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Fuzzy Entropy Thresholding Method Using Adaptive Genetic Algorithm

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Abstract. In image processing, image segmentation is an important technique to separate the object from the background based on the specific criteria. As a widely used segmentation technique, the fuzzy entropy thresholding (FET) algorithm acquires the optimal threshold using the maximum fuzzy entropy principle. However, the traditional FET method has such disadvantages as low computational efficiency and poor adaptability to the various images. To overcome the drawbacks of the traditional FET algorithm, the adaptive genetic algorithm (AGA) is introduced into the FET method in this paper. The AGA adopts uniform partition based initial population generation method, hybrid selection mechanism combining sort selection with proportion selection, adaptive crossover and mutation and updating strategy based on preference between two generations. Experimental results demonstrate that the AGA based FET method can realize the fast segmentation of the various images using the suitable optimal threshold and it has better performance than the traditional FET method and other GA based FET methods.

Keywords: Image processing, Image segmentation, Fuzzy entropy thresholding, Maximum fuzzy entropy, Genetic algorithm

Introduction

Image segmentation is to distinguish objects from background in the image using the proper thresholds. Among the various approaches to determine the thresholds, the fuzzy entropy thresholding (FET) method [1-4] has been widely used. But the traditional FET method is time consuming and it has poor adaptability to the various images because it requires presetting the bandwidth of membership function and involves exhaust algorithm in finding the optimal threshold [5,6]. To overcome the drawbacks of the traditional FET method, the genetic algorithm (GA) has been introduced into the FET method to [7,8]. As a probabilistic and heuristic search method based on biology evolution theory and genetics mechanism, GA has a high search efficiency and good global optimization performance. However, the standard GA generates the initial population randomly and fixes crossing probability and mutation probability throughout the evolution process, which will lead to pre-maturity and low convergence speed.

In this paper, the adaptive genetic algorithm (AGA) is proposed and incorporated into FET method. The AGA improves the performance of GA through such strategies as effective initial population generation method, suitable hybrid selection mechanism, novel crossover and mutation operation and distinctive updating strategy. Experimental results show that the AGA based FET method has both good adaptability to various images and high computational efficiency in acquiring the optimal threshold.

AGA based FET method

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(1) Encoding and fitness function

Let $x_{i,j}$ be the gray-level value of the image X of size $M \times N$ at pixel position (i,j). According to fuzzy subset theory, the image X can be represented as the following fuzzy matrix:

$$X = [\mu(x_{i,j})]_{M \times N} \qquad 1 \le i \le M; 1 \le j \le N \tag{1}$$

where $\mu(x_{i,j})$ ($0 \le \mu(x_{i,j}) \le 1$) is the membership degree of $f_{i,j}$. The membership degree $\mu(x_{i,j})$ and its Shannon function $S(\mu(x_{i,j}))$ are defined as [5-8]:

$$\mu(x_{i,j}) = \begin{cases} 0 & x_{i,j} < T_0 \\ \dfrac{(x_{i,j} - T_0)^2}{(T - T_0)(T_1 - T_0)} & T_0 \le x_{i,j} \le T_1 \\ 1 - \dfrac{(x_{i,j} - T_1)^2}{(T_1 - T_0)(T_1 - T_0)} & T \le x_{i,j} \le T_1 \\ 1 & x_{i,j} > T_1 \end{cases} \tag{2}$$

$$S(\mu(x_{i,j})) = -\mu(x_{i,j}) \ln(\mu(x_{i,j})) - (1 - \mu(x_{i,j})) \ln(1 - \mu(x_{i,j})) \tag{3}$$

The interval between T_0 and T_1 constitutes the fuzzy region. Let $\Delta T = T_1 - T_0$ and $T = (T_0 + T_1)/2$.

The fuzzy entropy $E(T, \Delta T)$ of image X is defined as:

$$E(T, \Delta T) = \frac{1}{MN \ln 2} \sum_{i=1}^{M} \sum_{j=1}^{N} Sn(\mu_{ij}(x_{ij})) \tag{4}$$

Let T and ΔT be encoded as 8 bit variables in the binary mode. The single chromosome is composed of the two variables. To get the threshold using the maximum fuzzy entropy principle, the fuzzy entropy (objective function) will be mapped into the fitness function as follows:

$$f(T, \Delta T) = E(T, \Delta T) \tag{5}$$

(2) Initial population generation

The standard GA generates initial population randomly. This method tends to produce a narrow search space, which is disadvantageous to the acquisition of the global optimal solution. To improve the convergence characteristics of GA, the initial population is generated using uniform partition based generation method. This method evenly divides the range of optimized parameters into regions with their number equal to population scale Gs. In every small region, an individual will be generated randomly. This method can quicken the convergence speed and increase the possibility of converging to global optimal solution.

