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Image Segmentation Research Based on GA and Improved Otsu Algorithm

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Abstract

In the face of the problem of high complexity of two-dimensional Otsu adaptive threshold algorithm, a new fast and effective Otsu image segmentation algorithm is proposed based on genetic algorithm. This algorithm replaces the segmentation threshold of the traditional two - dimensional Otsu method by finding the threshold of two one-dimensional Otsu methods it reduces the computational complexity of the partition from O (L4) to O (L). In order to ensure the integrity of the segmented object, the algorithm introduces the concept of small dispersion in class, and the automatic optimization of parameters are achieved by genetic algorithm. Theoretical analysis and experimental results show that the algorithm is not only better than the original two-dimensional Otsu algorithm, but also it has better segmentation effect.

***Keywords**: image segmentation, two-dimensional histogram, Otsu algorithm, scattered measure within clusters, genetic algorithm*

1. Introduction

Image segmentation is one of the basic and key technologies in image processing and computer vision. It is also a prerequisite for image comprehension and pattern recognition. It is also widely used in real life. For example, the division of magnetic resonance images in medicine, the target segmentation of synthetic aperture radar images in remote sensing applications, and the application of machine vision to product quality testing. In these applications, the quality of image segmentation directly affects the effect of subsequent image processing, and it even determine its success or failure, therefore, the role of image segmentation is essential.

Among the many segmentation methods, threshold segmentation is one of the common use and simple image segmentation methods it essentially boils down to the threshold selection problem. A lot of research has been done on domestic and foreign scholars to solve this problem, and a variety of threshold selection methods have been proposed. Among them, one-dimensional inter-class variance method (Otsu algorithm) was proposed by Otsu in 1978, [1], its segmentation effect is better, there are wide range of applications and simple and effective, it causes widespread concern, And it has been widely used. However, when the image gray-scale distinction is not obvious in the target and the background, the application of this method will make the image segmentation of information loss, there is a more serious segmentation error. Therefore, the literature [2] generalizes the one-dimensional Otsu threshold method to two dimensions, taking into account the situation of the pixel itself and the average gray-scale distribution of the neighborhood pixels, so that the noise immunity is improved. However, the two-dimensional Otsu threshold method improves the noise immunity and also increases the computational complexity of the algorithm it is not conducive to the wide application of real-time occasions. In the literature [3-6], the traditional two-dimensional Otsu algorithm is improved, and it also exist the above problems.The two-dimensional Otsu algorithm is extended to three dimensions [7]. Although the segmentation effect is good, it is also costly at the time of complex theoretical derivation and longer time. The gray value of the center pixel of the neighborhood and the gray value of all the pixels in the neighborhood are used to form the two-dimensional histogram [8], and then imades are segmented. In addition, in recent years, the theory of pattern division has been applied to image segmentation [9], it is as a new type of tool, but this segmentation method usually has high complexity, and real-time performance is also poor.

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2. Analysis of Two - Dimensional Otsu Algorithm

In two-dimensional Otsu method, the original image and its neighborhood smooth image are used to construct a two-dimensional histogram, it is with good anti-noise, the principle is as follows: Let f (x, y), (1 ≤ x ≤ M, 1 ≤ y ≤ N) is an image with a size of M × N and a grayscale L, and the average gray scale of its n × n neighborhood is calculated at each pixel, its neighborhood smoothing image g (x, y) is obtained, the gray scale is L. For any pixel in the image, it forms a binary: the pixel gray value and the neighborhood average gray value. Let f_{ij} denote the gray value of the pixel i in image f, and the number of pixels with the neighborhood mean gray scale j is the same number of spatial positions, and the two-dimensional histogram of the image point is obtained. The two-dimensional joint probability density is the formula (1):

$$p_{ij} = \frac{f_{ij}}{M \times N} \tag{1}$$

Where, $0 \le i, j \le (L-1). \sum_{i=1}^{L-1}\sum_{j=1}^{L-1} p_{ij} = 1.$

The grayscale g (m, n) of the image g can be calculated by using equation (2)

$$\mathrm{g}(m,n) = \frac{1}{k \times k} \sum_{i=-(k-1)/2}^{(k-1)/2} \sum_{j=-(k-1)/2}^{(k-1)/2} f(m+i, n+j). \tag{2}$$

Where k is the width of the square neighborhood of the pixel, and it is generally odd.

