A Comprehensive Survey of Brain Storm Optimization Algorithms

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***Abstract*—The development, implementation, variant, and future directions of a new swarm intelligence algorithm, brain storm optimization (BSO) algorithm, are comprehensively surveyed. Brain storm optimization 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. To the best of our knowledge, there are 75 papers, 8 theses, and 5 patents in total on the development and application of the BSO algorithm. 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. Based on the developments of brain storm optimization algorithms, different kinds of optimization problems and real-world applications could be solved.**

***Index Terms*—Brain storm optimization, Developmental swarm intelligence, Convergent operation, Divergent operation**

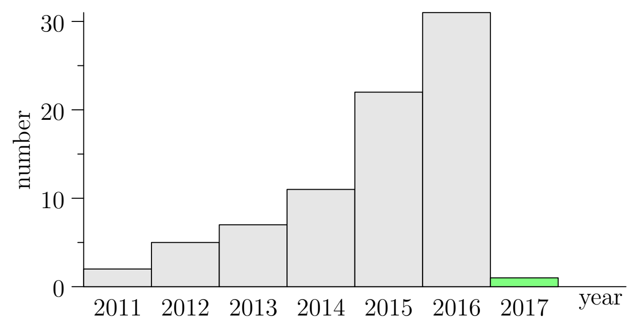

Fig. 1. The number of papers on brain storm optimization since 2011

I. Introduction

The Brain Storm Optimization (BSO) algorithm is a new kind of swarm intelligence algorithm, which is based on the collective behavior of human being, that is, the brainstorming process [1], [2]. Figure 1 gives the number of papers since 2011. To the best of our knowledge, there are 75 papers and 8 theses in total on the development and application of the BSO algorithm. There are 2 papers in 2011 [1], [2], 5 papers in 2012 [3]–[7], 7 papers in 2013 [8]–[14], 11 papers in 2014 [15]–[25] , 21 papers in 2015 [26]–[46], and 29 papers in 2016 [47]–[75]. From the tendency in Figure 1, it could be seen that the BSO algorithm has attracted more and more researches on the studies and applications of the BSO algorithms.

There are two major operations involved in BSO, i.e., convergent operation and divergent operation. A "good enough" optimum could be obtained through recursive solution divergence and convergence in the search space. The designed optimization algorithm will naturally have the capability of both convergence and divergence.

BSO possess two kinds of functionalities: capability learning and capacity developing. The divergent operation corresponds to the capability learning while the convergent operation corresponds to capacity developing. The capacity developing focuses on moving the algorithm's search to the area(s) where higher potential solutions may exist while the capability learning focuses on its actual search towards new solution(s) from the current solution for single point based optimization algorithms and from the current population of solutions for population-based swarm intelligence algorithms. The capability learning and capacity developing recycle to move individuals towards better and better solutions. The BSO algorithm, therefore, can also be called as a developmental brain storm optimization algorithm.

The capacity developing is a top-level learning or macro-level learning methodology. The capacity developing 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 potential 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 BSO algorithm can also 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.

The BSO algorithm related papers are scattered in various journals and conferences. Many papers on BSO have been published since its introduction in 2011. There are also special sessions on Brain Storm Optimization algorithm at conferences such as the IEEE Congress on Evolutionary Computation (CEC) and International Conference on Swarm Intelligence (ICSI) since the year 2014.

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. The state of the art BSO algorithms are given in Section II. In Section III, the original BSO and the BSO in objective space algorithm are reviewed, followed by future directions of BSO algorithms in Section IV. Finally, conclusions will be given in Section V.

II. Brain Storm Optimization: State-Of-The-Art

Since the invention of the Brain Storm Optimization (BSO) algorithm in 2011 [1], [2], it has attracted many attentions in the swarm intelligence research community. There are already 75 papers, 6 master theses, 2 PhD theses, and 5 patents on the developments and applications of BSO algorithm since then.

TABLE I
A list on the number of BSO papers each year

Year	Journal Paper	Conference Paper	Thesis	Total
2011	1	1	0	2
2012	0	5	1	6
2013	4	3	1	8
2014	5	6	3	14
2015	12	9	2	23
2016	13	16	1	30
Total	35	40	8	83

