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Brain storm optimization algorithm: a review

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Abstract For swarm intelligence algorithms, each individual in the swarm represents a solution in the search space, and it also can be seen as a data sample from the search space. Based on the analyses of these data, more effective algorithms and search strategies could be proposed. Brain storm optimization (BSO) algorithm is a new and promising swarm intelligence algorithm, which simulates the human brainstorming process. Through the convergent operation and divergent operation, individuals in BSO are grouped and diverged in the search space/objective space. In this paper, the history development, and the state-of-the-art of the BSO algorithm are reviewed. In addition, the convergent operation and divergent operation in the BSO algorithm are also discussed from the data analysis perspective. Every individual in the BSO algorithm is not only a solution to the problem to be optimized, but also a data point to reveal the landscape of the problem. Swarm intelligence and data mining techniques can be combined to produce benefits above and beyond what either method could achieve alone.

Keywords Brain storm optimization · Developmental swarm intelligence · Convergent operation · Divergent operation · Data analysis

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Nomenclature

x_i	The ith dimension of solution $\mathbf{x}$
$p_{\text{generation}}$	Pre-determined probability, which is used to determine a new individual being generated by one or two "old" individuals
$p_{\text{oneCluster}}$	Pre-determined probability, which is used to determine the cluster center or another normal individual will be chosen in one cluster generation case
$p_{\text{twoCluster}}$	Pre-determined probability, which is used to determine the cluster center or another normal individual will be chosen in two clusters generation case
r	Random value in the range [0, 1)
$\xi(t)$	Step size function
$f(\mathbf{x})$	Fitness value: objective function value of $\mathbf{x}$
t	Iteration number
T	Maximum number of iteration
S	Population size: the number of solutions in a population
D	Number of decision variables

1 Introduction

Optimization is concerned with finding the "best available" solution(s) for a given problem. An optimization problem is a mapping from decision space to objective space. For swarm intelligence algorithms, each individual in the swarm represents a solution in the search space. Based on the cooperation and competition among individuals, individuals are guided toward the better and better search areas until some stopping conditions is met. Swarm intelligence algorithms should have two kinds of ability: capability learning and capacity developing (Shi 2014). The capacity developing focuses on moving the algorithm's search to the area(s) where higher search potential may exist, while the capability learning focuses on its actually search from the current solution for single point based optimization algorithms and from the current population for population-based swarm intelligence algorithms. The swarm intelligence algorithms with both capability learning and capacity developing can be called as developmental swarm intelligence (DSI) algorithms.

The capacity developing is a top-level learning or macro-level learning methodology. It describes the learning ability of an algorithm to adaptively change its parameters, structures, and/or its learning potential according to the search states of the problem to be solved. In other words, the capacity developing is the search strength possessed by an algorithm. The capability learning is a bottom-level learning or micro-level learning. The capability learning describes the ability for an algorithm to find better solution(s) from current solution(s) with the learning capacity it possesses.

The brain storm optimization (BSO) algorithm was proposed in 2011 (Shi 2011a, b), which is a young and promising algorithm in swarm intelligence. It is based on the collective behavior of human being, that is, the brainstorming process (Shi 2011a, b; Shi et al. 2013. The speciation is a process of natural selection, which means that the population diverging into separate species. The solutions in BSO are also diverging into several clusters. The new solutions are generated based on the mutation of one individual or a combination of two individuals.

The BSO algorithm, which is a good example of developmental swarm intelligence algorithms, has two major operators: convergent operator and divergent operator. A "good enough" optimum could be obtained through solutions divergence and convergence in the search space. In the BSO algorithm, the solutions are clustered into several categories, and the new solutions are generated by the mutation of cluster or existing solutions. The capacity developing, i.e., the adaptation during the search, is another common feature of the BSO algorithm.

The aim of this paper is to give a comprehensive review on the state-of-the-art of brain storm optimization algorithms. The remaining paper is organized as follows. In Sect. 2, the original BSO and the tendency of BSO research are first reviewed, followed by BSO algorithm analysis from the data analytics perspective in Sect. 3. The state of the art BSO algorithms, which include the theoretical analysis, modified BSO algorithm, BSO for different optimization problems, and the real-world applications are given in Sect. 4. Finally, conclusions will be given in Sect. 5.

