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Short communication

Fuzzy entropy image segmentation based on particle swarm optimization

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Abstract

Particle swarm optimization is a stochastic global optimization algorithm that is based on swarm intelligence. Because of its excellent performance, particle swarm optimization is introduced into fuzzy entropy image segmentation to select the optimal fuzzy parameter combination and fuzzy threshold adaptively. In this study, the particles in the swarm are constructed and the swarm search strategy is proposed to meet the needs of the segmentation application. Then fuzzy entropy image segmentation based on particle swarm optimization is implemented and the proposed method obtains satisfactory results in the segmentation experiments. Compared with the exhaustive search method, particle swarm optimization can give the same optimal fuzzy parameter combination and fuzzy threshold while needing less search time in the segmentation experiments and also has good search stability in the repeated experiments. Therefore, fuzzy entropy image segmentation based on particle swarm optimization is an efficient and promising segmentation method.

Keywords: Image segmentation; Fuzzy entropy; Particle swarm optimization; Fuzzy parameter combinations; Fuzzy threshold

1. Introduction

Particle swarm optimization (PSO) is a new evolutionary computing method that was developed by Kennedy and Eberhart in 1995 through the simulation of simplified social models of bird flocks [1]. Due to its excellent performance, PSO has become one of the hotspots in evolutionary computing research and has been used in many applications such as function optimization, neural network training, and fuzzy control systems in recent years [2]. Image segmentation can be defined as the technique of dividing an image into disjoint homogeneous regions that usually contain similar objects of interest. And it is an important step in automatic image analysis and interpretation. However, due to the uncertainty and complexity of images encountered in actual applications, it is a very difficult task that affects directly the results of subsequent tasks such as feature extraction, object detection, and recognition. Because fuzzy set theory is an effective means of researching and processing fuzziness and uncertainty, fuzzy entropy has been used in image threshold segmentation [3,4]. Since the exhaustive search for all fuzzy parameter combinations is too costly, we introduced PSO into fuzzy entropy image segmentation to solve this optimal problem adaptively. This paper is organized as follows: in Section 2, the basic principle of PSO is described; in Section 3, the specific method of PSO applied in fuzzy entropy image segmentation is proposed; the experimental results are described and analyzed in Section 4 and conclusions are presented in Section 5.

2. Basic principle of PSO

PSO is a population-based algorithm that uses a population of individuals to probe the best position in the search space. In PSO, the individual is called a particle, which moves

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with an adaptable velocity in the search space. Each particle moves stochastically in the direction of its own best previous position and the whole swarm's best previous position. Suppose that the size of the swarm is N and the search space is M-dimensional, then the position of the ith particle is presented as $X_i(x_{i1}, x_{i2}, \ldots, x_{iM})$. The velocity of this particle is presented as $V_i(v_{i1}, v_{i2}, \ldots, v_{iM})$. The best previous position of this particle is denoted as $P_i(p_{i1}, p_{i2}, \cdots, p_{iM})$ and the best previous position discovered by the whole swarm is denoted as $P_g(p_{g1}, p_{g2}, \ldots, p_{gM})$. The particles are manipulated according to the following equations [1,5,6]:

$$v_{im}^{k+1} = \omega^k * v_{im}^k + c_1 * rand() * (p_{im} - x_{im}^k)/\Delta t + c_2 * rand() * (p_{gm} - x_{im}^k)/\Delta t \tag{1}$$

$$x_{im}^{k+1} = x_{im}^k + v_{im}^k * \Delta t \tag{2}$$

$$\omega^k = \omega_{\max} - k * (\omega_{\max} - \omega_{\min})/k_{\max} \tag{3}$$

where $1 \leqslant m \leqslant M$, and *rand*() is the random number with uniform distribution $U(0,1)$; c_1 and c_2 are acceleration coefficients; ω is the inertia weight; $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum value of ω, respectively; k and $k_{\max}$ are the current iterative time and the maximum iterative time, respectively; usually Δt is unit time.

