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Image segmentation based on the maximum between-cluster average deviation of the 2D bound histogram

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Abstract—In order to further improve the accuracy and real-time performance of image segmentation, a new method for image segmentation, which combines the virtues of 2D bound histogram and maximum between-cluster average deviation, is proposed. First, construct the bound set and limit the histogram to region of interest for purpose of reducing the interference of background and noise. And then, the optimal segmenting threshold is obtained by searching in the region of interest for image segmentation using the maximum between-cluster average deviation. Furthermore, the fast recurring algorithm, which is brought forward by the reference, is improved for accelerating the running speed of the algorithm. Different types of infrared images are selected to compare the results of purposed algorithm and the algorithms in literatures. Results show that the proposed algorithm has better segmentation effect, higher segmentation accuracy, less segmentation failure and the running speed is enhanced by more than thirty percent. The bound histogram can be constructed aiming at concrete problem, based on prior knowledge, so it has better generality.

Keywords-2D bound histogram; Image segmentation; Maximum between-cluster average deviation; Fast recursive algorithm

1. Introduction

Image segmentation has always been an important part of the research fields of computer vision and image processing. There are many image segmentation methods, including thresholding, edge detection and region tracking and matching method. Among the numerous methods, threshold segmentation method is the most universal for its simplicity and effectiveness. Traditional thresholding method is based on one-dimension histogram, which only contains gray information of the image but can not reflects the spatial distribution of gray, so the segmentation results are often not satisfactory, or even exist serious segmentation errors when the histogram is not ideal bimodal. Aiming at the problem, a large number of studies have been done by scholars at home and abroad and have acquired stage achievement. Otsu and the maximum entropy method are extended from one-dimension to two-dimension in [1] and [2] respectively, as it consider both the distribution of pixel gray and the neighborhood pixel gray information, so that segmentation results are significantly improved.

The bound histogram, which is the promoting of the concept of histogram, has the function of simplifying the problem as well as the feature of using flexible. According to specific task, algorithm complexity can be reduced by simplifying histogram based on prior knowledge of the image to process. The maximum entropy and OSTU methods are extended and applied to two-dimension bond histogram as the threshold segmentation criteria respectively[3] [4]. By way of constructing bound set to constrain and simplify the histogram, the interference components of the image have been reduced, search space has been compressed and the segmentation results have been improved greatly.

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As the histogram extended from one dimension to two, the increase in dimension will inevitably lead to an exponential increase in computing, so the real-time performance of segmentation can not meet the need of engineering. To solve the above problem, many scholars have proposed different fast algorithms, which greatly reduce the computation time and therefore can satisfy the engineering demand to some extent [5, 6, 7, 8,].

In this paper, image segmentation method using the maximum between-cluster average deviation of the 2D bound histogram is proposed and experiment results show that proposed algorithm presents better segmentation effect and real-time performance.

2. 2D BOUND HISTOGRAM

Let the input image I whose size is $M*N$ and gray level is L. All the pixels of the image are viewed as universe $I=\{0\le x\le M-1,\ 0\le y\le N-1\}$, where (x, y) denotes the pixel coordinate of the image. Let Q denotes the set with certain attribute, and$(x, y)\in Q$ means that the pixel has the attribute. Learning from the traditional two-dimension histogram establishment method, the two-dimension bound histogram is defined as discrete curve formed by $p_Q(i, j)$-i, j or $N_Q(i, j)$-i, j, where $p_Q(i, j)$ represents the occurrence probability of the point whose gray value is i and the neighborhood average gray value is j. In the image I, it is supposed that the number of the pixels with certain attribute is denoted by N_Q and $n_Q(i, j)$ denotes the occurrence frequency of the pixel pair, then

$$p_Q(i,j)=n_Q(i,j)/N_Q \tag{1}$$

Let $L1$, $L3$ represent the minimum and maximum gray value within the range of bound set and meanwhile $L2$,$L4$ represent the minimum and maximum neighborhood average gray value and in general $0\le L1,L2,L3,L4\le L-1$,then the corresponding bond histogram is a matrix whose size is $(L3-L1+1)*(L4-L2+1)$ as shown in Fig.1. The equation (2) can be developed from the equation (1).

$$\sum_{L1\le i\le L3}\sum_{L2\le j\le L4} p_Q(i,j)=1 \tag{2}$$

In some sense 2D bound histogram is a kind of incomplete histogram for it only takes to account the pixels with certain attribute. Aiming at specific condition, the interferential or unconcerned components are rejected according to the prior knowledge, thus the complexity of the algorithm based on two-dimension histogram will be reduced to some extent and meanwhile the real-time performance increased greatly. Different bound sets may produce different bound histograms, therefore the same image can corresponds to multiple two-dimension bound histograms, which are different from traditional histogram, and that makes it more flexible when used.

