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Infrared image segmentation with 2-D maximum entropy method based on particle swarm optimization (PSO)

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Abstract

The 2-D maximum entropy method not only considers the distribution of the gray information, but also takes advantage of the spatial neighbor information with using the 2-D histogram of the image. As a global threshold method, it often gets ideal segmentation results even when the image's signal noise ratio (SNR) is low. However, its time-consuming computation is often an obstacle in real time application systems. In this paper, the image thresholding approach based on the index of entropy maximization of the 2-D grayscale histogram is proposed to deal with infrared image. The threshold vector (t, s), where t is a threshold for pixel intensity and s is another threshold for the local average intensity of pixels, is obtained through a new optimization algorithm, namely, the particle swarm optimization (PSO) algorithm. PSO algorithm is realized successfully in the process of solving the 2-D maximum entropy problem. The experiments of segmenting the infrared images are illustrated to show that the proposed method can get ideal segmentation result with less computation cost.
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1. Introduction

Image segmentation is a technique decomposing an image into meaningful parts, or objects,

and infrared image segmentation plays a special role in automatic target recognition (Pal and Pal, 1993; Boskovitz and Guterman, 2002). Image thresholding is essentially a pixels classification problem (Weszka, 1978). Its basic objective is to classify the pixels of a given image into two classes: those pertaining to an object and those pertaining to the background. While one includes pixels with

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gray values that are below or equal to a certain threshold, the other includes those with gray values above the threshold. Thresholding is a popular tool for image segmentation for its simplicity, especially in the fields where real time processing is needed. Up to now, many threshold selection techniques have been proposed (Portes de Albuquerque et al., 2004).

In general, threshold selection techniques can be broadly divided into two groups, namely, global and local thresholding. A global technique may be point-dependent or region-dependent. The thresholding method is point-dependent if the threshold value is determined solely from the pixel gray tone as represented by gray-level histogram and is independent of the gray tone of the neighborhood of a pixel. On the other hand, a method is called region-dependent if the threshold value is determined from the local property within a neighborhood of a pixel. A global thresholding technique is one that segments the entire image with a single threshold value, whereas a local thresholding technique is one that partitions a given image into subimages and determines a threshold for each of these subimages. Though point-dependent global thresholding methods are comparatively simple, only a small part of the independent information of the image is used. Therefore, these techniques are not always useful. In this paper we propose a global threshold selection method to do infrared image segmentation, which uses both gray-level distribution and spatial information, namely, 2-D maximum entropy thresholding (Abutaleb, 1989; Kapur et al., 1985). What's more, taking consideration of the complexity of its computation, we introduce a new heuristic optimization algorithm, called the particle swarm optimization (PSO) algorithm to search the result (Kennedy and Eberhart, 1995). The work is organized as follows. In Section 2, the proposed thresholding method and its theoretical justifications are presented. In Section 3, the PSO algorithm and its modification are described. In Section 4, it is shown that how the two methods are extended together for segmenting infrared images. Finally, some concluding remarks regarding the proposed methods are given.

2. 2-D maximum entropy thresholding

The motivation of application of the maximum entropy method to solve threshold selection problem in our paper is that this method has been successfully applied in many real systems such as image reconstruction and target recognition (Zenzo et al., 1998; Pal and Pal, 1989). The maximum entropy principle states that, for a given amount of information, the probability distribution which best describes our knowledge is the one that maximizes the Shannon entropy subjected to the given evidence as constraints (Shannon, 1948; Klir and Folger, 1988). In this paper, we propose to use the 2-D maximum entropy method to do image segmentation. A lot of application examples have proved that the performance of the 2-D maximum entropy method is better than that of the 1-D maximum entropy method.

The 2-D maximum entropy method is based on the 2-D histogram of the image. The 2-D histogram is got as the following:

$$p_{ij} = \frac{n_{ij}}{N \times N} \qquad (1)$$

where $N \times N$ denotes the image size, and n_{ij} denotes the number of a pixel whose grey value equals i and local average value equals j. The 2-D histogram plane can be described as Fig. 1: where the area 1 and 2 denote objects and background respectively, and 3 and 4 denote edges and noise. So a threshold vector (t, s), where t is a threshold for pixel intensity and s is another threshold for the local average of pixels, should be determined to divide them. According to the maximum entropy principle, the determined threshold vector should make area 1 and area 2 have the maximum information.
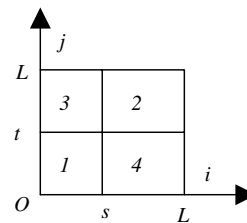

Fig. 1. The 2-D histogram plane.

