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Defect image segmentation using multilevel thresholding based on firefly algorithm with opposition-learning

Chen Kai[1] Dai Min[1] Zhang Zhisheng[1] Chen Ping[1] Shi Jinfei[2]

([1]Mechanical Engineering School, Southeast University, Nanjing 211189, China)
([2]Huaihai Institute of Technology, Lianyungang 222005, China)

Abstract: To segment defects from the quad flat non-lead (QFN) package surface, a multilevel Otsu thresholding method based on the firefly algorithm with opposition-learning is proposed. First, the Otsu thresholding algorithm is expanded to a multilevel Otsu thresholding algorithm. Secondly, a firefly algorithm with opposition-learning (OFA) is proposed. In the OFA, opposite fireflies are generated to increase the diversity of the fireflies and improve the global search ability. Thirdly, the OFA is applied to searching multilevel thresholds for image segmentation. Finally, the proposed method is implemented to segment the QFN images with defects and the results are compared with three methods, i. e., the exhaustive search method, the multilevel Otsu thresholding method based on particle swarm optimization and the multilevel Otsu thresholding method based on the firefly algorithm. Experimental results show that the proposed method can segment QFN surface defects images more efficiently and at a greater speed than that of the other three methods.

Key words: quad flat non-lead (QFN) surface defects; opposition-learning; firefly algorithm; multilevel Otsu thresholding algorithm

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The quad flat non-lead (QFN) package is a type of flat no-lead package that has been widely used. However, on the surface of the QFN package, there are different types of defects which are harmful to the quality of the QFN package. The defects are relatively small, so it is difficult to segment the defects from the surface image with a single threshold. Therefore, multilevel image segmentation is applied to segmenting QFN surface defects from the QFN board.

The Otsu thresholding segmentation algorithm[1] is a classical and efficient image segmentation algorithm. In the case of segmenting several objects from the background, Otsu thresholding needs to be extended to multilevel Otsu thresholding segmentation. However, multilevel Otsu thresholding segmentation is time-consuming and involves large computation. Thus, several meta-heuristics optimal algorithms have been introduced to solve the problems. Yin[2] presented an optimal thresholding using genetic algorithms. Ghamisi et al.[3] developed a fractional-order Darwinian particle swarm optimization and the Darwinian particle swarm optimization for determining thresholds. Gao et al.[4] designed an ant colony optimization segmentation algorithm for solving multilevel Otsu problems. Sathya and Kayalvizhi[5] introduced a bacterial foraging algorithm into finding thresholds.

Recently, Yang[6] presented a new meta-heuristic algorithm, called the firefly algorithm. Due to the good performance on global search, the firefly algorithm has been widely used for solving optimization problems. Horng et al.[7] proposed a multilevel minimum cross entropy threshold selection based on the firefly algorithm, and demonstrated that the firefly algorithm outperformed the particle swarm optimization (PSO) and the quantum particle swarm optimization. Hassanzadeh et al.[8] applied the firefly algorithm to Otsu's method. Nevertheless, in some cases, the firefly algorithm may easily fall into a local optimum which will lead to inappropriate results and slow convergence.

Hence, a novel firefly algorithm with opposition-learning is proposed to help fireflies escape from the local optimum and a multilevel Otsu thresholding based on the firefly algorithm with opposition-learning is applied to segmenting QFN surface defects.

1 Multilevel Otsu Thresholding Algorithm

The Otsu thresholding algorithm is a classical and efficient algorithm for image segmentation. Selecting a threshold to maximize the between-class variance is the core idea of the Otsu thresholding algorithm. Suppose that there are N pixels with L gray levels in an image I, the histogram represented the number of pixels with the specific gray level i is defined by h_i, where $i = 0, 1, \ldots, L$

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Biographies: Chen Kai (1986—), female, graduate; Zhang Zhisheng (corresponding author), male, doctor, professor, oldbc@seu.edu.cn.