As shown in Fig. 2, $f(x, y)$ denotes the gray value of the pixel point (x, y) and $g(x, y)$ denotes the neighborhood average gray value of the pixel point, and different bound sets correspond to different two-dimension bound histogram using the average gray value of the whole image as division threshold, which marked as Avr, to construct bound sets.

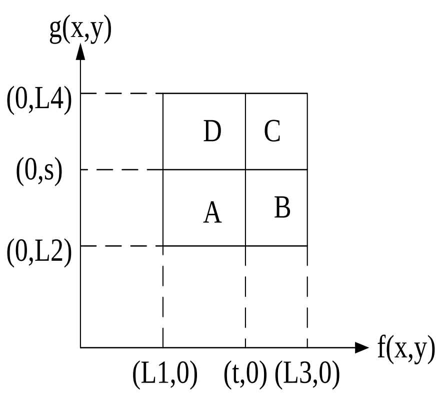
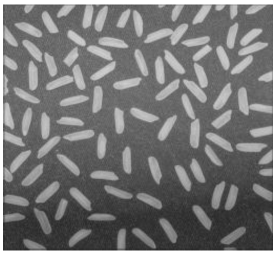
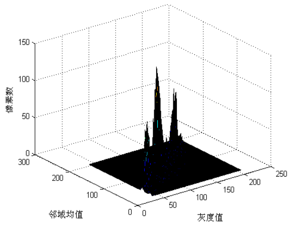
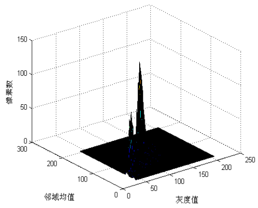


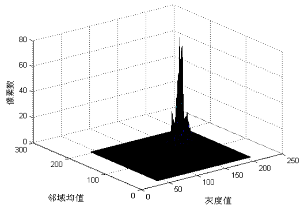
Fig.1 2D bound histogram





(a) Original image (b) 2D histogram





(c) $0 \le f(x, y), g(x, y) \le Avr$ 2D bound histogram (d) $Avr \le f(x, y), g(x, y) \le L$-1 2D bound histogram

Fig.2 Original image and different histograms

3. The Method of Using the Maximumbetween-Cluster Average Deviation of the 2d Dound Histogram

It is supposed that the intensity of the target is high relative to the background. The segmentation threshold is denoted by (t, s) and $\omega_o(t,s)$, $\omega_b(t,s)$ are the probability distribution of target and background and $\mu_o(t,s)$, $\mu_b(t,s)$ denote average value vector of target and background and μT denotes the general average vector of the whole histogram, then the between-cluster average deviation can be expressed as follow through derivation

$$\begin{aligned} d(t,s) &= \omega_o(t,s)d_o(t,s) + \omega_b(t,s)d_b(t,s) \\ &= 2*(|\mu'_{bi}(t,s) - \omega_b(t,s)\mu T_i| \\ &+ |\mu'_{bj}(t,s) - \omega_b(t,s)\mu T_j|) \end{aligned} \tag{3}$$

$$\omega_b(t,s) = \sum_{L1 \le i \le t} \sum_{L2 \le j \le s} p_Q(i,j) \tag{4}$$

$$\begin{aligned} \omega_o(t,s) &= \sum_{t+1 \le i \le L3} \sum_{s+1 \le j \le L4} p_Q(i,j) \\ &= 1 - \omega_b(t,s) \end{aligned} \tag{5}$$

$$\begin{aligned} \mu'_b\ (t,s) &= (\mu'_{bi}(t,s), \mu'_{bj}(t,s))^T \\ &= \omega_b(\mu_{bi}(t,s), \mu_{bj}(t,s))^T \\ &= (\sum_{L1 \le i \le t} \sum_{L2 \le j \le s} i * p_Q(i,j) \\ &\quad , \sum_{L1 \le i \le t} \sum_{L2 \le j \le s} j * p_Q(i,j))^T \end{aligned} \tag{6}$$

$$\begin{aligned} \mu'_o\ (t,s) &= (\mu'_{oi}(t,s), \mu'_{oj}(t,s))^T \\ &= \omega_o(\mu_{oi}(t,s), \mu_{oj}(t,s))^T \\ &= (\sum_{t+1 \le i \le L3} \sum_{s+1 \le j \le L4} i * p_Q(i,j) \\ &\quad , \sum_{t+1 \le i \le L3} \sum_{s+1 \le j \le L4} j * p_Q(i,j))^T \\ &= (\mu T_i - \mu_{bi}(t,s), \mu T_j - \mu_{bj}(t,s))^T \end{aligned} \tag{7}$$

$$\begin{aligned}\mu T &= (\mu T_i, \mu T_j)^T \\ &= (\sum_{L1\le t\le L3}\sum_{L2\le s\le L4} i * p_Q(i,j), \\ &\quad \sum_{L1\le i\le L3}\sum_{L2\le j\le L4} j * p_Q(i,j))^T\end{aligned} \tag{8}$$