Suppose the area 1 and area 2 have different probability distributions. According to the threshold vector (t,s), we denote P_1 and P_2 as:

$$P_1 = \sum_{i=0}^{s-1} \sum_{j=0}^{t-1} p_{ij}, \quad P_2 = \sum_{i=s}^{L-1} \sum_{j=s}^{L-1} p_{ij}. \tag{2}$$

Then the 2-D discrete entropy can be defined as:

$$H = -\sum_{i} \sum_{j} p_{ij} \lg p_{ij}. \tag{3}$$

The 2-D entropy of area 1 can be got:

$$
\begin{aligned}
H(1) &= -\sum_{i=0}^{s-1} \sum_{j=0}^{t-1} (p_{ij}/P_1) \lg(p_{ij}/P_1) \\
&= -(1/P_1) \sum_{i=0}^{s-1} \sum_{j=0}^{t-1} (p_{ij} \lg p_{ij} - p_{ij} \lg P_1) \\
&= (1/P_1) \lg P_1 \sum_{i=0}^{s-1} \sum_{j=0}^{t-1} p_{ij} \\
&\quad - (1/P_1) \sum_{i=0}^{s-1} \sum_{j=0}^{t-1} p_{ij} \lg p_{ij} \\
&= \lg(P_1) + H_1/P_1.
\end{aligned} \tag{4}
$$

The entropy of 2nd area can also be got:

$$H(2) = \lg(P_2) + H_2/P_2, \tag{5}$$

where H_1 and H_2 are described as,

$$H_1 = -\sum_{i=0}^{s-1} \sum_{j=0}^{t-1} p_{ij} \lg p_{ij},$$

$$H_2 = -\sum_{i=s}^{L-1} \sum_{j=t}^{L-1} p_{ij} \lg p_{ij}. \tag{6}$$

Then the function of entropy is:

$$\phi(s,t) = H(1) + H(2), \tag{7}$$

where $H(1)$ and $H(2)$ are described in the formula (4) and (5).

According to the maximum entropy principle, the threshold vector (s^*, t^*) should be satisfied to

$$\phi(s^*, t^*) = \max\{\phi(s,t)\}. \tag{8}$$

3. The particle swarm optimization (PSO) algorithm

The particle swarm optimization (PSO) is a parallel evolutionary computation technique developed by Kennedy and Eberhart (1995) based on the social behavior metaphor. Due to the limitation of space, we only briefly introduce PSO in this paper. For more information, we refer reader to Kennedy et al. (2001), a standard textbook on PSO, treating both the social and computational paradigms. PSO differs from traditional optimization methods in that a population of potential solutions is used in the search. The direct fitness information, instead of function derivatives or related knowledge, is used to guide the search. As mentioned above, it is promising to solve 2-D maximum entropy problem by adopting PSO.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. Particles profit from the discoveries and previous experience of other particles during the exploration and search for higher objective function values. Let i indicate a particle's index in the swarm. Each of m particles fly through the n-dimensional search space $\mathbb{R}^n$ with a velocity v_i, which is dynamically adjusted according to its own previous best solution s_i and the previous best solution $\hat{s}$ of the entire swarm. The velocity updates are calculated as a linear combination of position and velocity vectors. The particles interact and move according to the following equations

$$v_i^{(t+1)} = w v_i^{(t)} + c_1 r_1^{(t)} (s_i^{(t)} - p_i^{(t)}) + c_2 r_2^{(t)} (\hat{s}^{(t)} - p_i^{(t)}), \tag{9}$$

$$p_i^{(t+1)} = v_i^{(t+1)} + p_i^{(t)}, \tag{10}$$

where $r_1^{(t)}, r_2^{(t)} \sim \text{UNIF}(0,1)$ are random numbers between zero and one. c_1, c_2 are learning factors, usually $c_1 = c_2 = 2$. And w is an inertia weight. It is possible to clamp the velocity vectors by specifying upper and lower bounds on v_i, to avoid too rapid movement of particles in the search space. Then we can use the standard procedure to find the optimum. The searching is a repeat process, and the stop criteria are that the maximum iteration number is reached or the minimum error condition is satisfied.