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-1, and the total number of pixels can be calculated as $\sum_{i=0}^{L-1} h_i$. The probability distribution of the gray level i can be defined by $p_i = \frac{h_i}{N}$, where $\sum_{i=0}^{L-1} p_i = 1$. The mean value of the image is $\mu_T = \sum_{i=0}^{L-1} ip_i$. Suppose that an image is divided into two classes by a threshold t. Class C_1 includes the pixels $i \leqslant t$ and class C_2 includes the pixels $i > t$. The probability of C_1 is $\omega_1 = \sum_{i=0}^{t} p_i = \omega(t)$, and the probability of C_2 is $\omega_2 = \sum_{i=t+1}^{L-1} p_i = 1 - \omega(t)$. The mean values of the two classes are calculated as $\mu_1 = \sum_{i=0}^{t} \frac{ip_i}{\omega_1} = \sum_{i=0}^{t} \frac{ip_i}{\omega(t)}$, $\mu_2 = \sum_{i=t+1}^{L-1} \frac{ip_i}{\omega_2} = \sum_{i=t+1}^{L-1} \frac{ip_i}{1-\omega(t)}$. The between-class variance can be defined by

$$\sigma^2 = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2 \tag{1}$$

In the situation of complex or multi-target image segmentation, an image needs to be classified into j classes C_1, C_2, …, C_j with the set of thresholds t_1, t_2, …, t_{j-1}. Otsu thresholding should be expanded to multilevel Otsu thresholding. The between-class variance in multilevel Otsu thresholding can be defined by

$$\sigma_{\text{mul}}^2 = \sum_{k=1}^{j} \omega_k(\mu_k - \mu_T)^2 \tag{2}$$

where

$$\mu_k = \begin{cases} \sum_{i=0}^{t_k} \frac{ip_i}{\omega_k} & \omega_k = \sum_{i=0}^{t_k} p_i;\ k = 1 \\ \sum_{i=t_{k-1}+1}^{t_k} \frac{ip_i}{\omega_k} & \omega_k = \sum_{i=t_{k-1}+1}^{t_k} p_i;\ 1 < k < j \\ \sum_{i=t_{k-1}+1}^{L-1} \frac{ip_i}{\omega_k} & \omega_k = \sum_{i=t_{k-1}+1}^{L-1} p_i;\ k = j \end{cases} \tag{3}$$

In other words, the core idea of multilevel Otsu thresholding is searching a set of thresholds t_1^*, t_2^*, …, t_{j-1}^* that can maximize the between-class variance. The optimization problem can be defined by

$$(t_1^*, t_2^*, \ldots, t_{j-1}^*) = \max_{0 < t_1 < \ldots < t_{j-1} < L-1} \sigma_{\text{mul}}^2(t_k) \tag{4}$$

Clearly, the multilevel Otsu thresholding algorithm is time-consuming and involves a large computation. Hence, the firefly algorithm with opposition-learning is proposed to solve the multilevel Otsu thresholding problem in the next section.

2 Multilevel Otsu Thresholding based on Firefly Algorithm with Opposition-Learning

2.1 Opposition-learning algorithm

The opposition-learning algorithm was presented by Tizhoosh[9]. Let x be a solution to a given optimal problem, and $\tilde{x}$ be the opposite solution of x. The opposite solution $\tilde{x}$ can be calculated as

$$\tilde{x} = a + b - x \tag{5}$$

where $x \in [a, b]$. In some cases, the opposite solution $\tilde{x}$ is closer to the optimum solution than x. Suppose that the optimal problem is a multidimensional problem, and the opposite solution in a multidimensional case is defined by

$$\tilde{x}_i = a_i + b_i - x_i \tag{6}$$

where $x_i \in [a_i, b_i]$, $i \in [1, n]$.

The opposition-learning algorithm can be concluded as follows: Let $f(x)$ be the fitness function. If $x \in [a, b]$ is an initial solution and $\tilde{x}$ is its opposite value, then $f(x)$ and $f(\tilde{x})$ are calculated in every iteration. The learning continues with x if $f(x) > f(\tilde{x})$; otherwise with $\tilde{x}$.

2.2 Firefly algorithm with opposition-learning

The firefly algorithm[6] is a new meta-heuristic algorithm for optimization. In the firefly algorithm, there are three idealized rules: 1) All the fireflies are unisex so that one firefly is attracted to other fireflies regardless of their sex; 2) Attractiveness is proportional to their brightness; thus for any two flashing fireflies, the less brighter one moves towards the brighter one. If there is no brighter one than a particular firefly, it will move randomly; 3) The brightness of a firefly is affected or determined by the landscape of the objective function to be optimized. The movement of firefly i attracted to another more attractive firefly j is determined by

$$X_i = X_i + \beta(r)(X_j - X_i) + \alpha\left(K_{\text{rand}} - \frac{1}{2}\right) \tag{7}$$

where X_i and X_j represent the solution for firefly i and firefly j, respectively; $\beta(r) = \beta_0 e^{-\gamma r_{ij}^2}$ represents the attraction between firefly j to firefly i, where r_{ij} is the distance between firefly i and firefly j, β_0 is the attractiveness at $r_{ij} = 0$, and γ is the light absorption coefficient. If there is no one brighter than the firefly with the maximum fitness, it will move randomly according to the third term of Eq. (7). The third term is randomization with α being the randomization parameter. K_{rand} is a random number generator uniformly distributed in [0, 1].