Then use the between-cluster average deviation as the measurement of deviation and select the threshold vector denoted by (t_0, s_0), which maximize the between-cluster average deviation, as the optimum threshold vector.

$$(t_0, s_0) = \max_{L1\le t\le L3, L2\le s\le L4} |d(t,s)| \tag{9}$$

From the formula of the above threshold selecting method we can see that $\omega_b(t,s)$, $\mu'_{bi}(t,s)$, $\mu'_{bj}(t,s)$, μT_i, μT_j, among which the general average vector is constant for the same image, need to be recalculated every time calculating d(t, s),which will produce massive duplication calculation if every time starting calculating the parameters of *d(t, s)* from *i=0* and *j*=0. The fast recursive algorithm proposed in [8] make the algorithm complexity reduced from $O(L^4)$ to $O(L)$.In the paper the first fast recursive algorithm is extended and applied to proposed algorithm to increase the running speed of the algorithm.

4. Experiment Results

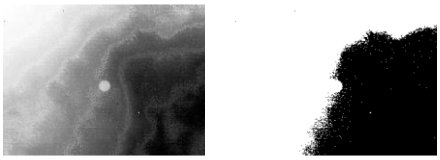
In order to verify the efficiency of the proposed algorithm in the paper, we have selected two different types of infrared pictures, where Fig.3 (a) is an infrared single target picture and Fig.4 (a) is an infrared multiple targets picture. The size of neighborhood window is set to 3×3, and the segmentation results and running time of the proposed algorithm are compared to the algorithms in [7] and [8].

In infrared image, intensity features of the target is always more prominent compared to the surrounding background and the background presents brightness and darkness interleaving for the difference of radiation intensity everywhere. Target is always combined with background and noise and that makes it easy that the infrared target submerged in the background, thus the image segmentation is impossible to carry out. The Otsu method based on traditional histogram is sensitive to the size of target and the segmentation efficiency is weak when the proportion of background and target has huge difference. The same problem is also for the maximum between-cluster average deviation method. To solve the problem, the bound set is constructed for the purpose of limiting the histogram to region of interest so as to reduce the influence of background and noise for segmentation to maximal extent and then the segmentation result can be improved greatly. The character of the infrared image is that the gray level of target is greater than the background and there exists large block of region in which gray changes slowly and the region of interest is manly distributed in the high gray level region, which will be retained when constructing bound set. The bound histogram can be expressed as

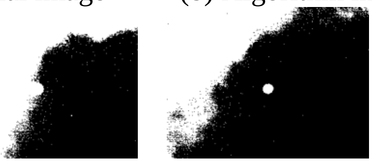
$$\begin{aligned}Q = \{(x,y) \mid\, & th \le f(x,y) \le L-1 \\ & th \le g(x,y) \le L-1, \\ & 0 \le x \le M-1, 0 \le y \le N-1, \\ & 0 \le th \le L-1\}\end{aligned} \tag{10}$$

where *f(x, y)*、*g(x, y)* represent the same as before and *th* denotes the division threshold of the bound histogram. Because the area of target is far less than that of background, which is more influential for segmentation, in order to reduce the influence of background, *th* is set a value that is not less than the average gray value of the whole image as the threshold of the bound set. $th = \bar{g} + k*(g^m - \bar{g})$, where $\bar{g}$ denotes the average gray value of image, g^m denotes the maximum gray value of image, and k is the weight which can be adjusted according to the features of target and background. In the experiment, the gray of the single target image mainly distribute around the average gray value and the contrast is low between target and background so that k=0.Meanwhile, the gray of the background change slowly and is lower and the gray of target is higher representing as isolate bright spot so k =0.15. Fig.3 (b), (c), (d) and Fig.4 (b), (c), (d) are the segmentation results of proposed algorithm and that of algorithms in reference. Otherwise the segmentation threshold is listed in Table1 and the running time of different algorithms is listed in Table 2.

According to the experimental compare, it is not difficult to find that the proposed algorithm is superior to the algorithms in reference. For the infrared single target image, the segmentation result of the proposed algorithm in the paper is better, and the edge of the target is more accurate and clear. In contrast, the target has been submerged in the background for the algorithms in literatures. For the infrared multiple targets image, the correct segmentation probability which is the rate of the number of targets that has been correctly divided and the actual number of small targets, is up to 89.8%(see Table.3) and that leaves the algorithms in reference far behind. Moreover, the segmentation result has less isolated noise spots and background disturbance. In respect of the computation times, because of the use of fast recursive algorithm the running speed has been greatly improved compared to original algorithm. However, compared to other methods developed before, the running speed has increased by more than 30% because of the use of two-dimension bound histogram, which greatly simplify the computation for the algorithm compared to using the traditional histogram, thus the real-time performance of the algorithm is further improved.

