



Weighted bee colony algorithm for discrete optimization problems with application to feature selection



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ARTICLE INFO

Article history:

Received 12 September 2014

Received in revised form

30 April 2015

Accepted 1 June 2015

Available online 20 June 2015

Keywords:

Bee colony optimization

Categorical optimization

Classification

Feature selection

Weighted bee colony optimization

ABSTRACT

The conventional bee colony optimization (BCO) algorithm, one of the recent swarm intelligence (SI) methods, is good at exploration whilst being weak at exploitation. In order to improve the exploitation power of BCO, in this paper we introduce a novel algorithm, dubbed as weighted BCO (wBCO), that allows the bees to search in the solution space deliberately while considering policies to share the attained information about the food sources heuristically. For this purpose, wBCO considers global and local weights for each food source, where the former is the rate of popularity of a given food source in the swarm and the latter is the relevancy of a food source to a category label. To preserve diversity in the population, we embedded new policies in the recruiter selection stage to ensure that uncommitted bees follow the most similar committed ones. Thus, the local food source weighting and recruiter selection strategies make the algorithm suitable for discrete optimization problems. To demonstrate the utility of wBCO, the feature selection (FS) problem is modeled as a discrete optimization task, and has been tackled by the proposed algorithm. The performance of wBCO and its effectiveness in dealing with feature selection problem are empirically evaluated on several standard benchmark optimization functions and datasets and compared to the state-of-the-art methods, exhibiting the superiority of wBCO over the competitor approaches.

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1. Introduction

Swarm intelligence (SI) is one of the well-known classes of optimization and refers to algorithms relying on the intelligence of a swarm to locate the best parts of the solution space. Particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), ant colony optimization (ACO) (Dorigo et al., 1999) and BCO (Nikolic and Teodorovic, 2013; Teodorovic et al., 2006), are examples of SI algorithms. Many problems such as text clustering (Dziwiński et al., 2012), feature selection (Forsati et al., 2014; Forsati et al., 2012; Unler and Murat, 2010), etc., can be modeled as discrete optimization problems and solutions obtained through SI algorithms.

BCO is one of the most recent developments of swarm intelligence proposed by Teodorovic et al. (2006), which has been successfully applied to many fields of science including image analysis (Ghareh

Mohammadi and Saniee Abadeh, 2014), bioinformatics (Li et al., 2014), etc. The algorithm simulates the natural behavior of the bees in locating food resources. In summary, the BCO algorithm has five main stages: (1) initialization, (2) solution creation, (3) fitness assessment, (4) loyalty measurement, and (5) recruiters selection.

In the first step, the algorithm parameters are initialized (*initialization*). Then in the second step the solutions are created, partially in the sense that the whole solution will not be created at once while during several forward and backward steps a complete solution will be created (*solution creation*). In BCO a forward step occurs once the bees leave their hive to create solutions and explore the solution space, while the backward stage occurs once the bees return to their hive to measure the goodness of the produced solutions, share the attained information and finally select the follower and recruiters.

During the solution creation steps, after each forward movement, the bees return to their hive to assess the solutions (*fitness assessment*). The fitness assessment occurs in the backward step, where each bee also measures how loyal it is to the created partial solution (*loyalty measurement*). Finally, before performing the next forward movement, the bees must be divided into two sets of committed (recruiter) and uncommitted (followers) bees to decide

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which bees will follow the other bees (*recruiter selection*). Within a generation the algorithm iterates between the second and the fifth stages until all the bees create their full solutions. For further details about BCO interested readers may refer to the work of Forsati et al. (2015).

The advantage of BCO is its ability in tuning the search direction in the early stages of exploration, while other SI algorithms such as ACO require full traversals by all ants to adjust pheromone weights accurately and finally identifying the worthwhile exploration paths. Once the bees perform the backward movement they in fact try to distinguish worthwhile and non-worthwhile solution paths. This action allows the search direction to be tuned toward the most optimal parts of the solution space found so far. Similarly, PSO has the same characteristic, in which the flock of birds flies toward the global and/or local best solutions while exploring the solution space.

Mainly swarm intelligence algorithms (including BCO) rely on randomness to search the solution space. This might give absolute freedom to the swarm to search the solution space, but randomness might degrade the exploitation ability of BCO, in the sense that the worthwhile parts of the space remain undiscovered or unintentionally ignored. In other words, the bee colony has weak exploitation ability while having a good level of exploration (Kang et al., 2011). Therefore to increase the exploitation ability of BCO, we introduce a new variation called weighted bee colony optimization (wBCO) which considers new policies in measuring the loyalty degrees of the bees and also recruiter selection. The formulation of recruiter selection will make the algorithm applicable for classification and regression problems.