The standard procedure is described as below:

(1) Set the iteration number t to zero. Initialize randomly the swarm S of m particles (population number) such that the position p_i^0 of each particle to meet the prescribed conditions.

(2) Evaluate the fitness of each particle ($F(p_i^{(t)})$, object function).

(3) Compare the personal best of each particle to its current fitness, and set $s_i^{(t)}$ to the better performance, i.e.

$$s_i^{(t)} = \begin{cases} s_i^{(t-1)} & \text{if } f(p_i^{(t)}) \leqslant f(s_i^{(t-1)}), \\ p_i^{(t)} & \text{if } f(p_i^{(t)}) > f(s_i^{(t-1)}). \end{cases} \qquad (11)$$

(4) Set the global best $\hat{s}^{(t)}$ to the position of the particle with the best fitness within the swarm, i.e.

$$\hat{s}^{(t)} \in \{s_1^{(t)}, s_2^{(t)}, \ldots, s_m^{(t)}\} \mid F(\hat{s}^{(t)})$$
$$= \max\{F(s_1^{(t)}), F(s_2^{(t)}), \ldots, F(s_m^{(t)})\}. \qquad (12)$$

(5) Change the velocity vector for each particle according to Eq. (9).

(6) Move each particle to its new position, according to Eq. (10).

(7) Let $t = t + 1$.

(8) Go to step 2, and repeat until meets the stop criteria.

It can be easily seen that there are two key steps when applying PSO to optimization problems: the representation of the solution and the fitness function. One of the desirable merits of PSO is that PSO takes real numbers as particles. It is not like genetic algorithm (GA) (Davis, 1991), where transformation of binary encoding and special genetic operators are needed. The complete application of PSO, as well as the method to do image segmentation, is discussed in the following section.

4. Image segmentation based on the proposed method

Considering the 2-D maximum entropy method and PSO together, we set the threshold vector (t, s) as the particle, and $\phi(s, t)$ as the fitness to guide the search. After getting the 2-D histogram of the image, we adopt the standard PSO procedure to search the optimum result of (s^*, t^*) which can produce the maximum fitness. Then, the infrared image can be segmented according to the value of (s^*, t^*).

Fig. 2. The first original infrared image.

Experiments on image segmentation are used to illustrate the validation of the proposed algorithm. The first original image used contains 290×200 pixels, which is shown as Fig. 2, and Fig. 3 is its segmentation result of the proposed method. The optimum answer is $(143, 132)$ with the greatest entropy of 10.6285. As we can see, the segmentation result is ideal. Because there is a lot of papers have demonstrated the 2-D histogram entropy method is better than the 1-D histogram entropy method, we pay more attention on the advantage of its computation speed. If the maximum entropy of 2-D histogram is obtained by exhaustive search method, it needs to do 256×256 times computation of entropy function (8). However, with the method of PSO, some nice results can be shown in the following tests. When the population number of particles is initiated with 15 and max itera-
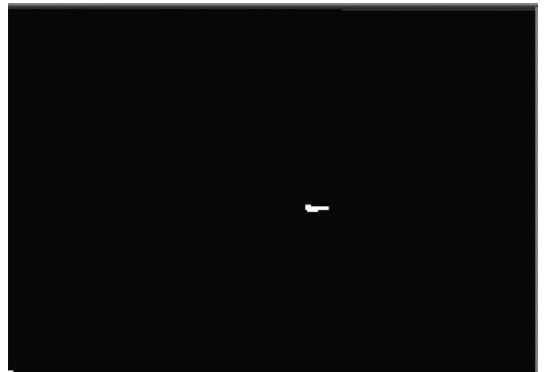

Fig. 3. Segmented result of the first one.

tion number is set as 30, the results can be shown as follows.