(3) Selection operation

The proportion selection and sort selection will be generally used by the standard GA. For proportion selection, the pre-maturity is easy to occur when the evolution process is dominated by few chromosomes with much higher fitness in the population. When there exists some

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chromosomes with close fitness, the GA intends to search randomly and its convergence speed will be reduced. The sort selection can solve these problems, but it deflects the individual fitness too far. Combining the two selection methods, the mixed selection method is adopted. This method first sorts the individual fitness in descending order and then uses proportion selection to find the individuals until their number reaches the population scale.

(4) Adaptive crossover and mutation

Crossover probability P_c and mutation probability P_m are fixed in the standard GA. But they should vary with the distribution of individuals in the population. In the early evolutionary period, the individuals are distributed dispersedly and so P_c should take higher value to realize the combination of effective modes while P_m should take a small value to prevent the damage of effective gene. In the later evolutionary period, the individuals tend to have close fitness and so P_c should be reduced while P_m should be increased to avoid the inbreeding between two individuals and preserve the diversity of the population. Based on the above analysis, the crossover probability P_c^t at t-th generation will be defined as:

$$P_c^t = \begin{cases} P_{\max} - \dfrac{(P_{\max} - P_{\text{temp}})(f_b^t - f_{\text{avg}}^t)}{f_{\max}^t - f_{\text{avg}}^t} & f_b^t \geq f_{\text{avg}}^t \\ P_{\max} & f_b^t < f_{\text{avg}}^t \end{cases} \tag{6}$$

where:

$$P_{\text{temp}} = \begin{cases} P_{\min} & P_{\max} e^{-\frac{t}{T_l}} \leq P_{\min} \\ P_{\max} e^{-\frac{t}{T_l}} & P_{\max} e^{-\frac{t}{T_l}} > P_{\min} \end{cases} \tag{7}$$

where $P_{\max}$ and $P_{\min}$ are the maximum crossover probability and the minimum one, T_l be the maximum iteration times, f_b^t be the bigger fitness of two individuals chosen for crossover operation at t-th generation, $f_{\max}^t$ and f_{avg}^t denote the maximum fitness and average fitness of the population at t-th generation. Similarly, the mutation probability P_m^t at t-th generation will be defined as:

$$P_m^t = \begin{cases} P'_{\max} - \dfrac{(P'_{\max} - P'_{\text{temp}})(f_k^t - f_{\text{avg}}^t)}{f_{\max}^t - f_{\text{avg}}^t} & f_k^t \geq f_{\text{avg}}^t \\ P'_{\max} & f_k^t < f_{\text{avg}}^t \end{cases} \tag{8}$$

where:

$$P'_{\text{temp}} = \begin{cases} P'_{\min} & P'_{\max}(1 - e^{-\frac{t}{T_l}}) \leq P'_{\min} \\ P'_{\max}(1 - e^{-\frac{t}{T_l}}) & P'_{\max}(1 - e^{-\frac{t}{T_l}}) > P'_{\min} \end{cases} \tag{9}$$

where $P'_{\max}$ and $P'_{\min}$ are the maximum mutation probability and the minimum one, f_k^t be fitness of the individual chosen for mutation operation at t-th generation.

(5) Generation updating

There are such regenerating methods as E method, G method, B method and N method. E method preserves only one parental individual. G method regenerates partial individuals in a certain proportion. B method regenerates the new individuals by choosing the excellent ones simultaneously among parents and children. N method completely replaces the previous generation. Because these methods can not achieve both excellent global searching capability and excellent

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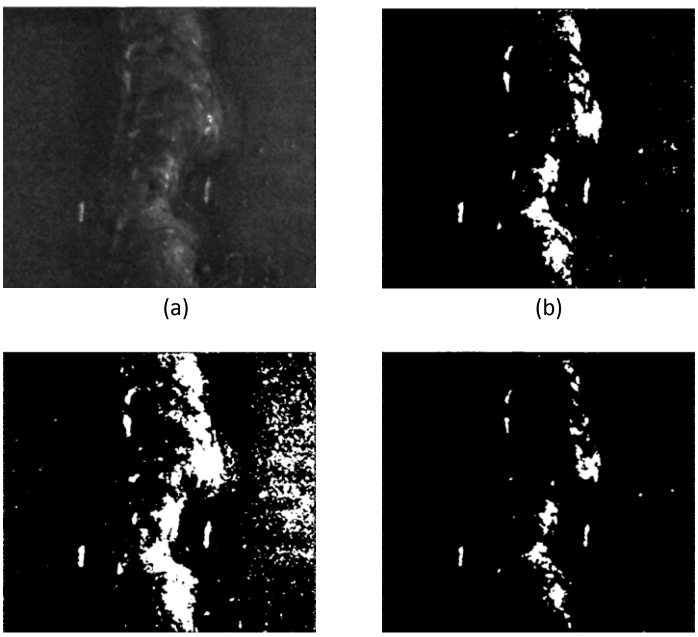
convergence speed, the updating strategy based on preference between two generations is proposed. In the new updating strategy, the fitness of all the individuals in the parent generation and child generation is first separately sorted in the descending order. Then the fitness of the individual in the sorted parent generation is compared with that of the corresponding individual in the child generation. The individual with greater fitness will be preserved in the new generation. The new updating strategy preserves the excellent individuals between the two generations, which is conducive to the improvement of both global searching capability and convergence speed.