v_{im}^{k+1} and x_{im}^{k+1} should be under the constrained conditions as follows:

$$v_{im}^{k+1} = \begin{cases} v_{im}^{k+1} & -v_{\max} \leqslant v_{im}^{k+1} \leqslant v_{\max} \\ v_{\max} & v_{im}^{k+1} > v_{\max} \\ -v_{\max} & v_{im}^{k+1} < -v_{\max} \end{cases} \tag{4}$$

$$x_{im}^{k+1} = \begin{cases} x_{im}^{k+1} & x_{\min} \leqslant x_{im}^{k+1} \leqslant x_{\max} \\ x_{init} & x_{im}^{k+1} > x_{\max} \\ x_{init} & x_{im}^{k+1} < x_{\min} \end{cases} \tag{5}$$

$$x_{init} = x_{\min} + rand() * (x_{\max} - x_{\min}) \tag{6}$$

where $v_{\max}$ is the maximum value of v; $x_{\max}$ and $x_{\min}$ are the maximum and minimum value of x, respectively.

3. Specific method of PSO applied in fuzzy entropy image segmentation

Fuzzy entropy image segmentation [3,4], which takes the fuzziness and uncertainty of images into account, has had great success in image threshold segmentation. Let Y denote an image of size $I \times J$ with L gray levels ranging from $L_{\min}$ to $L_{\max}$, and y_{ij} denote the gray level of the (i,j)th pixel in Y. According to fuzzy set theory, Y can be transformed into an array of fuzzy singletons A by a membership function.

$$A = \{\mu_Y(y_{ij}), \quad i = 1, 2, \ldots, I; \quad j = 1, 2, \ldots, J\} \tag{7}$$

where $0 \leqslant \mu_Y(y_{ij}) \leqslant 1$ and $\mu_Y(y_{ij})$ denotes the degree of some property such as brightness possessed by the (i,j)th pixel.

The standard S-function is a commonly used membership function and is defined as follows:

$$\mu_Y(y) = \begin{cases} 0 & y < a \\ 2 \times [(y-a)/(c-a)]^2 & a \leqslant y < b \\ 1 - 2 \times [(c-y)/(c-a)]^2 & b \leqslant y < c \\ 1 & y \geqslant c \end{cases} \tag{8}$$

where a, b and c are fuzzy parameters.

The fuzzy parameter b is the cross-over point and $b = (a+c)/2$. The interval $[a, c]$ is the fuzzy region and the width of the fuzzy region is defined as $2\Delta b = c - a$. The interval $[L_{\min}, a]$ and the interval $[c, L_{\max}]$ are non-fuzzy regions.

Fuzzy entropy is a measure of the uncertainty of a fuzzy set and can be defined as follows:

$$H(Y) = \frac{1}{IJ \ln 2} \sum_{i=1}^{I} \sum_{j=1}^{J} S_n(\mu_Y(y_{ij})) \tag{9}$$

where $S_n(\cdot)$ is the Shannon's function defined by:

$$S_n(\mu_Y(y_{ij})) = -\mu_Y(y_{ij}) \ln \mu_Y(y_{ij}) - (1 - \mu_Y(y_{ij})) \ln(1 - \mu_Y(y_{ij})) \tag{10}$$

According to information theory, the larger the fuzzy entropy of a fuzzy set, the more information the fuzzy set has. Therefore, when the fuzzy set has the maximum fuzzy entropy, the corresponding fuzzy parameter combination (a,c) is the best fuzzy parameter combination. Then Y can be segmented into the object and the background according to the fuzzy threshold b as follows:

$$y_{ij} = \begin{cases} 0 & y_{ij} < b \\ 255 & y_{ij} \geqslant b \end{cases} \tag{11}$$

where $i = 1,2, \ldots ,I$ and $j = 1,2, \ldots ,J$.