(s, t) is used to divide the image into background and target, where s is the grayscale segmentation threshold, and t is the neighborhood grayscale mean segmentation threshold, 0 ≤ s ≤ L-1, 0 ≤ t ≤ L-1, then the proportion of the background and the target part is as shown in equation (3) and (4):

$$\omega_b = \sum_{i=0}^{s}\sum_{j=0}^{t} p_{ij} = \omega_b(s,t) \tag{3}$$

$$\omega_o = \sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} p_{ij} = \omega_o(s,t) \tag{4}$$

In the vast majority of cases, the probability of noise and edge points is very small, that is, the probability of being far from the diagonal is negligible. So that we can assume that $\omega_b + \omega_o = 1$, at this time, the two corresponding means vector is the following formula:

$$\mu_{\mathrm{b}}(s,t) = (\mu_{b1}, \mu_{b2})^T = [\frac{\sum_{i=0}^{s}\sum_{j=0}^{t} i p_{ij}}{\omega_b(s,t)}, \frac{\sum_{i=0}^{s}\sum_{j=0}^{t} j p_{ij}}{\omega_b(s,t)}]^T \tag{5}$$

$$\mu_{\mathrm{o}}(s,t) = (\mu_{o1}, \mu_{o2})^T = [\frac{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} i p_{ij}}{\omega_o(s,t)}, \frac{\sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} j p_{ij}}{\omega_o(s,t)}]^T \tag{6}$$

The overall mean is the following formula:

$$\mu\ (s,t) = (\mu_1, \mu_2)^T = [\sum_{i=0}^{\text{L-1}}\sum_{j=0}^{\text{L-1}} i p_{ij}, \sum_{i=0}^{\text{L-1}}\sum_{j=0}^{\text{L-1}} j p_{ij}]^T \tag{7}$$

Define the dispersion matrix the following formula as:

$$\omega_B = \omega_b[(\mu_b - \mu)(\mu_b - \mu)^T] + \omega_o[(\mu_o - \mu)(\mu_o - \mu)^T] \quad (8)$$

The trace of the dispersion matrix is used as the distance measure function of the background and the target class:

$$\mathrm{tr}(\omega_B) = \omega_b[(\mu_{b1} - \mu_1)^2 + (\mu_{b2} - \mu_2)^2] + \omega_o[(\mu_{o1} - \mu_1)^2 + (\mu_{o2} - \mu_2)^2] \quad (9)$$

When tr(σ_B) is large, the obtained threshold is the optimal threshold (s *, t *).

For the two-dimensional Otsu algorithm, although its segmentation effect is better, because of its traversing the entire image, the calculation is too large, a tr(σ_B) need be calculated to each (s, t), the algorithm requires a double cycle, and a tr(σ_B) is calculated for each. All need do the cumulative operation to s × t + (L-s) × (L-t) points, so the total cumulative number is $\mathrm{Num} = \sum_{s=0}^{L-1}\sum_{t=0}^{L-1}(s \times t + (L-s) \times (L-t))$, The time complexity is O (L^4), and the computational complexity is large. In this paper, the original two-dimensional algorithm is improved; ot is combined with the genetic algorithm, so that the operation speed has been greatly improved.

3. An Improved Threshold Selection Algorithm

Aiming at the problem of high computational complexity of two-dimensional Otsu algorithm, an improved Otsu algorithm is proposed in this paper, it divides the traditional two-dimensional algorithm into two one-dimensional Otsu algorithm: one-dimensional square graph obtains a threshold, it purpose is to extract the target; a threshold is obtained from a one-dimensional histogram based on the neighborhood average gray scale value, the aim is filtering out the noise. The thresholds of the original two-dimensional Otsu algorithm are replaced by the two thresholds, the thresholds are obtained by the two one-dimensional Otsu algorithms. Compared with the one-dimensional Otsu algorithm, this algorithm not only considers the gray information of the image itself, but also considers the information of its neighborhood pixel, so that the algorithm has good denoising ability. In addition, because it uses two one-dimensional Otsu algorithms, so its computational complexity in the above greatly improved.

