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A case study of innovative population-based algorithms in 3D modeling: Artificial bee colony, biogeography-based optimization, harmony search ☆

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ABSTRACT

Deterministic or analytical methods for computing the global optima of a functional have been extensively applied in a wide range of engineering applications. Nevertheless, it is wellknown they usually lack of effectiveness when dealing with complex nonlinear optimization problems. In particular, such a shortcomings have been addressed by using approximate approaches, named metaheuristics. Among them all, those methods using a population-based scheme, e.g. the evolutionary algorithms, have been the most successful optimization strategies. Recently, innovative population-based algorithms such as ABC, BBO, and HS have arisen as promising optimization methods due to they provide a good tradeoff between design and performance when compared to other more elaborated methods. In this work, we aim to first introduce the particular design of these three cutting edge algorithms, and additionally analyse their performance when tackling a challenging real-world optimization problem. In particular, our case study of numerical optimization tackles a computer vision problem named 3D range image registration for 3D modeling tasks. Computational experiments have been conducted comparing the performance of ABC, HS, and BBO against other contributions in the state-of-the-art of 3D image registration.
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1. Introduction

Optimization problems are often complex situations to cope with in several areas of knowledge such as engineering. The objective function may have many local optima and in many cases finding the best solution (named global optimum) is so time-consuming that goes beyond the admissible in practical applications. Those problems cannot be handled by classical methods (e.g. gradient-based algorithms) which are likely to compute local optima. Thus, there remains a need for efficient and effective numerical optimization methods for tackling challenging real-world engineering problems. In the last few decades, approximate algorithms, named metaheuristics (MHs) (Glover & Kochenberger, 2003; Luke, 2009), have demonstrated their good performance in these kinds of problems, where the guarantee of finding the optimal solution is relaxed in order to obtain high quality solutions in a much more reduced time interval.

There are different kinds of MHs. Among them all, population-based techniques work on a population of solutions based on analogies with natural phenomena. This approach has been applied to a large amount of engineering optimization problems and it has being proved to be effective in solving well-known challenging problems. Within population-based techniques, we can find classical techniques such as genetic algorithms (GAs) (Goldberg, 1989; Michalewicz, 1996), particle swarm optimization (PSO) (Clerc, 2006; Kennedy & Eberhart, 2001) and ant colony optimization (ACO) (Dorigo & Di Caro, 1999; Dorigo & Stützle, 2004; Farhana et al., 2012; Zhou & Wang, 2012). Recently, many new population-based approaches have been arised: artificial bee colony (ABC) (Karaboga & Basturk, 2007a, 2007b), differential evolution (DE) (Price, 1999; Storn, 1997), harmony search (HS) (Geem, Kim, & Loganathan, 2001), cats swarming (CS) (Chu & Tsai, 2007), and biography-based optimization (BBO) (Simon, 2008), among others.

Testing these new population-based approaches and carrying out a comparison with other state of the art methods may serve the field to analyse both their shortcomings and googness in

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performance, thus allowing the field to propose more advanced variants, e.g. addressing hybrid strategies. In this work, we aim at analysing the performance of three cutting edge algorithms: ABC, BBO, and HS. To do so, we have considered a case study of numerical optimization within the field of computer vision, known as the image registration (IR) problem (Zitová & Flusser, 2003). In particular, we addressed several IR problem instances for 3D modeling by using laser range scanners (Santamaría, Cordón, & Damas, 2011). Moreover, these results were compared to those provided by other state-of-the-art population-based algorithms in the field of IR.

The structure of this contribution is as follows. In Section II, a description of the optimization design of the population-based algorithms ABC, BBO, and HS. Then, in Section III, we are introducing the basics of the real-world problem tackled which is known as range image registration (RIR) (Bernardini & Rushmeier, 2002). A revision of IR methods using population-based approaches will also be followed in this section. the mos relevant conclusions will be shown in section IV. Finally, Section V collects some concluding remarks as well as possible works for the near future.

2. Recent advancements on population-based algorithms

2.1. Background

Numerical optimization problems are encountered in many domains, e.g. science, engineering, management, and business. Formally, they may be defined as a couple $P = (X, F)$ where X is named as search space and it represents the set of feasible problem solutions $X = \{x_1, \ldots, x_{|X|}\}$. Each of the latter d-dimensional vectors, $x \in X$, consists of a set of design variables, $x = (x^1, \ldots, x^d)$, each one ranging to a particular continuous domain $x^j \in [LB^j, UB^j]$ $(1 < j < d)$. A function $F : X \rightarrow \mathrm{IR}^+$, so-called the objective function which assigns a real value to every solution $x \in X$ indicating its quality.