Since an exhaustive search for all fuzzy parameter combinations is too costly, in this paper PSO is introduced into fuzzy entropy image segmentation to find the best fuzzy parameter combination adaptively. Considering the optimal problem mentioned above, the particles in the swarm are constructed and the swarm search strategy is proposed. We choose 2 as the dimension of the search space and the position and velocity of the particle in the swarm are both two-dimensional vectors of real numbers. The fuzzy entropy function (9) is the given fitness function. The procedure is described as follows:

1. Initialize the position matrix X and the velocity matrix V of the particle swarm as follows:

$$x_{im} = x_{\min} + (x_{\max} - x_{\min}) * rand() \tag{12}$$

$$X = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \cdots & \cdots \\ x_{N1} & x_{N2} \end{bmatrix} \tag{13}$$

$$v_{im} = -v_{\max} + 2v_{\max} * rand() \tag{14}$$

$$V = \begin{bmatrix} v_{11} & v_{12} \\ v_{21} & v_{22} \\ \cdots & \cdots \\ v_{N1} & v_{N2} \end{bmatrix} \tag{15}$$

where $i = 1,2,\ldots,N$ and $m = 1,2$; N is the size of the swarm; *rand*() is the random number with uniform distribution $U(0,1)$; $v_{\max}$ is the maximum value of v; $x_{\max}$ and $x_{\min}$ are the maximum and minimum value of x, respectively; $x_{\max} = L_{\max}$, $x_{\min} = L_{\min} + 1$ and $x_{i2} - x_{i1} \geqslant 2$; $L_{\max}$ and $L_{\min}$ are the maximum and minimum gray level of the image, respectively.

2. Evaluate the fitness value of each particle in the swarm using the fuzzy entropy function (9).
3. Compare the evaluated fitness value of each particle with the fitness value of its best previous position. If the current value is better, then set the current position as its best previous position.
4. Compare the evaluated fitness value of each particle with the fitness value of the whole swarm's best previous position P_g. If the current value is better, then set the current position as the whole swarm's best previous position.
5. Update the velocity of each particle according to Eqs. (1), (3) and (4).
6. Update the position of each particle according to Eqs. (2), (5) and (6). If $x_{i2} - x_{i1} < 2$, initialize the position of the ith particle.
7. Select some particles in the swarm according to the mutation rate and apply Gaussian Mutation to them as follows [7]:

$$mut(x_{im}) = x_{im} \times (1 + gaussian(\sigma)) \tag{16}$$

where $mut(x_{im})$ is the position after mutation. If the fitness value of the particle after mutation is better than the fitness value of the particle before mutation, the mutation result is saved. Otherwise, the mutation result is canceled.

8. Exit the loop if the stop criterion is satisfied. The stop criterion is the predefined maximum iterative time. Otherwise, go to step 2.
9. Search in the local region around P_g for the best fuzzy parameter combination (a, c).
10. Calculate the fuzzy threshold b using the best fuzzy parameter combination (a, c) and segment the image according to Eq. (11).

4. Experimental results

In order to validate the effectiveness of the proposed method, two IKONOS images, covering two areas of Hongkong, and three Landsat-5 TM images, covering three areas of Wuhan, were selected as experimental data. The segmentation algorithms were developed in MATLAB 6.5 on the Acer Aspire5583 notebook computer. The parameters of the proposed method were: the size of the swarm was 20, the maximum iterative time was 100, $c_1 = c_2 = 2$, $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$, the mutation rate was 0.2, and the range of the local search was ± 10 around P_g. Original IKONOS image and its segmentation result by the proposed method are shown in Fig. 1 where (a) is the original IKONOS image, (b) is the corresponding segmentation result. And original Landsat-5 TM image and its segmentation result by the proposed method are shown in Fig. 2 where (a) is the original Landsat-5 TM image, (b) is the corresponding segmentation result. IKONOS and Landsat-5 TM images are widely used in actual remote sensing applications, while being quite different in their spatial characteristics. As can be seen from Figs. 1 and 2, the proposed method obtains satisfactory segmentation results in that these two kinds of remote sensing images are reasonably divided into the objects and the background. The proposed method has good adaptability when applied to different kinds of remote sensing images, because it takes the fuzziness and uncertainty of images into