From the frequency f_{ij} appearing in the two-dimensional histogram (i, j), we can deduce the frequency $q_i = \sum_{j=0}^{L-1} f_{ij}$ of the pixel gray scale value i and the frequency $r_j = \sum_{i=0}^{L-1} f_{ij}$ of the neighborhood gray scale value j. And so on, the one-dimensional histogram distribution of the pixel gray scale value i and the neighborhood gray scale value j can be obtained from the probability distribution P_{ij}, and their probabilities are $U_i = \sum_{j=0}^{L-1} P_{ij}$, $V_j = \sum_{i=0}^{L-1} P_{ij}$, where i = 0, 1, ..., L-1; j = 0, 1, ..., L-1.

In most cases, the two-dimensional Otsu method is used in the edge and noise points, these accounted for a minority, that is, the noise and the edge of the corresponding probability can be approximated to 0, that is to say : $\sum_{i=s+1}^{L-1}\sum_{j=0}^{t} p_{ij} = 0$ and $\sum_{i=0}^{s}\sum_{j=t+1}^{L-1} p_{ij} = 0$. Therefore, in the one-dimensional histogram corresponding to the pixel gray scale value i, the ratios ω_o and ω_b of the target and the background can be obtained, respectively.

$$\omega_b = \sum_{i=0}^{s}\sum_{j=0}^{t} p_{ij} + \sum_{i=0}^{s}\sum_{j=t+1}^{L-1} p_{ij} = \sum_{i=0}^{s}\sum_{j=0}^{L-1} p_{ij} = \sum_{i=0}^{s} U_i = \sum_{j=0}^{t} V_j \quad (10)$$

$$\omega_o = \sum_{i=s+1}^{L-1}\sum_{j=t+1}^{L-1} p_{ij} + \sum_{i=s+1}^{L-1}\sum_{j=0}^{t} p_{ij} = \sum_{i=s+1}^{L-1}\sum_{j=0}^{L-1} p_{ij} = \sum_{i=s+1}^{L-1} U_i = \sum_{j=t+1}^{L-1} V_j \tag{11}$$

The corresponding mean vector for the two classes is the following formula:

$$\mu_b(s,t) = (\mu_{b1}, \mu_{b2})^T = [\frac{\sum_{i=0}^{s} i U_i}{\omega_b}, \frac{\sum_{j=0}^{t} j V_j}{\omega_b}]^T,\ \mu_o(s,t) = (\mu_{o1}, \mu_{o2})^T = [\frac{\sum_{i=s+1}^{L-1} i U_i}{\omega_0}, \frac{\sum_{j=t+1} j V_j}{\omega_o}]^T \tag{12}$$

While the overall mean vector is the following formula:

$$\mu\ (s,t) = (\mu_1, \mu_2)^T = [\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} i p_{ij}, \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} j p_{ij}]^T = [\sum_{i=0}^{L-1} i U_i, \sum_{j=0}^{L-1} j V_j]^T \tag{13}$$

From the above formula the one-dimensional variance between the class can be derived, it is corresponding to pixel gray value i:

$$\sigma_{B1}(s) = \omega_b(\mu_{b1} - \mu_1)^2 + \omega_o(\mu_{o1} - \mu_1)^2 \tag{14}$$

Similarly, we can get the one-dimensional variance between the class of the neighborhood squared value j:

$$\sigma_{B2}(t) = \omega_b(\mu_{b2} - \mu_2)^2 + \omega_o(\mu_{o2} - \mu_2)^2 \tag{15}$$

According to the one-dimensional Otsu principle, the optimal threshold s *, t * should be satisfied in the following formula:

$$\sigma_{B1}(s^*) = \max_{0 \le s \le L-1}\{\sigma_{B1}(s)\}, \sigma_{B2}(t^*) = \max_{0 \le t \le L-1}\{\sigma_{B1}(t)\} \tag{16}$$