The firefly algorithm has shown good performance in solving optimization problems. However, in some cases, the firefly algorithm may fall into local optima. In order to improve its performance, a new firefly algorithm with opposition-learning (simplified OFA) is proposed. The aim of OFA is to combine the firefly algorithm and the opposition-learning algorithm. The main steps of OFA are as follows:

1) Initialize the parameters of OFA, including the number of firefly n, the light absorption coefficient γ, the initial attraction β_0, the maximum iteration number iter, and a decision value p_0.

2) If rand(0, 1) $< p_0$, go to 3); otherwise, go to 6).

3) Calculate the number of opposite fireflies according to Eq. (6), and calculate the fitness value of the fireflies and opposite fireflies.

4) Rank the fitness values of the fireflies and opposite fireflies, and select the best n fireflies as the new fireflies.

5) If the iteration number reaches the maximum iteration number iter, go to 8); otherwise, go to 2).

6) Calculate the fitness values of the fireflies, and rank the fitness values.

7) If the iteration number reaches the maximum iteration number iter, go to 8); otherwise, update fireflies according to Eq. (7), and go to 2).

8) Output the maximum fitness value and the corresponding firefly.

In the OFA, the role of the opposition-learning algorithm is different from the random disturbance term in the firefly algorithm. With the advantage of the opposition-learning algorithm, fireflies can easily escape from local optima and the diversity of fireflies can be increased. As a result, the global optima can be quickly found by the OFA.

2.3 Multilevel Otsu thresholding method based on OFA

In order to solve the optimization problem of the multilevel Otsu thresholding method, an OFA-based multilevel Otsu thresholding method is proposed.

The main steps of the OFA-based multilevel Otsu thresholding method are: 1) Input image; 2) Initialize the parameters of the OFA and let the maximum between-class variance σ^2_{mul} be the fitness function of OFA; 3) Use OFA to obtain a set of thresholds t_1^*, t_2^*, ..., t_{j-1}^* which can maximize Eq. (2); 4) Segment image with thresholds t_1^*, t_2^*, ..., t_{j-1}^*. The flowchart of the OFA-based multilevel Otsu thresholding method is shown in Fig. 1. In the flowchart, iter is the maximum iteration number and p_0 is the decision value.

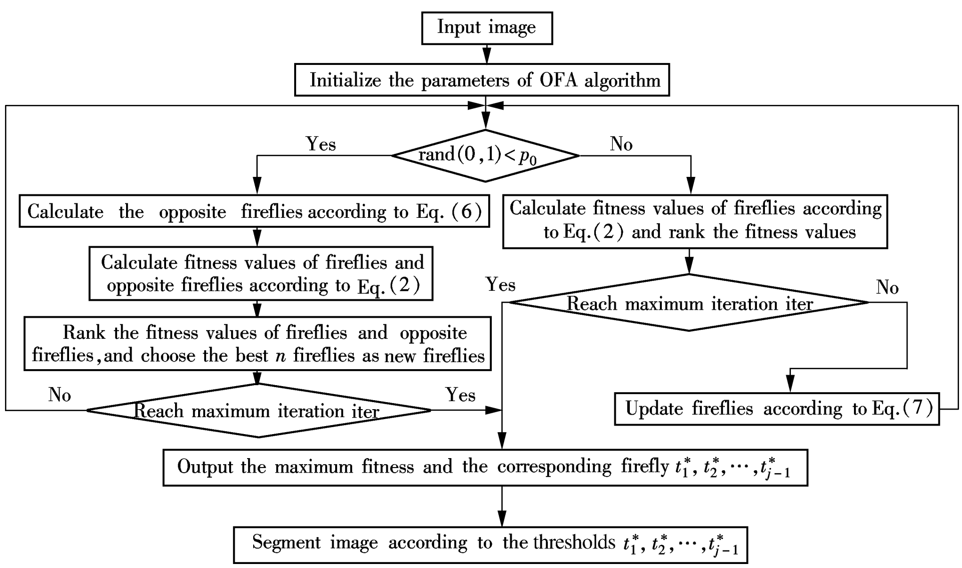

Fig. 1 Flowchart of the OFA-based multilevel Otsu thresholding method

3 Experiment

In order to verify the efficiency of the proposed method, three QFN defect images (QFN images with scratch defect, scrape defect and void defect) acquired from the test handler for QFN were tested in this paper and three other methods were programmed for comparison. All the experiments were implemented in a Matlab on a computer with Intel Core 2.26 GHz and 2 GB memory.