2 Brain storm optimization algorithm: the history of the development

2.1 The trend of brain storm optimization research

Since the invention of the Brain Storm Optimization (BSO) algorithm in 2011, it has attracted many attentions in the swarm intelligence research community. There are already more than 40 papers, master thesis on the developments and application of BSO algorithm since then.

Figure 1 gives the number of papers and theses since 2011. To the best of our knowledge, there are 43 papers and theses in total on the development and application of the BSO algorithm. There are 19 papers which were published on the peer-reviewed journals, such as International Journal of Swarm Intelligence Research (IJSIR) (Shi 2011b, 2014; Shi et al. 2013), IEEE Computational Intelligence Magazine (Sun et al. 2013), IEEE Transactions on Magnetics (Duan et al. 2013; Duan and Li 2015), Soft Computing (Yang et al. 2014; Arsuaga-Ríos and Vega-Rodríguez 2014b), Journal of Artificial Intelligence and Soft Computing Research (JAISCR) (Cheng et al. 2014b), Journal of Zhejiang University (Engineering Science) (Yang et al. 2013), Nonlinear Dynamics (Qiu and Duan 2014), Aerospace Science and Technology (Li and Duan 2015), Optik (Qiu et al. 2015), *etc*. There are 22 papers published on the peer-reviewed conferences, such as IEEE Congress on Evolutionary Computation (CEC) (Zhan et al. 2012; Cheng et al. 2014a; Shi 2015), IEEE Symposium on Swarm Intelligence (SIS) (Cheng et al. 2013; Zhan et al. 2013), the Conference Companion on Genetic and Evolutionary Computation (GECCO) (Zhang et al. 2014), International Conference on Swarm Intelligence (ICSI) (Shi 2011a; Xue et al. 2012; Zhou et al. 2012; Guo et al. 2014, 2015; Xie and Wu 2014; Chen et al. 2015; Cao et al. 2015a), International Conference on Advanced Computational Intelligence (ICACI) (Yang and Shi 2015; Zhu and Shi 2015), just to name a few. In addition, there are two master theses focused on the BSO algorithms (Zhao 2013; Shen 2014). From the tendency in Fig. 1, it can be seen that the BSO algorithm has attracted more and more researches on the algorithm studies and applications. Based on the research of the BSO algorithms, more and more problems could be more effectively and efficiently solved by this swarm intelligence method.

2.2 The basic brain storm optimization algorithm

The original BSO algorithm is simple in concept and easy in implementation. The main procedure is given in Algorithm 1. There are three strategies in this algorithm: the solution clustering, new individual generation, and selection (Cheng et al. 2013).

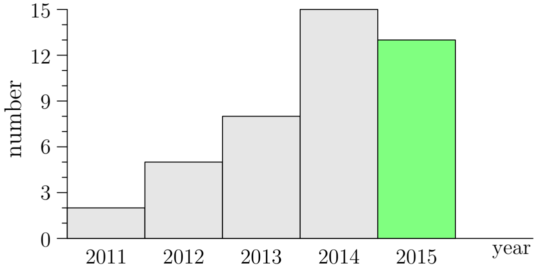

Fig. 1 The number of publications on brain storm optimization since 2011

In a brain storm optimization algorithm, the solutions are separated into several clusters. The best solution of the population will be kept if the new generated solution at the same index is not better. New individual can be generated based on one or two individuals in clusters. The exploitation ability is enhanced when the new individual is close to the best solution so far. While the exploration ability is enhanced when the new individual is randomly generated, or generated by individuals in two clusters.

The brain storm optimization algorithm is a kind of search space reduction algorithm (Cheng et al. 2012a); all solutions will get into several clusters eventually. These clusters indicate a problem's local optima. The information of an area contains solutions with good fitness values are propagated from one cluster to another (Cheng et al. 2012b). This algorithm will explore in decision space at first, and the exploration and exploitation will get into a state of equilibrium after iterations.

Algorithm 1: Procedure of the brain storm optimization algorithm

Initialization: Randomly generate n potential solutions (individuals), and evaluate the n individuals;
while *have not found "good enough" solution or not reached the pre-determined maximum number of iterations* **do**
    Clustering: Cluster n individuals into m clusters by a clustering algorithm;
    New individuals' generation: randomly select one or two cluster(s) to generate new individual;
    Selection: The newly generated individual is compared with the existing individual with the same individual index; the better one is kept and recorded as the new individual;
    Evaluate the n individuals;

The brain storm optimization algorithm also can be extended to solve multiobjective optimization problems (Xue et al. 2012; Shi et al. 2013). Unlike the traditional multiobjective optimization methods, the brain storm optimization algorithm utilized the objective space information directly. Clusters are generated in the objective space; and for each objective, individuals are clustered in each iteration (Shi et al. 2013) or clustered in the objective space (Xue et al. 2012). The individual, which performs better in most of objectives are kept to the next iteration, and other individuals are randomly selected to keep the diversity of solutions.

