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Chaotic species based particle swarm optimization algorithms and its application in PCB components detection

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A R T I C L E I N F O

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A B S T R A C T

An improved particle swarm optimizer using the notion of chaos and species is proposed for solving a template matching problem which is formulated as a multimodal optimization problem. Template matching is one of the image comparison techniques. This technique is widely applied to determine the existence, location and alignment of a component within a captured image in the printed circuit board (PCB) industry where 100% quality assurance is always required. In this research, an efficient auto detection method using a multiple templates matching technique for PCB components detection is described. The new approach using chaotic species based particle swarm optimization (SPSO) is applied to the multi-template matching (MTM) process. To test its performance, the proposed Chaotic SPSO based MTM algorithm is compared with other approaches by using real captured PCB images. The Chaotic SPSO based MTM method is proven to be superior to other methods in both efficiency and effectiveness.

1. Introduction

Particle swarm optimization (PSO) (Kennedy & Eberhart, 1995) is a newly developed evolutionary technique. Due to its simple concept, easy implementation, and quick convergence, nowadays, PSO has nowadays gained much attention and wide applications in different fields. For examples, Sun (2009) applied PSO to roundness measurement under a machine vision system and Omran and Engelbrecht (2005) proposed a PSO-based image clustering method. However, the standard PSO greatly depends on its parameters and exists as a premature phenomenon, especially in solving complex multi-hump problems (Angeline, 1998). The notion of species based PSO (SPSO) was proposed by Li (2004), for solving multimodal optimization problems. Chaos is a kind of characteristic of nonlinear systems and chaotic motion can traverse every state in a certain region by its own regularity, and nowadays, it has been applied in different fields (Jiang, Kwong, Chen, & Ysim, 2012; Lu, Shieh, & Chen, 2003; Wong, Kwok, & Law, 2008; Zhao, Sun, Sun, & Jiang, 2011). Due to the unique ergodicity and special ability in avoiding being trapped in local optima, chaos search is much higher than some other stochastic algorithms (Li & Jiang, 1998). Recently, several attempts for PSO using chaos methods were made (Liu, Wang, Jin, Tang, & Huang, 2005; Song, Chen, & Yuan, 2007; Xie, Zang, & Yang 2002) and obtained rich harvests. Xie et al. (2002) introduced chaos into the system by randomly reinitializing the particle positions with a small constant probability. Liu et al. (2005) incorporated chaos into PSO with adaptive inertia weight factor to construct a chaotic PSO. Song et al. (2007) combined tent map chaos with particle swarm optimization and proposed a new tent map chaotic particle swarm optimization (TCPSO). In this paper, the notion of chaos was introduced into the species based PSO and a novel Chaotic SPSO algorithm was proposed. The algorithm was analyzed on a test function and then applied into the components placement inspection of printed circuit boards (PCB).

Further research in multiple templates matching using the SPSO algorithm for PCB inspection has been undertaken recently (Wang, Wu, Ip, Chan, & Wang, 2008; Wu et al., 2009). Normalized cross correlation (NCC) has been used as the similarity function in template matching. It has been proven to greatly reduce the data storage and also reduce the sensitivity in acquiring images when compared with traditional image subtraction, and hence enhances the robustness of the system (Moganti & Ercal, 1996). Smaller components and greater component density are the two main elements affecting PCB inspection, but they are not the only ones. Speed always restricts the performance for completing an inspection task. To satisfy the requirements in the inspection task, the proposed Chaotic SPSO is introduced into the detection of the PCB components. The effectiveness of the Chaotic SPSO algorithm in locating multiple components is fully illustrated through simulations and comparisons.

Section 2 explains about the idea of multi-template matching method (MTM) and normalized cross correlation (NCC) value.

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The concept of Chaotic SPSO, its simulation results in different benchmark tests, the formulation of the multiple template matching problem to a multimodal optimization problem and the idea of Chaotic SPSO for MTM are presented in Section 3. The experimental results of the proposed Chaotic SPSO based method for solving the PCB components detection problem are shown in Section 4. Section 5 draws the conclusion.

2. Multi-template matching for components detection

Template matching can be used to find out how well a sub image (template image) matches the window of a captured image (Seul, O'Gorman, & Sammon, 2000). The degree of matching is often determined by evaluating the NCC value. The NCC has long been an effective similarity measurement method in feature matching. The basic idea of template matching is to loop the template through all the pixels in the captured image and compare the similarity. While this method is simple and easy to implement, it is the slowest method. To improve the efficiency of the correlation based template matching, the idea of multi-template matching (MTM) to solve such a problem was mooted.