The parameters of the OFA-based method are set in Tab. 1. The images of segmentation results with two and three thresholds are shown in Fig. 2. In Fig. 2, the first column is the tested images (QFN image with scratch defect, scrape defect and void defect from up to down); the second column and the third column are the corresponding images of the segmentation results with two thresholds and three thresholds.

Tab. 1 Parameters of OFA-based method

Parameters	Value
Number of fireflies	50
Number of maximum iteration	100
Light absorption coefficient γ	1
Inertial attractiveness β_0	1
Randomization parameter α	0.5
Decision value p_0	0.3

Three benchmark methods (i. e., the exhaustive search, PSO-based multilevel Otsu thresholding and FA-based multilevel Otsu thresholding) were implemented for comparison. The parameters of the PSO-based multilevel Otsu thresholding are shown in Tab. 2 and the parameters of the FA-based method are set the same as the proposed method. Tab. 3 gives the thresholds and the corresponding fitness values of the four methods. It can be found that: 1) The results of the OFA-based method and the FA-based method are equal to that of the exhaustive method; 2) The PSO-based method cannot find the global best results.

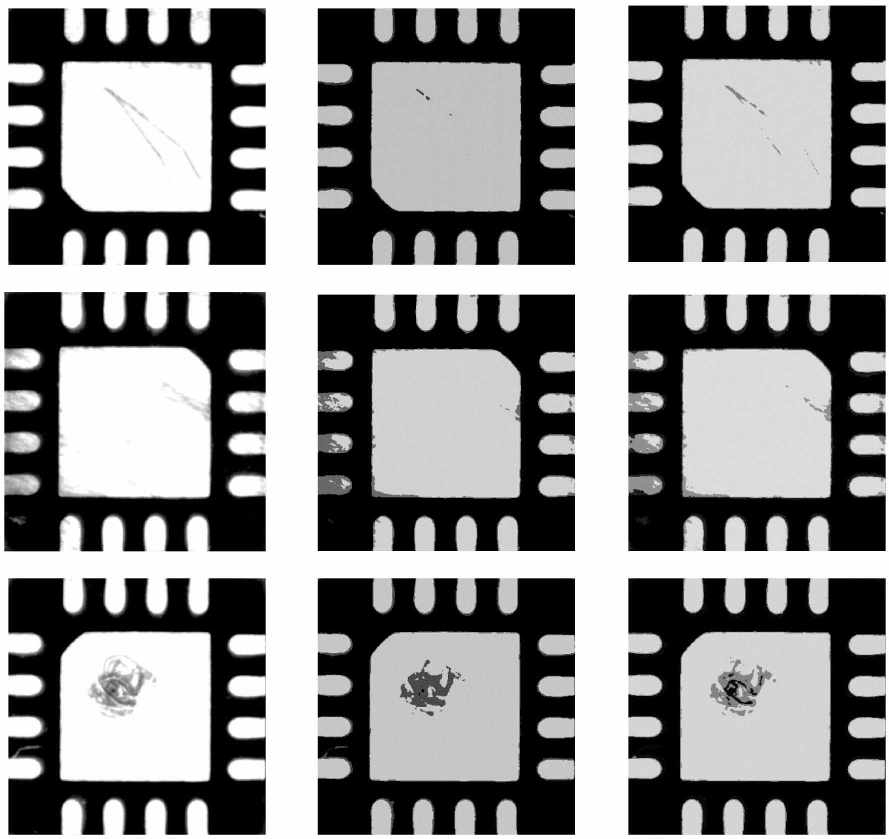

Fig. 2 Images of segmentation results

Tab. 2 Parameters of PSO-based method

Parameters	Value
Number of particles	50
Number of maximum iteration	100
Cognitive coefficient c_1 and c_2	1.5
Velocities range	[−2, 2]
Inertial weight	1.2

In order to further verify the superiority of the proposed method, the computation time and PSNR (peak signal-to-noise ratio) evaluation criteria are used to analyze the performance. The formula of PSNR is

$$\mathrm{PSNR} = 20\lg \frac{255}{\mathrm{RMSE}} \tag{8}$$

where $\mathrm{RMSE} = \sqrt{\left(\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - \hat{I}(i,j))^2\right)/MN}$ is the mean square error between the original image $I(i, j)$ and the segmented image $\hat{I}(i, j)$; M and N represent the height and width of the image. Tab. 4 shows the computation time and PSNR value obtained by the four methods. It can be found that: 1) The PSNR values of the exhaustive search method, the FA-based method and the OFA-based method are the same and the values are greater than the corresponding values of the PSO-based method; 2) The OFA-based method costs the least time of the four methods.

