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Fast artificial bee colony and its application to stereo correspondence

Phuc Nguyen Hong, Chang Wook Ahn*

Department of Computer Engineering, Sungkyunkwan University, Republic of Korea

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ABSTRACT

Nature-inspired meta-heuristics have gained popularity for solutions to many real-world complex problems, and the artificial bee colony algorithm is one of the most powerful optimisation methods among meta-heuristics. However, inefficient exploitation of onlooker bees prevents the artificial bee colony algorithm from finding the final result accurately and efficiently for complex problems. In this paper, a novel optimisation method is proposed based on the artificial bee colony algorithm. The proposed optimisation method adaptively exploits onlooker bees over generations. In addition, the proposed optimisation method is applied to a stereo-matching problem to minimise the segment-based integer energy function, which is also introduced in this paper. The experimental results show that the proposed optimisation method outperforms state-of-the-art population-based meta-heuristics, such as the genetic algorithm, differential evolution, conventional artificial bee colony, and clonal selection algorithm, for benchmark functions as well as for the stereo-matching problem.

1. Introduction and related work

Meta-heuristic optimisation approaches have gained significant popularity for solving complex problems that are challenging to solve by using derivative-based techniques. In recent decades, several nature-inspired meta-heuristic optimisation algorithms have been developed. These algorithms are also referred to as population-based meta-heuristics or general-purpose algorithms due to the fact that they can be applied to a wide range of problems. Some popular population-based meta-heuristics are the genetic algorithm (GA) (Holland, 1975), differential evolution (DE) (Storn & Price, 1997), artificial bee colony (ABC) (Karaboga & Basturk, 2007b), and clonal selection algorithm (CSA)(Leandro & Leandro, 2002).

Since ABC was introduced from the work in Karaboga and Basturk (2007a), Karaboga and Basturk (2007b), Akay and Karaboga (2009), ABC has been developed and used to address several problems in different fields (Akay, 2013; Apalak, Karaboga, & Akay, 2014). The work in Tsai, Pan, Liao, and Chu (2009) presents a comprehensive survey for ABC applications and its improved versions. ABC has been implemented in parallel in order to improve its performance (Narasimhan, 2009; Subotic, Tuba, Chen, & Stanarevic, 2011; Subotic, Tuba, & Stanarevic, 2010; Zou, Zhu, Chen, & Sui, 2010). The ABC-improved versions often increase computation costs and are more complicated than the conventional ABC algorithm (Cavdar, Mohammad, & Alavi, 2013).

In our observation, ABC is not efficient for obtaining optimal solutions, because it treats candidate solutions equally over generations. However, after a number of generations, a population usually converges and approaches optimal regions. Solutions in this stage should be exploited more than those in the early stages. This paper presents a novel optimisation method, fast artificial bee colony (FABC), that can overcome the aforementioned obstacle of ABC. The method exploits the fitness value of the best solution of the current population to estimate the factor value that determines the level of solution exploitation. Therefore, FABC can obtain better optimisation values with fewer function evaluations. The proposed method is experimentally evaluated and compared with population-based optimisation methods, such as GA, DE, and CSA, for CEC2015 optimisation functions. Furthermore, FABC is applied to a stereo-matching problem as an optimisation method, and its performance is compared with those of the other population-based optimisation methods.

Stereo matching aims to find the correspondence between two or more images of the same scene (as shown in Fig. 1), and it is successfully applied in 3D modelling, view interpolation, robotics, and autonomous vehicles. Stereo-matching algorithms can be classified as local and global algorithms (Scharstein & Szeliski, 2002), and most stereo-matching algorithms perform the following steps: matching cost (Nguyen, Nguyen, Nguyen, Dinh, & Jeon, 2014; Zabih & Woodfill, 1994), cost aggregation (He, Sun, & Tang, 2010; Tomasi & Manduchi, 1998), disparity optimisation (Felzenszwalb & Huttenlocher, 2006; Kolmogorov & Zabih, 2001), and disparity refinement (Fua, 1993). The disparity of each pixel in local stereo matching is computed from the intensities within a window of finite size, whereas the stereo-matching problem in global matching is modelled by an

* Corresponding author. Tel.: +82 312994588.
E-mail addresses: hongphuc@skku.edu (P.N. Hong), cwan@skku.edu (C.W. Ahn).

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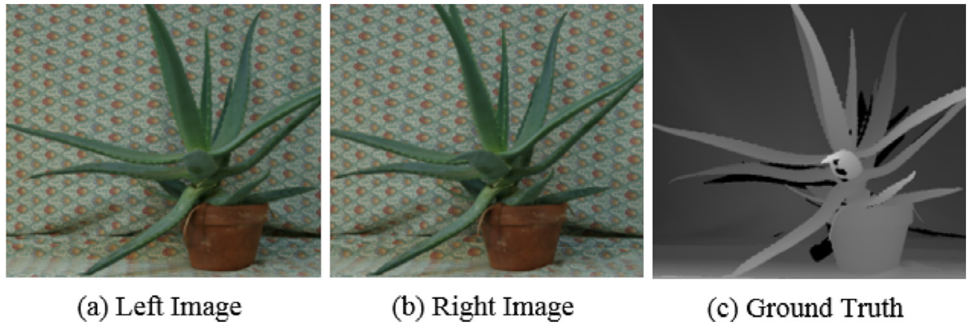

Fig. 1. A stereo pair and its disparity map. (a) Left image. (b) Right image. (c) Disparity map from (a) and (b).

energy function that is then optimised by an optimisation method. In global stereo matching, an energy function is first defined and then solved as an energy minimisation problem. A disparity map with high energy is bad, whereas a disparity map with low energy is good.