2.2.1 Solution clustering

The aim of solution clustering is to converge the solutions into small regions. Different clustering algorithms can be utilized in the brain storm optimization algorithm. In the original BSO algorithm, the basic k-means clustering algorithm is utilized. The clustering strategy has been replaced by other convergence methods, such as simple grouping method (SGM) (Zhan et al. 2012), affinity propagation clustering (Chen et al. 2015).

Clustering is the process of grouping similar objects together. From the perspective of machine learning, the clustering analysis is sometimes termed as unsupervised learning. There are N points in the given input, $\mathcal{D} = \{\mathbf{x}_i\}_{i=1}^{N}$, the useful and functional patterns can be obtained through the similarity calculation among points (Murphy 2012). Every solution in the brain storm optimization algorithm spreads in the search space. The distribution of solutions can be utilized to reveal the landscapes of a problem.

The procedure of solution clustering is given in Algorithm 2. The clustering strategy divides individuals into several clusters. This strategy could refine a search area. After many iterations, all solutions may be clustered into a small region. A probability value $p_{\text{clustering}}$ is utilized to control the probability of replacing a cluster center by a randomly generated solution. This could avoid the premature convergence, and help individuals "jump out" of the local optima.

Algorithm 2: The solution clustering strategy

1. **Clustering**: Cluster n individuals into m clusters by k-means clustering algorithm;
2. Rank individuals in each cluster and record the best individual as its cluster center in each cluster;
3. Randomly generate a value $r_{\text{clustering}}$ in the range [0, 1);
4. **if** *the value $r_{clustering}$ is smaller than a pre-determined probability $p_{clustering}$* **then**
5.   Randomly select a cluster center;
6.   Randomly generate an individual to replace the selected cluster center;

2.2.2 New individual generation

The procedure of new individual generation is given in Algorithm 3. A new individual can be generated based on one or several individuals or clusters. In the original brain storm optimization algorithm, a probability value $p_{\text{generation}}$ is utilized to determine a new individual being generated by one or two "old" individuals. Generating an individual from one cluster could refine a search region, and it enhances the exploitation ability. On the contrast, an individual, which is generated from two or more clusters, may be far from these clusters. The exploration ability is enhanced under this scenario.

The probability $p_{\text{oneCluster}}$ and probability $p_{\text{twoCluster}}$ are utilized to determine the cluster center or another normal (or non-cluster center) individual will be chosen in one cluster or two clusters generation case, respectively. In one cluster generation case, the new individual from center or normal individual can control the exploitation region. While in several clusters generation case, the normal individuals could increase the population diversity of swarm.

The new individuals are generated according to the functions (1) and (2).

$$x_{\text{new}}^i = x_{\text{old}}^i + \xi(t) \times \text{rand}() \tag{1}$$

$$\xi(t) = \text{logsig}\left(\frac{0.5 \times T - t}{c}\right) \times \text{rand}() \tag{2}$$

where x_{new}^i and x_{old}^i are the ith dimension of $\mathbf{x}_{\text{new}}$ and $\mathbf{x}_{\text{old}}$; rand() is a random function to generate uniformly distributed random numbers in the range [0, 1); and the value $\mathbf{x}_{\text{old}}$ is a copy of one individual or the combination of two individuals. The parameter T is the maximum number of iterations, t is the current iteration number, c is a coefficient to change logsig() function's slope of the step size function $\xi(t)$, which can be utilized to balance the convergence speed of the algorithm. A modified step size and individual generation was proposed in Zhou et al. (2012).