In the threshold segmentation method of the traditional Otsu algorithm: although it takes into account the variance between the foreground class and the background class, and the segmentation effect is better, because it does not take into account the discrete nature of each class, it does not reflect the good or bad of the classification more comprehensively itself, a more accurate division is achieved. Based on the above algorithm, this paper introduces the intraclass dispersion, so that the segmentation result not only achieves the variance between classes, but also better achieves the consistency within the class. The discrete measure of the classification of the pixel gray value is defined as the following formula:

$$\begin{aligned} \tau_{d1} &= \omega_b d_{b1} + \omega_o d_{o1} \\ d_{b1} &= \frac{\sum_{i=0}^{s} |\mu_{b1} - i| U}{\omega_b}{}_i \\ d_{o1} &= \frac{\sum_{i=s+1}^{l-1} |\mu_{o1} - i| U}{\omega_o} \end{aligned} \tag{17}$$

From the formula (14) and (17), a new threshold recognition function is constructed, it is shown in equation (18):

$$\psi_1 = \omega_o(1-\omega_o)\times\sigma_{B1}/\tau_{d1} \tag{18}$$

Similarly, for the one-dimensional histogram composed of neighborhood gray mean values, a threshold recognition function is also constructed:

$$\psi_2 = \omega_o(1-\omega_o)\times\sigma_{B2}/\tau_{d2},\quad \tau_{d2} = \omega_b d_{b2} + \omega_o d_{o2}$$
$$d_{b2} = \frac{\sum_{i=0}^{s} |\mu_{b2} - i| U}{\omega_b},\quad d_{o2} = \frac{\sum_{i=s+1}^{l-1} |\mu_{o2} - i| U}{\omega_o} \tag{19}$$

In order to make the segmentation effect good, so that the dispersion is small within the class, we need get ψi, ψj large value, that is, τdi, τdj are small. This will enable the class to achieve a better separation, but also it can achieve better consistency within the class, so that the segmentation effect is better.

When the gray level of the image is L, the time complexity of the original two-dimensional Otsu algorithm is $O(L^4)$. By calculating the two-dimensional Otsu algorithm, the algorithm complexity is about O(L+L) = O(L), this algorithm reduces the time complexity.

In order to determine the image segmentation threshold quickly and effectively, the appropriate threshold vector (s, t) can be obtained by using the optimal characteristics of the genetic algorithm as follows: formula (18) and (19) are used as the fitness function. Two - Dimensional threshold segmentation of gray image can be achieved.

4. Threshold Optimization Based on Genetic Algorithm

From the equations (18) and (19), it can be seen that the threshold problem of image segmentation is an optimization problem. In this paper, the equations (18) and (19) are used as the fitness Function, through the selection, crossover and mutation, the image segmentation excellent threshold vector (s^*, t^*) is found. Genetic algorithm is used to find excellent threshold, its flow chart is shown in Figure 1.

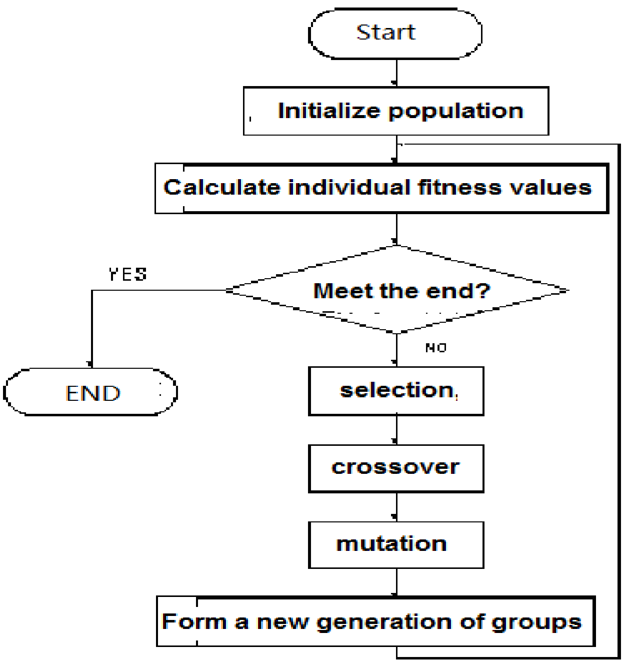


Figure 1. Flowchart of searching for the best threshold based on genetic algorithms

