parameters in models were detailed analysis. Corresponding reference values were identified[10].

In PSO algorithm model, choices of parameters are the focus of research. There are six important control parameters in PSO algorithm. They are population size、cognitive learning rate c_1、social learning rate c_2、the maximum of particle flying speed $V_{\max}$, the inertia weight factor ω、constriction factor K. The population size of particles refers the number of particles in iterative process.

In these algorithm models, the basic and earliest PSO model was defined by Eberhart and Kennedy[11]. It was called simple PSO model. The speed and location are computed by formula 9 and formula 10.

$$v_{id}(t+1) = v_{id}(t) + c_1 r_1(P_{id}(t) - x_{id}(t)) + c_2 r_2(P_{gd}(t) - x_{id}(t)) \quad (9)$$
$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (10)$$

B. Computation of SDAIVE Maximum

In this paper, the simple PSO algorithm is used. Because the sum of c_2 and c_1 should be 4, the values of parameters c_2 and c_1 are 2. The values of parameters r_1 and r_2 are 0.5. Therefore, the iterative formula of speed is simplified as formula 11:

$$v_{id}(t+1) = v_{id}(t) + P_{id}(t) + P_{gd}(t) - 2x_{id}(t) \quad (11)$$

Because gray value of pixel is integer, the solution of SDAIVE maximum can take as integer planning problem. In the whole searching process, V_v and V_d represent particle speed in two directions. G_B represents the location of SDAIVE maximum. That is said, it is location of optimal threshold in computation process. Pixel particles move along the gray value(V-direction) and the gray D-value(µ-direction) at the same time. Speed and location of particles need iterate in two directions at the same time.

In this paper, t denotes the particle generation. i denotes serial number of particle. v_{iv} denotes the speed change in gray value direction. $v_{i\mu}$ denotes the speed change in gray D-value direction. x_{iv} denotes the location change in gray value direction. $x_{i\mu}$ denotes the location change in gray D-value direction. $P_{iv}(t)$ and $P_{i\mu}(t)$ are the corresponding particle locations of the SDAIVE maximum in the t generation. Formula 12-15 is the iterative formula of speed and location.

$$v_{iv}(t+1) = v_{iv}(t) + P_{iv}(t) + P_{gv} - 2x_{iv}(t) \quad (12)$$
$$x_{iv}(t+1) = x_{iv}(t) + v_{iv}(t+1) \quad (13)$$
$$v_{i\mu}(t+1) = v_{i\mu}(t) + P_{i\mu}(t) + P_{g\mu} - 2x_{i\mu}(t) \quad (14)$$
$$x_{i\mu}(t+1) = x_{i\mu}(t) + v_{i\mu}(t+1) \quad (15)$$

C. Execution of PSO-SDAIVE Algorithm

The PSO-SDAIVE algorithm has 5 steps.

1).Input image and calculate the number of image pixels. Compute the parameter spatial gray average and spatial information. Draw the 2D D-value histogram;

2).According to 2D D-value attribute histogram, compute information quantity of object region and background region in gray range;

3).Compute SDAIVE with formula and obtain associated discriminate function;

4).Solve the threshold pair(*s,w*) with PSO algorithm;

5).Ensure the optimal threshold and segment image with optimal threshold.

V. EXPERIMENT AND RESULTS ANALYSIS

In order to validate the capability of PSO-SDAIVE algorithm, different grayscale images are segmented in experiment. Experiment results are analyzed and compare with other segmentation results.

A. Experiment Process and Results

At first, grayscale images without noises are segmented. Figure Ⅱ shows the two original gray images and segmented images with different methods. Then, grayscale image with noise is segmented. Figure Ⅲ shows the segmentation results of noise grayscale. .

(a) the original grayscale images

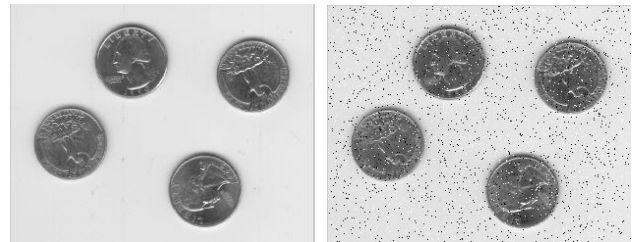(b) the segmentation results with traditional threshold method

(c) the segmentation results with improved threshold method
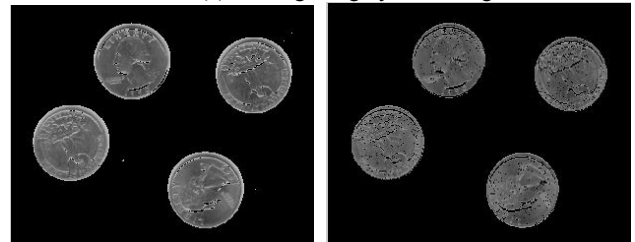FIGURE Ⅱ GRAYSCALE IMAGES SEGMENTATION

B. Experiment Results Analysis

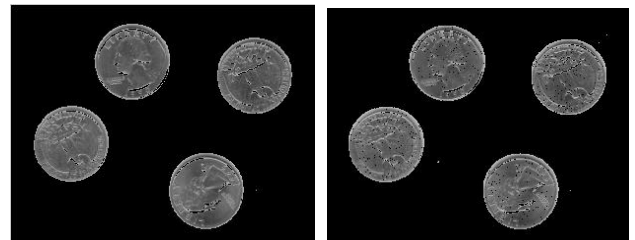Comparing two segmentation results, the segmentation result with

improved method is clearer. Otherwise, the attribute conditions narrow the search space and the cost time of solving optimal threshold is decreased. The PSO-SDAIVE method has good anti-noise capability.

(a) the original grayscale images

(b) the segmentation results with traditional threshold method

(c) the segmentation results with improved threshold method
FIGURE Ⅲ GRAYSCALE IMAGES SEGMENTATION

VI. CONCLUSION

PSO-SDAIVE algorithm not only considers the spatial information, but also considers the gray information and decreases the computing quantity. Otherwise, the neighboring pixel control parameter is set. The overly-smoothness of images can be avoided.

In this paper, simple PSO model is used. In fact, there are many different PSO models. In future, we will research the solving method of SDAIVE with different PSO models.

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