Algorithm 3: The new individual generation strategy

New individual generation: randomly select one or two cluster(s) to generate new individual;
Randomly generate a value $r_{\text{generation}}$ in the range [0, 1);
if *the value $r_{generation}$ is less than a probability $p_{generation}$* **then**
    Randomly select a cluster, and generate a random value $r_{\text{oneCluster}}$ in the range [0, 1);
    if *the value $r_{oneCluster}$ is smaller than a pre-determined probability $p_{oneCluster}$;*
    then
        Select the cluster center and add random values to it to generate new individual;
    else
        Randomly select a normal individual from this cluster and add random value to the individual to generate new individual;
else
    randomly select two clusters to generate new individual;
    Generate a random value $r_{\text{twoCluster}}$ in the range [0, 1);
    if *the value $r_{twoCluster}$ is less than a pre-determined probability $p_{twoCluster}$* **then**
        the two cluster centers are combined and then added with random values to generate new individual;
    else
        two normal individuals from each selected cluster are randomly selected to be combined and added with random values to generate new individual;
The newly generated individual is compared with the existing individual with the same individual index; the better one is kept and recorded as the new individual;

2.2.3 Selection

The selection strategy is utilized to keep good solutions in all individuals. The better solution is kept by the selection strategy after each new individual generation, while clustering strategy and generation strategy add new solutions into the swarm to keep the diversity for the whole population.

3 Brain storm optimization algorithm: data analysis approach

The BSO algorithm can be considered as a combination of swarm intelligence algorithms and data mining techniques. Generally, there are two types of approaches that apply the swarm intelligence as data mining techniques (Martens et al. 2011). The first category consists of techniques where individuals of a swarm move through a solution space and search for solution(s) for the data mining task, e.g., the parameter tuning. This is a search approach. In the second category, swarms help move and place data instances on a low-dimensional feature space in order to come up with a suitable clustering or low-dimensional mapping solution of the data, e.g., dimensionality reduction of the data. This is a data organizing approach.

The data mining techniques can also be applied to design swarm intelligence algorithms. Massive information exists during the search process. For swarm intelligence algorithms, there are several individuals existed at the same time, and each individual has a corresponding fitness value. The individuals are created iteration over iteration. There is also massive volume of information on the "origin" of an individual, such as that an individual was created by applying which strategy and parameters to which former individual(s). The data-driven evolutionary computation/swarm intelligence is a new approach to analyze and guide the search in evolutionary algorithms/swarm intelligence. These strategies could be divided into off-line methods and online methods. An off-line method is based on the analysis of previous

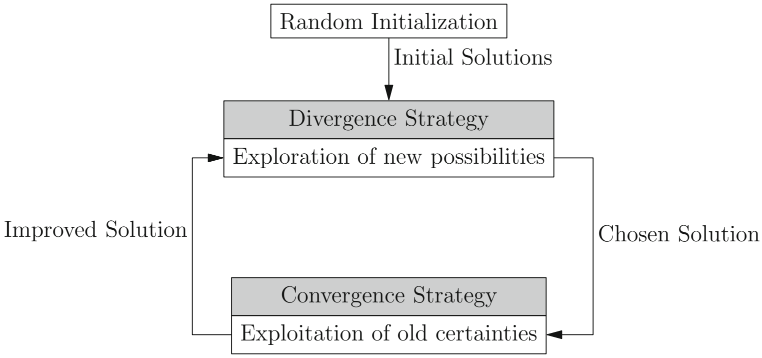

Fig. 2 The framework of divergence and convergence in swarm intelligence

storage search history, such as history based topological speciation for multimodal optimization (Li and Tang 2015) or maintaining and processing submodels (MAPS) based estimation of distribution algorithm on multimodal problems (Yang et al. 2015). While for an online method, the parameters could be adaptively changed during the different search states.

More researches should be conducted on the combination of data mining and swarm intelligence, especially for the online analysis. Not only the parameter could be adjusted, but also the algorithm, i.e. the whole swarm could be adaptively adjusted during the search. The above can be considered from the framework of the DSI algorithm. The BSO algorithm and the Fireworks algorithm (FWA) (Tan and Zhu 2010; Tan 2015) are two good examples of DSI algorithms. They have the same operators: divergence operator and convergence operator; but two operators are utilized in different sequence. The "good enough" optimum could be obtained through the solutions divergence and convergence in the search space. The BSO algorithm and FWA algorithm can be analyzed by the convergence and divergence framework. In BSO algorithm, the random initialized solutions are convergent to different areas. This is a convergence strategy, and the new solutions are generated to diverge in the search space. The firework algorithm (Tan and Zhu 2010; Tan 2015) also utilized convergence and divergence strategies in optimization. Mimicking the explosion of fireworks, the solutions are generated to diverge into large search space. The solutions with good fitness values are selected, which indicates that the solutions are converged to small areas. The convergence and divergence strategies process iteration over iteration. Based on the iterations of convergence and divergence, the solutions could be clustered to small regions finally.

