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A novel gravitational search algorithm for multilevel image segmentation and its application on semiconductor packages vision inspection

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A B S T R A C T

Multilevel image segmentation is an important technique and indispensable process in vision inspection on semiconductor packages to sort out defective products from the qualified ones, classify and identify the defect types. Conventional multilevel image segmentation methods are computationally expensive, and lack accuracy and stability. To address this issue, this paper proposes a novel gravitational search algorithm (NGSA) for multilevel image segmentation. Two major improvements to the update mechanism (UM) have been made in NGSA, i.e., adaptive gravitational constant and normal mutation of global best agent, to help agents jump out of local optima and improve the calculation accuracy. The experimental results based on multilevel Otsu criterion demonstrate that the proposed NGSA can obtain optimal multilevel thresholds for the quad flat non-lead (QFN) defect images and the segmentation results are promising. Three different methods, firefly algorithm (FA), cuckoo search (CS) and gravitational search algorithm (GSA), are compared with the proposed method. Numerical illustrations show that the proposed NGSA outperforms FA and GSA, and performs as well as, or is better than CS in solution quality, computational efficiency, and operation stability. Hence, NGSA in combination with multilevel Otsu criterion can be accurately and efficiently used in multilevel image segmentation of vision inspection on semiconductor packages.

1. Introduction

Vision inspection on semiconductor packages plays a critical role in the final testing process to ensure the quality of integrated circuit products. The quad flat non-lead (QFN) package is a very desirable package for high speed and high power components, benefiting from its electrical and thermal performance [1]. However, there are several different types of defects on the surface of the QFN package, which will seriously affect its stability and durability. Many scholars in recent years have been studying on detection, classification and recognition of defects on QFN packages. In 2009, Wang et al. proposed an image segmenting method and a set of features for detecting and classifying the resin bleed and melting defects of QFN packages [2]. In 2014, Chen et al. proposed a multilevel thresholding method based on firefly algorithm (FA) with opposition-learning to segment QFN defect images [3].

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Thresholding is one of the most direct and simple approaches to image segmentation. Multilevel image segmentation, as an extension to image segmentation, has the ability to segment multiple objects from background [4]. However, it suffers from high computing complexity, which can hardly satisfy the requirements of real-time processing [5]. Otsu algorithm [6], also known as the maximum between-class variance method, is one of the commonly used methods in image segmentation. It can be easily extended to multilevel thresholding problems and has been widely applied. To overcome the drawback of time-consuming computation in multilevel Otsu criterion, Gao et al. in 2013 presented a particle swarm optimization (PSO) with intermediate disturbance searching strategy to enhance the global search ability of particles and increase their convergence rates [7]. Bhandari et al. in 2015 presented a modified artificial bee colony (ABC) to segment complex satellites images [8]. Cuckoo search (CS) was introduced by Yang et al. in 2009 [9], and achieved more encouraging results in multilevel image segmentation than ABC, PSO and genetic algorithm (GA) [10]. Abhinaya et al. in 2015 presented the Otsu based CS algorithm to solve multilevel image thresholding problems and concluded that Lévy flight based CS had better convergence results [11]. The gravitational search algorithm (GSA), first introduced in 2009 by Rashedi et al., is one of the modern meta-heuristic algorithms [12]. It is inspired by the law of gravity and mass interaction. The efficiency of the GSA as a global optimizer in solving various nonlinear continuous benchmark functions has been revealed and it outperforms PSO and GA in search ability and convergence rate. However, in some cases, GSA can be trapped into local optima and results in premature convergence when applied to multilevel image segmentation.

In order to segment small and unconspicuous defects from the surface of QFN packages fast and accurately, a novel gravitational search algorithm (NGSA) is proposed and then applied to search for the multilevel thresholds using multilevel Otsu criterion in this paper. Two major improvements to the update mechanism (UM) have been made in NGSA to help agents jump out of local optima and improve the calculation accuracy. The four different methods – FA, CS, GSA, and NGSA – are implemented in several experimental images and QFN defect images for purpose of comparison.

The remainder of the paper is organized as follows: Section 2 gives an overview of FA, CS and GSA. Section 3 presents the proposed NGSA for multilevel image segmentation. Experimental results and discussions are presented in detail in Section 4. Finally, some conclusions are made in Section 5.

2. Overview of FA, CS and GSA

Let N, $Ngen$, represent the number of solutions (called fireflies in FA, nests in CS and agents in GSA) and generations. Most meta-heuristic algorithms, e.g., PSO, ABC, FA, CS, GSA, and the proposed NGSA, initialize solutions randomly with population size N and then search for optimal solutions by updating generations. It is evident that large N and $Ngen$ will slow down the optimization process, while small N and $Ngen$ will be unable to find a satisfied solution.

Let $X_i^t = (x_{i,1}^t, x_{i,2}^t, \ldots, x_{i,D}^t)$ be the ith solution at generation t, D be the number of dimensions (number of thresholds in multilevel image segmentation), $x_{i,j}^t$ be the jth variable of X_i^t, and $f({X_i}^t)$ be the fitness function of X_i^t. The major difference among all meta-heuristic algorithms is the UM that is used to update the current solutions. Hence, the UMs of FA, CS, GSA and NGSA will be focused on in the rest of the study.

2.1. FA

In FA [3,13], attractiveness between fireflies is proportional to their brightness and is affected or determined by the landscape of the fitness function to be optimized. The quality of the possible solution X_i^t (called the movement of firefly i attracted to another more attractive firefly j) is defined as

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

where ${X_i}^t$ and X_j^t represent the solution for firefly i and firefly j respectively; $\beta(r) = \beta_0 e^{-\gamma r_{ij}^2}$ represents the attraction from firefly j to i, where r_{ij} is the distance between them, 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. (1), where α is the randomization parameter and K_{rand} is a random number generator uniformly distributed in [0,1].

2.2. CS

CS is inspired by the aggressive reproduction strategy of some cuckoo species, and improved by Lévy flight [9]. In CS, cuckoos lay their eggs in communal nests, though they may remove others' eggs to increase the hatching probability of their own eggs. Each egg in a nest represents a solution and the aim is to use the new and potentially better solutions to replace a not-so-good solution in the nests. In addition, there is a probability $p_a \in [0, 1]$ of old nests being replaced by new nests (with new random solutions). When generating new solutions X_i^t for cuckoo i, Lévy flight is performed using Eq. (2):

$$X_i^t = X_i^{t-1} + \alpha \oplus \text{Lévy}(\lambda) \tag{2}$$

where $\alpha > 0$ represents a step size set to 1 in most cases. The product $\oplus$ means entry-wise multiplications.