1) **Initialization:** the initial size of the population is size, through the random number generator randomly generated the initial population with the matrix of size lines, 16 columns.
2) **Coding:** For two-dimensional Otsu, since the threshold to be split is two-dimensional, the 16-bit binary code is used to represent the two-dimensional segmentation threshold, x = (x_0, …, x_7, x_8, …, x_{15}) The first eight represent the split threshold s and the last eight bits represent the split threshold t.
3) **Fitness function:** the formula (18) and (19) are used as a fitness function, when it is large. The corresponding parameters are s, t, they are good split thresholds.
4) **Selection:** Traditional genetic algorithm used in the roulette choice, it usually lead to loss of diversity of the population, genetic algorithm will prematurely lost its evolutionary ability. The fitness ratio method is selected, it is the size of the fitness for the proportion of the genetic process of the parent selection, the higher the fitness of the individual, the greater the probability is selected. The population structure not only ensures that the outstanding individuals enter the next generation, but also ensure the diversity of the population, so that the probability of similar individuals is reduced in the population, the efficiency of genetic operation is improved, and the convergence of the whole algorithm is improved.
5) **Cross:** in the implementation process of traditional genetic algorithm, it is possible that some individuals can not cross a cross, it will waste a lot of computing resources. An adaptive crossover probability is used to give a lower crossover probability for individuals, the fitness values are higher than the population mean fitness values; for individuals with fitness values below the population mean fitness values, a larger crossover probability is given, to make it out. The adaptive crossover probability is as follows:

$$\begin{aligned} &if\ f_1 < f_{avg}, \quad P_c = P_{c1} \\ &else \quad P_c = P_{c2}\frac{f_{\max} - f_1}{f_{\max} - f_{avg}} \end{aligned}$$

Where f_1 is the greater fitness value for the two individuals to be crossed, f_{avg} is the average fitness value for each generation population, f_{max} is the large fitness value in the population, P_{c1} is the large crossover probability, P_{c2} is the small cross Probability.

6) **Mutation:** the value of a bit of the chromosome symbol string is randomly changed with a small mutation probability p_m.

$$\begin{aligned} &if\ f_2 < f_{avg}, \quad P_m = P_{m1} \\ &else \quad P_m = P_{m2}\frac{f_{\max} - f_2}{f_{\max} - f_{avg}} \end{aligned}$$

Where: f_2 is the fitness value of the individual to be mutated, P_{m1} is the probability of large mutation, P_{m2} is the probability of small mutation. This method is based on the average fitness value of each generation population, and the individuals with good fitness values have different probabilities. This can better retain the fine individuals, the poor individuals are eliminated, it can speed up the convergence rate and greatly improve the solution quality.

Algorithm termination condition: Determines whether the algorithm terminates based on the number of large iterations' set, or whether the difference between the average fitness value of the current population and the average fitness value of the previous generation is less than 1×10^{-4}.

5. Experimental Results and Analysis

In order to verify the performance of the algorithm, three gray images were selected and it was compared with the literature [2] and the literature [6]. In the experiment, the parameters are set, window neighborhood is 3; population size is 10; iteration number is 150; encoding length is 16; Large crossover probability is 0.85, small crossover probability is 0.25; large mutation probability is 0.1; small mutation probability is 0.02.

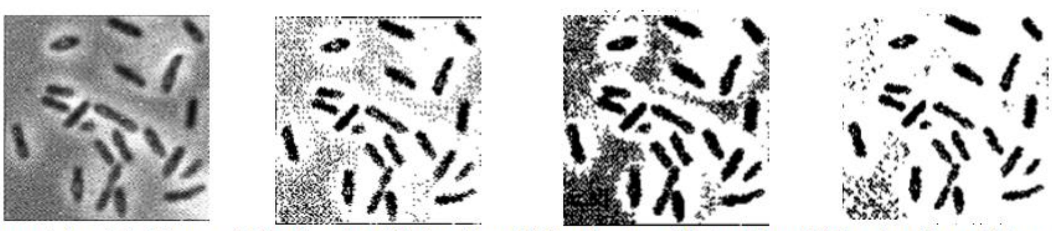
It can be seen from Figure 2 that the literature [2] algorithm segmentation results lost part of the details, such as the car's seats are filtered out or blurred, and our algorithm segmentation effect is better, it greatly retained the details In the Figure 3, the denoising of (c) and (d) is better than (b), and (d) is smoother than the edge portion of (c). In Figure 4, the denoising effect of the proposed method is significantly better than the previous two, so that the particles are better separated. From the experimental data of Table 2, it can be concluded that the proposed algorithm in this paper is basically 1/3 of the algorithm [2] and the algorithm [6] in the execution time. Therefore, the proposed algorithm satisfies the real-time requirement in this paper.