Convergence and divergence are two common phenomena in swarm intelligence. Convergence is that all/most individuals are grouped to the same position, while the divergence is that all/most individuals diverge to difference search positions. The convergence and divergence information also can be utilized on the search. The framework of divergence and convergence is shown in Fig. 2. The divergence strategy is utilized to explore new possible search regions, while the convergence strategy is utilized to exploit existing regions which may contain good solutions.

3.1 Convergent operation

The aim of convergent operation is to cluster/categorize the solutions into different groups. This clustering/categorization could be conducted in the solution space (Shi 2011a, b) or objective space (Shi et al. 2013; Shi 2015).

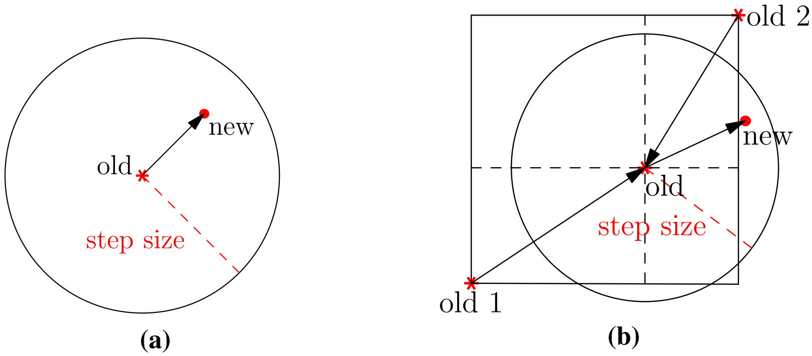

Fig. 3 The new individual generation in the BSO algorithm, **a** generate new individual from one parent, **b** generate new individual from two parents

The solutions with more similarity, such as close distance or similar fitness value, are categorized into the same class. For the clustering in the solution space (Shi 2011a, b), all solutions are divided into different groups by the distances among them. Several clustering strategies have been used to replace the k means algorithm in the original BSO algorithm, such as simple grouping method (SGM) (Zhan et al. 2012), affinity propagation clustering (Chen et al. 2015), k-medians clustering algorithm (Zhu and Shi 2015), *etc*. For optimization problems, the dimensions of objective space are usually significant less than the dimension of the solutions space. For the categorization in the objective space (Shi et al. 2013; Shi 2015), the computational burden is greatly reduced due to that all operations are conducted in the objective space. All solutions are divided into different classes according to their fitness values in the objective space.

3.2 Divergent operation

The aim of divergent operation is to generate new solutions from the promising search areas, *i.e.*, to diverge solutions to potential spaces that may contain better solutions.

The new solution is generated from one or two existed solution(s). Figure 3 shows the two kinds of solution generations. In Fig. 3a, a solution is generated by mutation on a previous solution; while in Fig. 3b, a solution is generated by mutation on the combination of two previous solutions. In the first scenario, the new solution is generated in a hypersphere, where the largest distance to the old solution in one dimension is the step-size. In the second scenario, the old solution is a combination of two existed solutions. The old solution may be far from two existed solutions when these two solutions have a large distance.

4 Brain storm optimization: state-of-the-art

A good swarm intelligence algorithm needs to be implemented simply and to run fast. In addition to the theoretical analysis of the BSO algorithm, the developments of modified BSO algorithms also focus on the following directions:

1. To improve the search efficiency, *i.e.*, speedup the convergence of swarms.
2. To apply the BSO algorithm in various optimization problems, such as multiobjective optimization, multimodal optimization.
3. To apply the BSO algorithm to solve real-world problems.

4.1 Theoretical analyses

The theoretical analyses are important in the BSO algorithm even though it is simple in concept. To study the effect of different parameter settings on the search performance, the parameters of the BSO algorithm are investigated (Zhan et al. 2013). To study the solution clustering phenomena in the BSO algorithm, the average number of clusters change during the optimization are observed (Cheng et al. 2013). The population diversity definition of the BSO algorithm has also been proposed (Cheng et al. 2014a, b). Several partial re-initializing solutions strategies were tested to enhance the population diversity and to help solutions jump out of local optima. The idea behind the re-initialization is to increase the possibility for solutions "jumping out" of local optima, and to keep the ability for the algorithm to find "good enough" solutions. The BSO algorithm is a typical example of the developmental swarm intelligence algorithms (Shi 2014). The convergent and divergent operations in BSO correspond to the capacity developing and capability learning in DSI, respectively.