The contributions of this paper are three-fold. First, we introduce an improved version of ABC that can operate better than ABC in both continuous and discrete problems. Second, we propose a stereo-matching framework that can use a meta-heuristic algorithm to optimise the modelled stereo-matching problem. In addition, we propose the reduced energy function for meta-heuristic algorithms to solve the stereo-matching problem. The reduced energy function can reduce the number of variables from the original energy function significantly. Finally, we apply FABC to stereo correspondence as an optimisation algorithm. The qualitative and quantitative experimental results show that FABC is a promising optimisation algorithm, and the proposed reduced energy function can be used as a real application for meta-heuristic algorithms.

The remainder of the paper is structured as follows. In Section 2, ABC is presented. In Section 3, FABC is presented. The construction of a stereo-matching energy function is presented in Section 4. In Section 5, the experimental results of the algorithms are reported. Finally, the conclusions of the paper are given in Section 6.

2. ABC

The ABC algorithm (Karaboga & Basturk, 2007b) mimics the foraging behaviour of real honeybees and contains three groups of bees: Employed, onlooker, and scout bees. Employed bees have associations with specific food sources (solutions); onlooker bees within the hive watch the dances of employed bees to select food sources; and scout bees search for food sources randomly.

The general procedure of the original ABC algorithm consists of four steps. The algorithm first generates an initial population randomly according to a uniform distribution within a feasible space, and then the iteration repeats until the termination criteria are met. In each iteration, employed, onlooker, and scout bees phases are performed in an orderly manner. In the initialisation step, the control parameters of ABC are set and the population of food sources is initialised by scout bees using Eq. (5):

$$\mathbf{P}_{i,j} = lb_j + rand(0,1) \times (ub_j - lb_j), \tag{1}$$

where i indicates the ith candidate solution index in the population $\mathbf{P}$, j indicates the jth variable index of a solution, the value $\mathbf{P}_{i,j}$ is maintained by the lower bound lb_j and the upper bound ub_j, and $rand(0, 1)$ is a random function that generates a random number between 0 and 1 with a uniform distribution.

In the employed bee step, the employed bees search for solutions neighbouring the candidate solution $\mathbf{P}_i$ in their memory to find solutions that have better fitness. After finding a neighbouring solution, $\mathbf{s}$, and evaluating its fitness, a greedy selection is performed between $\mathbf{s}$ and $\mathbf{P}_i$. $\mathbf{s}$ is created by stochastically changing a randomly selected variable j of $\mathbf{P}_i$ as follows:

$$\mathbf{s}_j = \mathbf{P}_{i,j} + rand(-1,1) \times (\mathbf{P}_{i,j} - \mathbf{P}_{l,j}). \tag{2}$$

Here, l indicates the l^{th} candidate solution index, randomly selected from candidate solutions, and the random function $rand(-1, 1)$ generates a random number between -1 and 1 with uniform distribution. The new value of $\mathbf{s}_j$ is stochastic and belongs to $\varphi = [\mathbf{P}_{i,j} - |\mathbf{P}_{i,j} - \mathbf{s}_j|, \mathbf{P}_{i,j} + |\mathbf{P}_{i,j} - \mathbf{s}_j|]$. The employed bees then dance in the dancing area to share the information regarding their solutions with the onlooker bees in the hive. Note that the other variables (different from j) of $\mathbf{s}$ obtain the same corresponding values as $\mathbf{P}_i$.

In the onlooker bee step, the onlooker bees select promising candidate solutions probabilistically based on the fitness information from employed bees. After a candidate solution is selected, the neighbourhood of the solution is produced using Eq. (2), and a greedy selection is applied. The fitness, fit_i, of $\mathbf{P}_i$ is computed as follows:

$$fit_i = \begin{cases} \dfrac{1}{f_i} & if\ f_i \geq 0 \\ 1 + abs(f_i) & if\ f_i < 0, \end{cases} \tag{3}$$

where f_i is the objective value of the solution $\mathbf{P}_i$.

The probability values, $prob_i$, for the $\mathbf{P}_i$ solutions according to their fitness values are computed as:

$$prob_i = \frac{fit_i}{\sum_{i=1}^{FN} fit_i}, \tag{4}$$

where FN is the number of food sources.

In the scout bee step, the employed bees whose fitness values are not increased in the pre-determined number of iterations, L, become scout bees, and the scout bees replace their old solutions by searching for new solutions randomly according to Eq. (1). In the original ABC, no more than one employed bee is allowed to become a scout bee in each iteration.

Let n be the problem size of the considered problem, and N_{ABC} be the population size (employed bees and onlooker bees). According to Karaboga and Basturk (2007b), Kang, Junjie, and Zhenyue (2011), the number of candidate solutions, FN, should be half of the population size, so that $FN = N/2$ and $L = n \times FN$.

3. FABC

A major drawback of conventional ABC is that it considers solutions over generations equally. In complex problems with a large number of variables, this problem can have a significant influence on the efficiency and accuracy of ABC. Hence, this problem should be overcome for ABC to operate robustly with large dimensional problems. The stereo-matching problem is modelled by an energy function, where the smoothness value for each pair of neighbourhood variables depends on their values. When the value of one variable changes, this directly affects its neighbourhood variables and indirectly affects the others. To accurately and efficiently minimise the energy function, ABC should be made more efficient.