In multi-template matching, at each point (x, y), the *MTM_NCC* value is defined as the maximum of a set of calculated *NCC* values which is obtained using corresponding templates. $\bar{f}$ is the average grey level intensity of the captured image region coincident with the kth template image. $\bar{w}_k$ is the average grey level intensity of the kth template image. A "perfect" match between f and w_k will result in a maximum value. For example, at point (x, y), *NCC* values are obtained through formula (1), NCC_1 is computed by using template 1, and NCC_2, calculated by using template 2 respectively. The *MTM_NCC* value at (x, y) can be obtained through formula (2):

$$NCCk(x,y)=\frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[f(x+i,y+j)-\bar{f}]\cdot[wk(i,j)-\bar{w}k]}{\left\{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[f(x+i,y+j)-\bar{f}]^2\cdot\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[wk(i,j)-\bar{w}k]^2\right\}^{1/2}} \tag{1}$$

$$MTM\_NCC(x,y)=\max\{NCC1(x,y),NCC2(x,y),\ldots,NCCk(x,y)\} \tag{2}$$

3. Multimodal optimization for multiple templates matching problem

Multimodal optimization is used to locate all the optima within the searching space, rather than one and only one optimum, and has been extensively studied by many researchers (Petalas, Antonopoulos, Bountis, & Vrahatis, 2009). Many algorithms based on a large variety of different techniques have been proposed in the literature. Among them, 'niches and species', and a fitness sharing method (Goldberg, 1987) were introduced to overcome the weakness of traditional evolutionary algorithms for multimodal optimization.

Recently, a speciation based particle swarm optimization method (Li, 2004; Li, Balazs, Parks, & Clarkson, 2002; Parrott & Li, 2006) was introduced to solve multimodal problems. It is an accepted fact that speciation to PSO is a successful method for locating all the global optima of a multimodal function. 'Niche' corresponds to a peak of the fitness searching space, while a 'species' means a sub population of individuals that exhibits similar features to those determined by particular metrics. The SPSO aims to identify multiple species within a population and determines the neighborhood best for each species. The multiple species are produced adaptively, in parallel, and used to optimize multiple optima.

3.1. Species based particle swam optimization

Central to the SPSO is the notion of species. A species can be defined as a group of individuals sharing common attributes according to some similarity metric. This similarity metric could be based on the Euclidean distance for genotypes using a real coded representation, or the Hamming distance for genotypes with a binary representation. The smaller the Euclidean (or the Hamming) distance between two individuals, the more similar they are. The definition of species also depends on another parameter γ_s, which denotes the radius measured in Euclidean distance from the center of a species to its boundary. The center of a species, the so called species seed, is always the fittest individual in the species. All particles that fall within the γ_s distance from the species seed are classified as the same species. The particles start searching for the optimum of a given objective function by moving through the search space at a random initial position. The manipulation of the swarm can be represented by Eqs. (3) and (4). Eq. (3) updates the particle velocity and Eq. (4) updates each particle's position in the search space, where ω is the inertia weight, c_1, c_2 are cognitive coefficients and r_1, r_2 are two uniform random numbers from U(0, 1), p_{id} is the personal best position and l_{besti} is the neighborhood best of particle i.

$$V_{id}^{k+1}=\omega v_{id}^{k}+c_1 r_1\left(p_{id}^{k}-x_{id}^{k}\right)+c_2 r_2\left(lbest_{id}^{k}-x_{id}^{k}\right) \tag{3}$$

$$x_{id}^{k+1}=x_{id}^{k}+v_{id}^{k+1} \tag{4}$$

Once the species seeds have been identified from the population, one can then allocate each seed to be the l_{best} to all the particles in the same species at each iteration step. The SPSO accommodating the algorithm for determining species seeds described above can be summarized in the following steps:

Step (1) Generate an initial population with randomly generated particles.
Step (2) Evaluate all particle individuals in the population.
Step (3) Sort all particles in descending order of their fitness values (i.e., from the best fit to least fit ones).
Step (4) Determine the species seeds for the current population.
Step (5) Assign each species seed identified as the l_{best} to all individuals identified in the same species.
Step (6) Adjust the particle positions according to (3) and (4).
Step (7) Go back to Step (2), unless the termination condition is met.

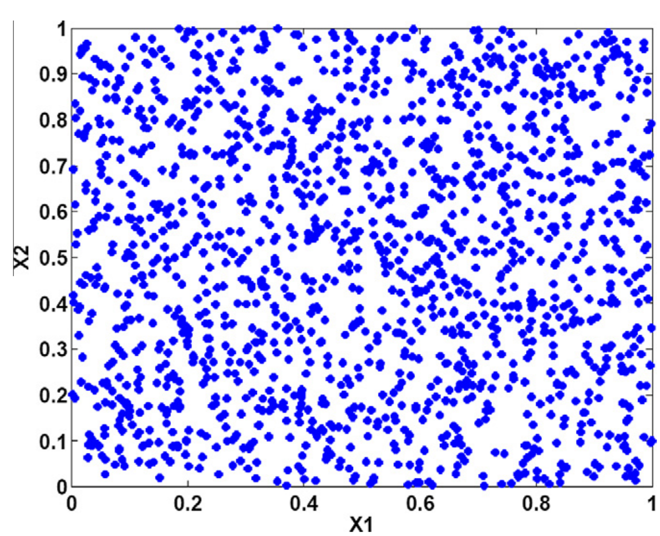

Fig. 1. Distribution of the chaos variables.