4.2 Variants of BSO algorithm

In order to enhance the computational efficiency of the original BSO algorithm, or to solve different type of optimization problems, several variants of BSO algorithms have been proposed. The modified BSO algorithms can be categorized into three approaches: computational efficiency, new individual generation, and hybrid algorithms.

4.2.1 Computational efficiency

Several variants of BSO algorithms were proposed to enhance the computational efficiency of the original BSO algorithm. The k-means clustering algorithm was used in the original BSO algorithm, which needs several iterations to cluster solutions into several groups. In Zhan et al. (2012), to reduce the algorithm computational burden, a simple grouping method (SGM) in the grouping operator was introduced to replace the clustering method. Other clustering algorithms were also proposed to replace the k-means algorithm, such as affinity propagation clustering (Chen et al. 2015), k-medians clustering algorithm (Zhu and Shi 2015), and random grouping strategy (Cao et al. 2015a).

Unlike other algorithms, clustering strategy is removed from the BSO in objective space algorithm. The solutions are divided into elitist (the solutions with better fitness values) and normal (the others) classes (Shi 2015). A new solution is generated based on one or two solution(s) from the elitist or normal class. Due to the computational burden reduction in the BSO in objective space algorithm, it could be utilized to solve large scale problems with good search efficiency.

4.2.2 New individual generation

Utilizing new individual generation strategy is another approach to improve the search efficiency of the BSO algorithm. To solve different problems, the real-time search information should be adaptively used in optimization algorithms. The modified step-size and individual generation strategy was proposed in Zhou et al. (2012), the values of step-size are adjusted according to the dynamic range of the population of individuals. In Chen et al. (2014), new individuals are generated in a batch-mode and then selected into the next generation adaptively. To promote the population diversity of the BSO algorithm, especially when all solutions are clustered into a small range, the partial re-initialization strategy was utilized to create new solutions (Cheng et al. 2014a, b). To enhance the global search ability and avoid being trapped into local optima, the chaotic operation was used as part of the individual generation strategy (Yang and Shi 2015). To adaptively change the number of clusters during the search, the structure information of single or multiple clusters was utilized to create new solutions (Chen et al. 2015). The incorporation of inter- and intra-cluster discussions were utilized into the brain storm optimization algorithm (BSO) to control global and local searching ability in advanced discussion mechanism-based brain storm optimization algorithm (Yang et al. 2013, 2014).

4.2.3 Hybrid algorithms

Hybrid algorithms play a prominent role in improving the search capability of swarm intelligence algorithms. Hybridization aims to combine the advantages of each algorithm to form a hybrid algorithm, while simultaneously tries to minimize any substantial disadvantage (Ting et al. 2015). The BSO algorithm has been combined with the simulated annealing algorithm for continuous optimization problems (Jia et al. 2015), with the teaching-learning-based algorithm (Krishnanand et al. 2013), and with differential evolution strategy for applications of ANNs (Cao et al. 2015b).

4.3 Different optimization problems

The original BSO algorithm was proposed to solve single-objective optimization problems. With modifications, BSO algorithm variants have been utilized to solve different kinds of problems, such as multi-objective optimization problems (Xue et al. 2012; Shi et al. 2013; Xie and Wu 2014; Guo et al. 2015) and multimodal optimization problems (Guo et al. 2014; Zhou et al. 2014).

- Multiobjective Optimization: Several variants of BSO algorithms were utilized to solve multi-objective optimization problem since 2012 (Xue et al. 2012; Shi et al. 2013; Xie and Wu 2014; Guo et al. 2015).
- Multimodal Optimization: The aim of multimodal optimization is to locate multiple peaks/optima in a single run and to maintain these found optima until the end of a run. The modified BSO algorithm was utilized in solving multi-peak function optimization problems (Zhou et al. 2014) and multi-modal optimization problems (Guo et al. 2014) since 2014.