As explained, each backward step has three stages: fitness assessment, loyalty assessment, and recruiter selection. In the backward step for wBCO, where the bees measure how loyal they are to their created (partial) solutions, the algorithm considers two weights for each food source. One is a global weight, which measures how popular a given food source is in the swarm and the other is a local weight, which indicates the extent to which a selected food source can contribute to the category label of the classification problem. In the recruiter selection step, in order to preserve diversity the followers select their recruiters in a filtering stepwise process. We apply two filtering stages; one is based on similarity, and the other based on fitness values. In similarity filtering, for a given follower a set of recruiters is selected based on the traversal similarity and then the follower selects a recruiter bee which has the closest fitness value. This recruiter selection strategy is only applicable if the variables of a classification problem only accept discrete values (e.g., integers, binary, letters).

To investigate the effectiveness of the proposed algorithm in application, we further applied the proposed wBCO to feature selection (FS) and modeled the curse of dimensionality as a discrete optimization task to investigate if wBCO can have applicability in classification tasks. Also, other applications such as text classification can be modeled using wBCO, but as a result of wide applications of FS including bioinformatics (Chyzyk et al., 2014), systems monitoring (Shen and Jensen, 2004), text mining (Jensen and Shen, 2004), image processing (Da Silva et al., 2011), etc., we decided to model FS as a discrete optimization task with wBCO. The new feature selection algorithm is called FS-wBCO and successful implementation of FS-wBCO will indicate that the proposed wBCO is also applicable in the fields relying on FS. The contributions of this paper are summarized as follows.

- Modifying the loyalty assessment of the original BCO with the aim of using heuristics to weight the worth of each selected food source and consequently improving the exploitation power of BCO. For this purpose we use the global and local weight of a selected food source.

- In the introduced weighting scheme, each selected food source has two weights: local and global. In the former the algorithm measures how popular the food source is in the swarm, while in the latter the algorithm determines the extent to which the selected food source is relevant to a category label.
- In line with exploitation improvements, we modify the recruiter selection of the original BCO with the aim of using heuristics to preserve diversity in the bees' population by assigning each uncommitted bee to the most similar committed one.
- To investigate the utility of wBCO, feature selection is modeled as a discrete optimization problem resulting in another algorithm known as FS-wBCO. Experiments are carried out to investigate the efficacy of both wBCO and FS-wBCO.

The rest of the paper is organized as follows: Section 2 briefly reviews some of the recent literature in the area of bee colony improvements. In Section 3, the new bee colony optimization algorithm, wBCO, is proposed. In Section 4, the application of wBCO for feature selection is introduced. Section 5 provides some experimentation to show the effectiveness of wBCO and the feature selection algorithm (FS-wBCO) and finally Section 6 concludes the paper and lists future work.

2. Literature review

As we are introducing a new BCO algorithm, the focus of this section is on some of the recent developments of bee colony-based algorithms. Regarding feature selection algorithms, interested readers can refer to (Liu and Motoda, 1998). In the literature, two approaches to bee colony-based algorithms are proposed. One is the artificial bee colony (ABC) algorithm proposed by Karaboga and Akay (2009), Karaboga et al. (2014) and the other is BCO proposed by Teodorovic et al. (2006). As both of the algorithms rely on the natural behavior of the bees, we also consider the ABC algorithm in this paper.

As shown in Table 1, bee colony improvements mainly aim at improving either the exploration or the exploitation of the algorithm. Hence in this review, we divide the bee colony improvements into these two categories. A third category is related to algorithms targeting improvements in both exploration and exploitation powers of BCO.

There are some BCO algorithms focusing on improvements of exploration power. Gao and Liu (2011) proposed IABC that uses differential evolution, which is suitable for global optimization.

Table 1

An overview of the reviewed articles.

Articles	Exploration	Exploitation	Integrated (exploration and exploitation)
Kumar et al. (2012)	✓		
Lu et al. (2014)			✓
Huang and Lin (2011)	✓		
Kumar (2014)			✓
Forsati et al. (2015)			✓
Alzaqebah and Abdullah (2014)		✓	
Karaboga and Akay (2011)			✓
Gao and Liu (2011)	✓		
Li et al. (2012)		✓	
Akbari et al. (2012)			✓
Imanian et al. (2014)		✓	
Alatas (2010)		✓	
Kashan et al. (2012)			✓
wBCO		✓	

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