From the 2nd iteration to the 6th iteration, the fitness is convergent to a local extremum of 10.28991 with (94, 94), and from the 7th iteration to the 9th iteration, the object function is convergent to another local extremum of 10.577085 with (142, 141). And when it reaches the 10th iteration, the global maximum value of 10.6285 is got and the threshold is (143, 142). In other words, only with the cost of doing $15 \times 10 = 150$ times computation of entropy function, the optimum answer can be got. Comparing with exhaustive searching method, the speed is improved $256 \times 256/150 \approx 436$ times. What is more, when the population number of particles is initiated with 30, the best answer can be captured at the 4th iteration. It means the algorithm only does $30 \times 4 = 120$ times computation of entropy function. It is reasonable that the computation can be further reduced by trying more proper parameters.

We also do another image segmentation with Fig. 4, which contains 352×288 pixels.

And the result with the proposed method is shown like Fig. 5. Through exhaustive search, the optimum threshold is (123, 122) with the maximum value of 10.2882. Again, we focused on the advantage of its computation speed. Table 1 describes the process of the algorithm's convergence, where all the constants are set as the same as the first experiments. The optimum answer is got only

Fig. 5. Segmented result of the second one.

Table 1
The process of the convergence

Iteration number	Threshold	Object value
1th	(55, 58)	9.8942
2th	(114, 107)	10.2274
3th	(111, 108)	10.2427
4–10th	(120, 119)	10.2796
11–30th	(123, 122)	10.2822

with cost of doing $15 \times 11 = 165$ times computation of entropy function. Comparing with exhaustive searching method, the speed is improved $256 \times 256/165 \approx 397$ times.

It is well known that evaluating segmentation results and comparing segmentation algorithms are not simple tasks (Yasnoff et al., 1977; Hoover et al., 1996; Yu et al., 1994). However, one of the most widely used criteria for performance evaluation is whether the system can outline the desired or important regions in the image. In addition, Haralick and Shapiro (1985) pointed out that good segmentation results should present simple, uniform and homogeneous regions, with simple, not ragged and spatially accurate boundaries. We believe our results satisfy these requirements. Because sometimes there are more background pixels than object ones, it does not make sense the direct measure of the performance since both types of errors have not the same relevance. A balanced error measure to quantitatively evaluate our experimental results is proposed:

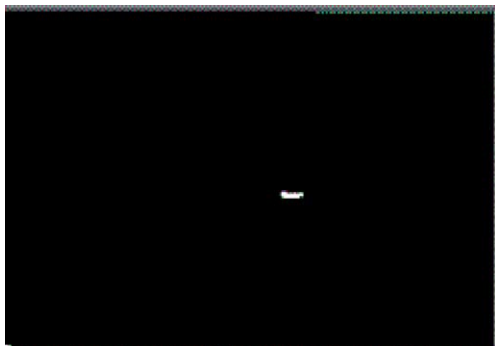Fig. 4. The second original infrared image.

Fig. 6. Manual segmented result of the first one.

Fig. 7. Manual segmented result of the second one.

$$\text{Error rate} = \frac{1}{2} \frac{\text{misdetections}}{\text{object pixels}}$$
$$+ \frac{1}{2} \frac{\text{false alarms}}{\text{background pixels}}, \qquad (13)$$

where the object pixels and background pixels can be got by manual method.

According to (13), the error rates of Figs. 3 and 5 are 4.77% and 3.79%, respectively. We think the results obtained by our method can be regarded as reasonably good and applicable in subsequent processing. The manual segmented results of Figs. 2 and 4 are shown in Figs. 6 and 7, respectively.

5. Conclusion

2-D histogram entropy is a good method to do infrared image segmentation except its complex computation. With the help of PSO method, the maximum threshold can be obtained easily with high efficiency. The image segmentation method of 2-D maximum entropy method based on PSO is a simple and effective method to do infrared image segmentation. Especially, it is full of importance in the system where real time processing is needed. What is more, although there are a lot of examples of applying PSO to the continuous optimization problem, there is relative less in the discrete fields. The maximum entropy problem is an example of discrete problem. Owing to the success of the proposed method in this paper, we can see the capability of PSO to deal with discrete problems is also promising.

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