The main challenge in solving an optimization problem is to find the global optimal solution. However, computing optimal solutions in many real-world applications would be so time-consuming that go beyond the admissible, basically due to the high dimension of the factible solutions space. In the last decades, MHs have emerged as a new kind of approximate search and optimization algorithms (Glover & Kochenberger, 2003; Luke, 2009). They combine basic heuristic methods in order to explore efficient and effectively the search space which will provide acceptable solutions in a reasonable time.

One of the main advantages of MHs is that they make use of a general purpose optimization framework requiring relatively few modifications to be applied to a specific problem. The MHs family include methods as Simulated Annealing (SA), tabu search (TS), multi-start local search (MS), iterated local search (ILS), variable neighborhood search (VNS), and greedy randomized adaptative search procedures (GRASP). These are usually termed as trajectory-based MHs. On the other hand, population-based MHs, e.g. evolutionary algorithms (EAs) (Bäck, Fogel, & Michalewicz, 1997; Fogel, 2005), consider populations of candidate problem solutions instead.

In particular, GAs are probably the most extended population-based algorithm in the literature to face real-world optimization problems. GAs are theoretical and empirically found to provide global near-optimal solutions for several problems of complex optimization. The search space represented in GAs is a collection of individuals (problem solutions) or chromosomes conforming a population, each of them operating simultaneously on several points of the search space. An initial set/population of solutions is randomly generated. Then, a pool of parents is randomly selected for reproduction on the basis of the *fitness function*,[1] which measures how good is each candidate solution and guides the search space exploration strategy.

The reproduction procedure, which is based on crossover and mutation operators is iteratively performed at every generation (iteration) in order to generate the offspring population. Crossover operators systematically/randomly mix parts (block of genes) of two individuals of the previous population, and additionally every new combined individual is subjected to random changes by using mutation operators. The next generation is produced using a replacement mechanism which selects individuals from the pool composed of the parents and the new offspring generated.

Regardless the approach (trajectory-based vs. population-based), MHs constitute a very interesting choice to achieve a good quality solution in a reasonable time. Specifically, optimization algorithms, already based on the evolution of populations of solutions, have obtained a remarkable success. The next section will be devoted to introduce the description of three innovative population-based MHs recently proposed in the literature, namely ABC, BBO, and HS.

2.2. Artificial bee colony

Swarm intelligence has become an interesting research nowadays (Bonabeau, Dorigo, & Theraulaz, 1999; Cui, Zeng, & Sun, 2006) been applied to solve optimization problems (Zhou & Wang, 2012). The ABC algorithm is a new swarming variant inspired in the population-based approach proposed by Karaboga and Basturk (2007a, 2007b) which is based on the intelligent behavior of honeybee swarms.

In the ABC algorithm, the colony of artificial bees is divided into the three following categories (Karaboga & Basturk, 2008):

- **Employed:** They take nectar from the food source to the hive and share information with onlookers about their location.
- **Onlookers:** Those specialized bees tend to select a food source (the most profitable one) according to their quality, which is given by shared information provided by employed bees in the hive.
- **Scouts:** They are employed bees whose food source has been abandoned. They start to search a new food source randomly.

The algorithm works just by including a common area in the hive so-called the *dancing area*, where bees share and exchange information about food sources. Bees identify the quality of food source by means of the duration of dancing which is determined by the nectar contained in the food source being exploited and its distance to the hive. From the optimization viewpoint, each food source represents a possible solution to the problem, where scouts perform exploration and employed and onlooker bees are focused on the exploitation of search space.

Specifically, the ABC algorithm is sketched in Fig. 1. It starts by associating all the employed bees to randomly generated food sources. Each food source x_i $(i = 1, 2, \ldots, N)$ is a *d-dimensional* vector where d is the number of optimization parameters. Next, each iteration is done as follows. Every employed bee determines a food source within the neighborhood of its current source when using the expression

$$v_i^j = x_i^j + \Phi_i^j (x_i^j - x_k^j) \qquad (1)$$

where k different to $i \in 1, 2, \ldots N$ and $j \in 1, 2, \ldots, d$ are randomly chosen indexes, and Φ_i^j is a random number between $[-1, 1]$ which

[1] The fitness or objective function is one of the most important components of heuristic methods whose design affects dramatically to the performance of the implemented method.

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