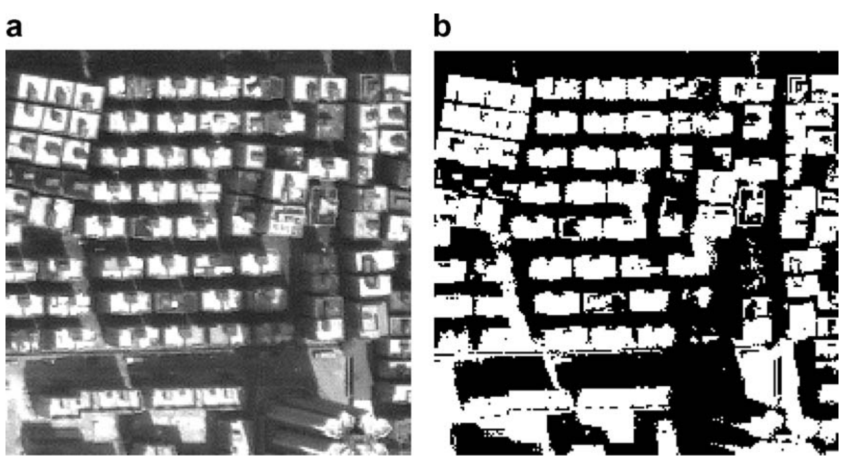

Fig. 1. Original IKONOS image and its segmentation result by the proposed method. (a) The original IKONOS image; (b) the corresponding segmentation result.

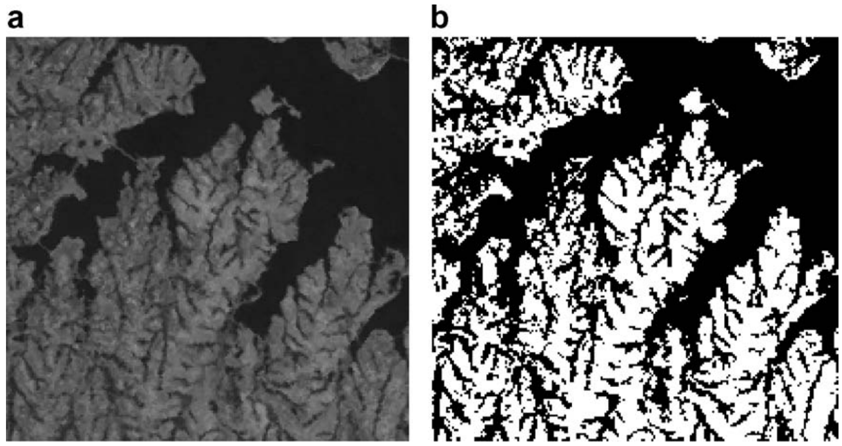

Fig. 2. Original Landsat-5 TM image and its segmentation result by the proposed method. (a) The original Landsat-5 TM image; (b) the corresponding segmentation result.

account and utilizes fuzzy set theory to process fuzziness and uncertainty in image segmentation.

Because the effects of fuzzy entropy image segmentation depend on the selected fuzzy threshold, it is essential to compare the fuzzy threshold selected by the PSO method with the fuzzy threshold selected by the exhaustive search method. Comparison of results and time of the PSO method and the exhaustive search is shown in Table 1 where FPC represents fuzzy parameter combination, FT represents fuzzy threshold, and time is the time cost in the search for the best fuzzy parameter combination. In Table 1, Image 1 and Image 2 are the IKONOS images and Image 3, 4, and 5 are the Landsat-5 TM images. As can be seen from Table 1, the PSO method can give the same optimal fuzzy parameter combination and fuzzy threshold as that of the exhaustive search. In contrast, the search time of the PSO method is less than that of the exhaustive search. For example, the PSO method and the exhaustive search obtain the same optimal fuzzy parameter combination (23,255) and fuzzy threshold 139 for Image 2, but the search time of the PSO method is approximately one tenth of that of the exhaustive search. Therefore, it can be concluded that the PSO method can greatly improve the efficiency of fuzzy entropy image segmentation. And from the search results of all the experimental images, we can conclude that the PSO method has good adaptability in selecting the optimal fuzzy parameter combination and fuzzy threshold when applied to different kinds of remote sensing images.