(a) car original (b) the literature [2] algorithm (c) the literature [6] algorithm (d) the algorithm of this paper

Figure 2. Comparison of segmentation results for the car image

(a) zebra original (b) the literature [2] algorithm (c) the literature [6] algorithm (d) the algorithm of this paper

Figure 3. Comparison of segmentation results for the horse image



(a) particle original image (b) the literature [2] algorithm (c) the literature [6] algorithm (d) the algorithm of this paper

Figure 4. Comparison segmentation results for the kernel image

Table 1. Threshold statistic of three kinds of algorithms

	[2] algorithm	[6] algorithm	our algorithm
Car image	(82, 164)	(107, 106)	(100, 100)
Zebra image	(83, 146)	(73, 127)	(96, 96)
Particle image	(116, 164)	(144, 148)	(125, 124)

Table 2. Time statistic of three kinds of algorithms

	[2] algorithm	[6] algorithm	our algorithm
Car image	6.978 1	6.783 1	2.312 5
Zebra image	2.937 5	2.984 4	1.118 8
Particle image	3.203 1	3.312 5	0.968 8

Table 3. Quantitative evaluation result of three kinds of algorithms

	[2] algorithm	[6] algorithm	our algorithm
Car image	0.642 3	0.763 6	0.859 1
Zebra image	0.875 3	0.907 9	0.985 6
Particle image	0.897 2	0.866 3	0.967 5

The result of the image segmentation usually is based on the subjective judgment of the person, but the effect is judged by the observation, it is very scientific, so the quantitative analysis of the results of different segmentation method is also necessary. In this paper, we use the image segmentation quality evaluation index regional consistency [14, 15], the performance of the three algorithms is quantitatively evaluated.

A good segmentation algorithm should be able to produce a segmentation result with similarity (consistency) within the interior of the partitioned region. This feature consistency can be obtained by calculating the characteristic variance in the region, $\mathrm{U} = 1 - \frac{(\sigma_1^2 + \sigma_2^2)}{\mathrm{c}}$, $\sigma_i^2 = \sum_{(x,y)\in R_i} [f(x,y) - \mu_i]^2$, $\mu_i = \sum_{(x,y)\in R_i} f(x,y)/A_i$, i = 1 or 2 represent the target area and the background area, A_i is the number of pixels in the region, σ_i is the variance of the pixel in the region, and c is the number of pixels of the whole image.

As can be seen from Table 3, this algorithm has a better indicator of regional consistency parameters, it is consistent with human vision. In summary, the proposed algorithm in this paper is better than the literature [2] algorithm, it is basically the same as or better than the effect of [6] algorithm.

6. Conclusions and Outlook

This paper presents a new adaptive two-dimensional Otsu algorithm. In order to improve the integrity of the segmented object, we introduce the threshold value of the two-dimensional Otsu method. In order to improve the integrity of the segmented object, we introduce the threshold value of the two-dimensional Otsu method, the integrity of the class is ensured. In addition, the algorithm uses the characteristics of genetic algorithm to search the global ability, and the threshold recognition function is used as the evaluation function of fitness, the automatic optimization of image threshold is realized in the genetic algorithm. This method not only considers the gray-level distribution information of the pixels, but also it considers the spatial information of the pixels around the pixels. The experimental results show that the thresholding method can calculate the good threshold by ensuring the good anti-noise of the original two-dimensional Otsu algorithm, it need a shorter time, and the image segmentation effect is better.

A new algorithm is proposed in this paper, it uses two one-dimensional Otsu algorithm to solve the traditional two-dimensional threshold, and the traditional two-dimensional Otsu threshold segmentation method has high computational complexity. The intraclass dispersion is introducted in algorithm, it is combined with the genetic algorithm to find a good threshold, it avoids the search of the entire image in the traditional two-dimensional algorithm, the performance has been greatly improved in time. The experimental results also further demonstrate the feasibility of the algorithm. Compared with other algorithms, it is proved that the algorithm is not only improved in time, but also it has better segmentation effect. Therefore, the proposed algorithm has better real-time in this paper.

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