Both multiobjective optimization and multimodal optimization aim to find a set of solutions instead of only one solution. The solutions are clustering into different clusters in the BSO algorithm. Ideally, different cluster could be a unique optimal solution in the search space. The search performance could be benefited from this inherent advantage.

4.4 Applications

Brain storm optimization algorithms have been utilized to solve several kinds of real-world problems. To solve these domain specific problems, several variants of BSO algorithms, which include closed-loop BSO algorithm (Sun et al. 2013), predator-prey BSO algorithm (Duan et al. 2013), and quantum-behaved BSO algorithm (Duan and Li 2015), were proposed. The applications of various BSO algorithms could be classified into following categories:

- Electric power systems: the goal of these problems is to find optimal location and setting of devices in electric power systems. The BSO algorithm has been utilized to solve different

problems in power systems, such as economic dispatch considering wind power problem (Jadhav et al. 2012), optimal FACTS devices (Jordehi 2015), electric power dispatch problems (Ramanand et al. 2012; Jadhav et al. 2012; Arsuaga-Ríos and Vega-Rodríguez 2014a; Zhang et al. 2014; Lenin et al. 2014; Zhao 2013; Jordehi 2015), and optimal power flow solution (Krishnanand et al. 2013).
- Design problems in aeronautics field: the BSO algorithm has been used to solve various problems in aeronautics field, such as optimal satellite formation reconfiguration problem (Sun et al. 2013), Loney's Solenoid problem (Duan and Li 2015), DC brushless motor efficiency problems (Duan et al. 2013), receding horizon control for multiple UAV formation flight (Qiu and Duan 2014), F/A-18 automatic carrier landing system (Li and Duan 2015), and agent routing and optical sensor tasking problems (Qiu et al. 2015).
- Wireless sensor networks (WSN): based on the WSN, the physical world is turning to be a kind of information system. Different sensors are connected to form a network; information is transferred in this network by communication techniques. Massive data will be generated from the long term and/or large scale WSN system. The BSO algorithm has been utilized to solve WSN deployment problems (Chen et al. 2015).
- Optimization problems in finance: due to the reason that the financial problems are usually combinatorial problems, new encoding strategy should be utilized in the BSO algorithm. The BSO algorithm has been used in stock index forecasting (Sun 2014), v-SVR problems (Shen 2014).
- Miscellaneous: an energy savings problem in large-scale and distributed resource centers is modelled as multiobjective problem, and energy consumption and execution time are two optimized objectives. A Multiobjective brain storm algorithm (MOBSA) was proposed to solve the multiobjective energy optimization in grid systems (Arsuaga-Ríos and Vega-Rodríguez 2014b). In addition, the BSO algorithm was also used in solving system of equations problems (Mafteiu-Scai 2015).

4.5 Brain storm optimization: future research

The BSO algorithm, which combines swarm intelligence and data mining techniques, is a promising swarm intelligence method. The future research of BSO algorithms could be directed to the following aspects:

- Theoretical analysis is important in swarm intelligence algorithms. Based on the understanding of an algorithm, problems could be solved more effectively and efficiently.
- New strategies should be proposed to enhance the computational efficiency of BSO algorithms.
- Hybrid algorithms could benefit from the strengths of both/several algorithms. The BSO algorithm could be combined with other evolutionary computation/swarm intelligence algorithms, or other mathematical optimization methods.
- Utilizing BSO algorithms on different kinds of optimization problems, such as dynamic optimization, computationally expensive numerical optimization, *etc*.
- More real-world applications should be solved via the BSO algorithm, such as data analysis, big data analytics, wireless sensor network, *etc*.

5 Conclusions

Swarm intelligence algorithms are usually evaluated by their performance on the benchmark functions. There is a lack of theoretical analysis on the algorithm's running times. Each individual in the swarm represents a solution in the search space, and it also can be seen as a data sample from the search space. Based on the analyses of these data, more effective algorithms and search strategies could be proposed.

The brain storm optimization (BSO) algorithm is a young and promising swarm intelligence algorithm. The developments and applications of BSO algorithm from the data analysis perspective have been reviewed in this paper. The BSO algorithm can be seen as a combination of swarm intelligence and data mining techniques. Every individual in the brain storm optimization algorithm is not only a solution to the problem to be optimized, but also a data point to reveal the landscapes of the problem. The swarm intelligence and data mining techniques can be combined to produce benefits above and beyond what either method could achieve alone.

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