Table 1
Comparison of results and time of the PSO method and the exhaustive search

Image	PSO method			Exhaustive search		
	FPC	FT	Time (s)	FPC	FT	Time (s)
1	22, 193	107.5	11.16	22, 193	107.5	100.70
2	23, 255	139.0	10.34	23, 255	139.0	99.45
3	21, 142	81.5	10.30	21, 142	81.5	25.49
4	15, 144	79.5	10.36	15, 144	79.5	30.45
5	17, 125	71.0	10.05	17, 125	71.0	20.05

Because PSO is a stochastic global optimization algorithm, we repeated experiments to test the search stability of the PSO method. Results and time of the PSO method in 20 repeated experiments are shown in Table 2 where FPC represents fuzzy parameter combination, FT represents fuzzy threshold and time is the time cost in the search for the best fuzzy parameter combination. The experimental results of the PSO method are marked with a gray background in the table when they are different from that of the exhaustive search. As can be seen from Table 2 that the PSO method has obtained the same optimal fuzzy parameter combination and fuzzy threshold as that of the exhaustive search at the rate of 80% for Image 1 and 100% for Image 3. Therefore, it can be concluded that the PSO method has good search stability in selecting the optimal fuzzy parameter combination and fuzzy threshold adaptively when applied to different kinds of remote sensing images.

Table 2
Results and time of the PSO method in 20 repeated experiments

No.	Image 1			Image 3		
	FPC	FT	Time (s)	FPC	FT	Time (s)
1	22, 193	107.5	10.95	21, 142	81.5	10.03
2	22, 194	108.0	11.09	21, 142	81.5	10.20
3	22, 193	107.5	10.89	21, 142	81.5	9.91
4	22, 193	107.5	10.89	21, 142	81.5	10.27
5	22, 193	107.5	11.03	21, 142	81.5	10.09
6	22, 193	107.5	10.86	21, 142	81.5	10.16
7	22, 193	107.5	10.98	21, 142	81.5	10.02
8	22, 186	104.0	10.84	21, 142	81.5	10.00
9	22, 187	104.5	11.00	21, 142	81.5	10.09
10	22, 192	107.0	10.84	21, 142	81.5	9.95
11	22, 193	107.5	11.09	21, 142	81.5	10.22
12	22, 193	107.5	10.77	21, 142	81.5	10.22
13	22, 193	107.5	10.84	21, 142	81.5	10.02
14	22, 193	107.5	11.02	21, 142	81.5	10.06
15	22, 193	107.5	11.14	21, 142	81.5	9.91
16	22, 193	107.5	10.86	21, 142	81.5	10.20
17	22, 193	107.5	10.83	21, 142	81.5	10.16
18	22, 193	107.5	11.05	21, 142	81.5	10.05
19	22, 193	107.5	11.02	21, 142	81.5	9.98
20	22, 193	107.5	10.84	21, 142	81.5	9.99

5. Conclusions

In this paper PSO is introduced into fuzzy entropy image segmentation to find the best fuzzy parameter combination and fuzzy threshold adaptively. IKONOS and Landsat-5 TM images are selected as the experimental data and the proposed method obtains satisfactory results in the segmentation experiments. The PSO method can obtain the same optimal fuzzy parameter combination and fuzzy threshold as that of the exhaustive search while its search time is less than that of the exhaustive search when applied to different kinds of remote sensing images. And the PSO method has good search stability in the repeated experiments. Therefore, fuzzy entropy image segmentation based on PSO is an efficient segmentation method.

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