Taking all into account, the OFA-based method can segment QFN surface defects images more efficiently and with greater speed than that of the other three methods.

Tab. 3 Thresholds and the corresponding fitness values obtained by the four methods

Images	Number of thresholds	Exhaustive		PSO-based		FA-based		OFA-based	
		Thresholds	Fitness/10^3	Thresholds	Fitness/10^3	Thresholds	Fitness/10^3	Thresholds	Fitness/10^3
QFN scratch	2	91 193	9.864 5	90 191	9.863 9	91 193	9.864 5	91 193	9.864 5
	3	68 133 215	9.926 0	67 130 212	9.925 2	68 133 215	9.926 0	68 133 215	9.926 0
QFN scrape	2	113 209	8.640 5	112 208	8.639 8	113 209	8.640 5	113 209	8.640 5
	3	80 145 220	8.713 4	80 144 217	8.712 4	80 145 220	8.713 4	80 145 220	8.713 4
QFN void	2	98 198	9.304 4	98 197	9.303 7	98 198	9.304 4	98 198	9.304 4
	3	72 133 212	9.377 1	70 126 207	9.375 5	72 133 212	9.377 1	72 133 212	9.377 1

Tab. 4 Computation time and PSNR value of the four methods

Images	Number of thresholds	Exhaustive		PSO-based		FA-based		OFA-based	
		PSNR	Time/s	PSNR	Time/s	PSNR	Time/s	PSNR	Time/s
QFN scratch	2	13.335 3	4.645 1	13.192 0	1.133 7	13.335 3	1.305 7	13.335 3	1.103 6
	3	15.589 5	9 911.024 9	15.376 6	1.271 9	15.589 5	1.486 4	15.589 5	1.206 9
QFN scrape	2	13.446 0	4.646 5	13.404 2	1.138 1	13.446 0	1.331 8	13.446 0	1.007 8
	3	14.822 2	10 138.008 2	14.665 3	1.269 7	14.822 2	1.551 2	14.822 2	1.211 6
QFN void	2	13.388 1	5.355 2	13.323 4	1.140 2	13.388 1	1.259 3	13.388 1	1.059 4
	3	15.066 5	9787.303 8	14.731 0	1.303 2	15.066 5	1.487 2	15.066 5	1.195 7

4 Conclusion

This paper presents a novel multilevel Otsu thresholding based on the firefly algorithm with opposition-learning for segmenting QFN surface defect image. The main contributions are: 1) The firefly algorithm with opposition-learning (OFA) is proposed; 2) The OFA is applied when searching multilevel thresholds for image segmentation. Experimental results show that the proposed method can efficiently deal with QFN surface defects segmentation and its speed is faster than that of the other three methods. In the future, the adaptive selection of threshold number and defect feature extraction for QFN surface defects images are the next problems to be solved.

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基于反向萤火虫算法的多阈值缺陷图像分割

陈 恺[1] 戴 敏[1] 张志胜[1] 陈 平[1] 史金飞[2]

([1] 东南大学机械工程学院,南京 211189)

([2] 淮海工学院,连云港 222005)

摘要:为了分割 QFN 表面的缺陷,提出一种基于反向萤火虫算法的大津多阈值分割法. 首先,将大津阈值分割扩展为大津多阈值分割. 其次,提出了一种基于反向学习的萤火虫算法. 在该算法中,生成的反向萤火虫用于增加萤火虫的多样性和全局搜索能力. 然后,将基于反向学习的萤火虫算法应用于多阈值分割. 最后,使用所提出的方法对 QFN 缺陷图像进行阈值分割实验,并将结果与穷举法、基于粒子群算法的大津多阈值分割法、基于萤火虫算法的大津多阈值分割法进行比较. 实验结果表明,所提方法能更有效地分割 QFN 表面缺陷,且分割速度快.

关键词:QFN 表面缺陷;反向学习;萤火虫算法;大津多阈值算法

中图分类号:TP391.41