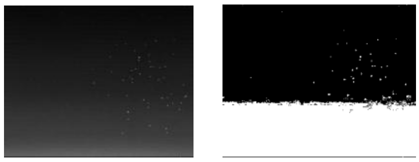


(a) Original image (b) Algorithm in [7]

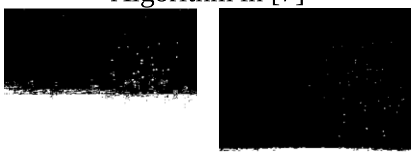


(c) Algorithm in [8] (d) Proposed algorithm

Fig.3 Segmentation results of infrared single target image



(a) Original image (b) Algorithm in [7]



(c) Algorithm in [8] (d) Proposed algorithm

Fig.4 Segmentation results of infrared multiple targets image

Table1. Threshold of image segmentation

image	Algorithm in [7]	Algorithm in [8]	Proposed algorithm
Single target	(108,134)	(108,116)	(188,194)
Multiply target	(43,51)	(35,35)	(76,75)

Table2. Processing time of image segmentation

image	Algorithm in [7]	Algorithm in [8]	Proposed algorithm
Single target	8.85	9.66	5.73
Multiply target	9.87	9.84	6.57

Table3. Correct segmentation probability of small targets

Algorithm in [8]	Algorithm in [9]	Proposed algorithm
63.3%	42.9%	89.8 %

5. Conclusion

In the paper, aiming at the problem that the traditional histogram contains global information of the image and the segmentation result is not satisfactory if the proportion that the target account for in the whole image is too small Construct bound set based on the prior knowledge to confine the histogram in a region of interest and that makes the interference of the background and noise greatly reduced, so the complexity of the algorithm would be decreased and the segmentation result is more accurate. Then search the optimal threshold for segmentation in the bound histogram using the between-cluster average deviation as criterion. For the large block of successive background and scattered noise spots after segmentation, it is possible to eliminate through post-processing and then the target can be divided accurately. In the experiment the infrared single target image and infrared multiple targets image are selected and according the compare of the segmentation results of the different algorithm, it is easy to find that the proposed algorithm is superior to the existing ones whatever the accuracy of segmentation or the anti-jamming performance. That's the conclusion given by comparing the segmentation results of the proposed algorithm with that in [7] and [8]. In addition, compared to others in literature, the running speed has been increased by more than 30% because of the use of the fast recursive algorithm and meanwhile simplifying the calculation by using bound histogram. The proposed algorithm has advantages of generalization in the case of awarded certain prior knowledge. It will also be pointed out that for those specific questions we can construct bound set flexibly to meet different needs according to its segmentation purpose.

6. References

[1] J. Z. Liu, W. Q. Li． The automatic thresholding of gray-level pictures via two-dimensional Otsu method, Acta Automatica Sinica, Vol. 19(1), pp. 101-105, 1993.

[2] ABUTALEB A S． Automatic thresholding of gray-level picture using two- dimensional entropies, Pattern Recognition, Vol. 47(1), pp. 22-32 1989.

[3] H. T. Guo, L. Y, Wang, et al. Automatic thresholding using the Otsu algorithm based on two-dimensional histogram. Journal of Optoelectronic.Laser, Vol. 16(6), pp. 739-742, 2005.

[4] H. T. Guo, T. Tian. Image segmentation using the maximum entropy of the two-dimensional bound histogram, Vol. 26(4), pp 506-509, 2006..

[5] Y. M. Hao, F. Zhu. Fast algorithm for two-dimensional Ostu adaptive threshold algorithm. Journal of Image and Graphics, Vol. 10(4), pp. 484-488, 2005.

[6] Y. Q. Wu, Z. Pan. A fast iterative algorithm for image segmentation based on 2D maximum between-cluster variance. CHINESE JOURNAL STEREOLOGY AND IMAGE ANALYSIS, Vol. 12(3), pp. 216-220, 2007.

[7] H. Y. Wang, D. L. Pan. A fast algorithm for two-dimensional Otsu adaptive threshold algorithm. Acta Automatica Sinica, Vol. 33(9), pp. 968-971, 2007.

[8] Y. Q. Wu, Z. Pan. Fast recursive two-dimensional maximum between-cluster average deviation thresholding algorithm. Journal of Image and Graphics, Vol. 14(3), pp. 471-476, 2009.