Experimental results

To evaluate the performance of the AGA-based FET method based on (AGA-FET), the adaptive FET method (AFET) [6] and the GA based FET method (GA- FET) [7] are adopted to make comparisons. The welded image with the linear defects and the welded image with the circular defects are segmented by the three methods. The binary images are shown in Fig. 1 and Fig. 2, respectively. The runtime of these methods and the optimal threshold are listed in Table 1. In the AGA-FET method, $P_{\max} = 0.8$, $P_{\min} = 0.5$, $P'_{\max} = 0.1$, $P'_{\min} = 0.01$, $T_l = 40$ and $G_s = 20$. In the GA-FET method, $P_c = 0.8$, $P_m = 0.1$. Here it must be noted that the runtime means the average time for every method to implement for 30 times on a personal computer equipped with 851-MHz CPU and 256-M RAM memory. The optimal threshold is the average value of all the optimal thresholds for 30 runs.

From these experimental results, it can be seen that the AGA-FET has similar computation time to the GA-FET and it has by far less runtime than that of AFET. On the other hand, AFET and GA-FET get the unreasonable optimal thresholds so that the two welded images, to some extent, suffer from false segmentation. For example, the segmented linear defects in Fig. 1(b) and Fig. 1(c) appear to be bigger than the true defects in Fig. 1(a). The circular defects in Fig. 2 (a) are missing in Fig. 2(b) and Fig. 2(c) because of false segmentation. By comparison, the AGA-FET can achieve satisfactory segmentation quality for both linear defects and circular defects shown in Fig. 1(d) and Fig. 2(d).



(a) (b) (c) (d)

Fig.1 Segmentation results for three FET methods for the welded image with the linear defects: (a) the welded image, (b) AFET, (c) GA-FET, (d) AGA-FET

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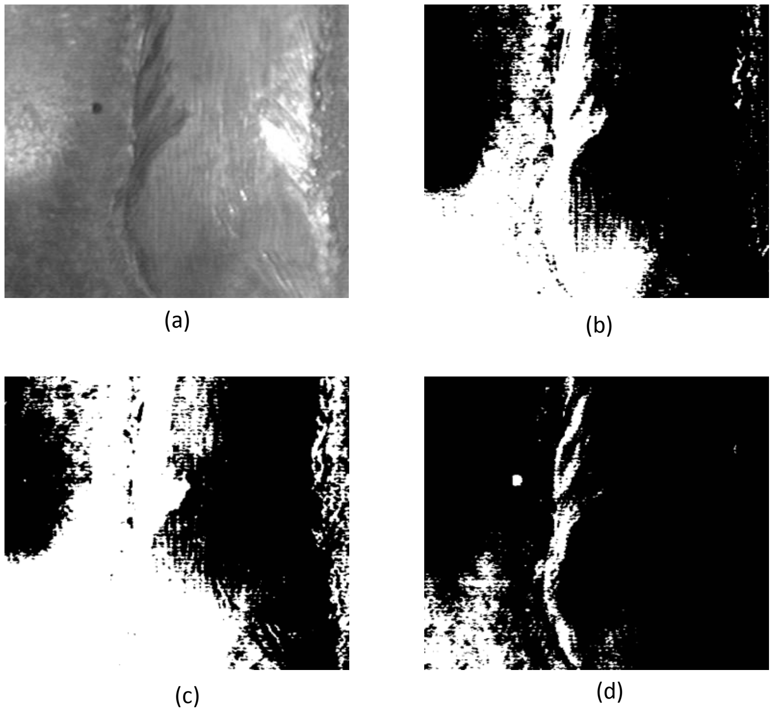

Fig.2 Segmentation results for three FET methods for the welded image with the circular defects: (a) the welded image, (b) AFET, (c) GA-FET, (d) AGA -FET

Table 1 Computation results of three FET methods for two welded images

Algorithm	welded image with the linear defects		welded image with the circular defects	
	threshold	runtime(ms)	threshold	runtime(ms)
AFET	72	300	112	280
GA-FET	57	100	130	90
AGA -FET	85	117	95	108

Conclusion

The AGA-FET method proposed in this paper overcomes such defects of the traditional FET method as low computation efficiency of the exhaust algorithm and poor adaptability to the various images resulting from presetting the bandwidth of membership function. In the meantime, the AGA-FET method performs better than the GA-FET method by overcoming the possible pre-maturity. Extensive simulations have demonstrated that the AGA-FET method can adaptively determine the bandwidth of membership function and optimal threshold and it has good robust performance and high computational efficiency.

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