Table I gives a list on the number of BSO papers each year. Table II gives a brief list of papers on brain storm optimization algorithms. There are more than 30 papers which were published on the peer-reviewed journals, such as International Journal of Swarm Intelligence Research (IJSIR) [2], [11], IEEE Computational Intelligence Magazine [12], IEEE Transactions on Magnetics [9], [26], Artificial Intelligence Review [50], International Journal of Bio-Inspired Computation [52], Soft Computing [41], [42], Journal of Artificial Intelligence and Soft Computing Research (JAISCR) [25], Journal of Zhejiang University (Engineering Science) [13], Nonlinear Dynamics [19], Aerospace Science and Technology [27], Optik [29], Applied Soft Computing [64], International Journal of Pattern Recognition and Artificial Intelligence [70], Circuits, Systems, and Signal Processing [72], *etc*. There are nearly 40 papers published on the peer-reviewed conferences, such as IEEE Congress on Evolutionary Computation (CEC) [6], [16], [34], [60]–[63], IEEE Symposium on Swarm Intelligence (SIS) [8], [14], the Conference Companion on Genetic and Evolutionary Computation (GECCO) [22], International Conference on Swarm Intelligence (ICSI) [1], [5], [7], [10], [17], [21], [35]–[37], [53]–[59], International Conference on Advanced Computational Intelligence (ICACI) [32], [33], [48], just to name a few. In addition, there are six master theses and two PhD theses focused on the BSO algorithms [76]–[79].

There are several special sessions on Brain Storm Optimization algorithm at the IEEE Congress on Evolutionary Computation (CEC) and International Conference on Swarm Intelligence (ICSI). The special sessions have successfully attracted many research papers on the theoretical analyses, performance improvement, and applications of BSO algorithms. Based on the research of the BSO algorithms, more and more problems could be effectively and efficiently solved by this swarm intelligence method.

III. Variants of BSO Algorithms

A. 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 [8].

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; 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. 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 [5], [11].

TABLE II
A BRIEF LIST OF PAPERS ON BRAIN STORM OPTIMIZATION ALGORITHMS

Type	Name	Number	References
Journal articles	IEEE Transactions on Magnetics	2	[9], [26]
	IEEE Computational Intelligence Magazine	1	[12]
	International Journal of Swarm Intelligence Research	2	[2], [11]
	Soft Computing	2	[41], [42]
	Artificial Intelligence Review	1	[50]
	Nonlinear Dynamics	1	[19]
	Aerospace Science and Technology	1	[27]
	Optik	2	[29], [31]
	International Journal of Bio-Inspired Computation	1	[52]
	Applied Soft Computing	2	[39], [64]
	Circuits, Systems, and Signal Processing	1	[72]
	Journal of Energy Engineering	1	[51]
Conference papers	International Conference on Swarm Intelligence (ICSI)	16	[1], [5], [7], [10], [17], [21], [35]–[37], [53]–[59]
	IEEE Congress on Evolutionary Computation (CEC)	7	[6], [16], [34], [60]–[63]
	IEEE Symposium on Swarm Intelligence (SIS)	2	[8], [14]
	Genetic and Evolutionary Computation Conference	1	[22]
Theses		7	[76]–[83]

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 [11] or clustered in the objective space [5]. 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.

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) [6], affinity propagation clustering [35].

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. 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

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

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).

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

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

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;

where x^i_{new} and x^i_{old} 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, k 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 [7].

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.

The BSO algorithm can be considered as a combination of swarm intelligence algorithms and data mining techniques.

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.

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 developmental swarm intelligence (DSI) algorithm. The BSO algorithm is a good example of DSI algorithms, including the same operators: divergence operator and convergence operator. The "good enough" optimum could be obtained through the solutions divergence and convergence in the search space. The BSO algorithm could 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 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.

B. The Brain Storm Optimization in Objective Space

In the original BSO algorithm, a lot computational resources are spent on the clustering strategy at each iteration. To reduce the computational burden, the brain storm optimization in objective space (BSO-OS) algorithm was proposed, and the clustering strategy was replaced by a simple classification strategy based on the fitness values [34]. The procedure of the BSO in objective space algorithm is given in Algorithm 4.

1) New individual generation: The main difference between the original BSO and the BSO-OS is the new individual

Algorithm 4: The procedure of the BSO in objective space algorithm

Initialization: Randomly generate n potential solutions (individuals), and evaluate them;
while *have not found "good enough" solution or not reached the pre-determined maximum number of iterations* **do**
  Classification: Classify all solutions into two categories: the solutions with better fitness values as elitists and the others as normals;
  New individual generation: randomly select one or two individuals from elitists or normal to generate new individual;
  Solution disruption: re-initialize one dimension of a randomly selected individual and update its fitness value accordingly;
  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 all individuals;

generation strategy. In the original BSO algorithm, individuals are clustered into several groups. For the BSO-OS algorithm, individuals are classified into two categories according to their fitness values. The procedure of new individual generation strategy is given in Algorithm 5.

2) Parameters: Two parameters, probability $p_{elitist}$ and probability p_{one}, are used in this strategy. The $p_{elitist}$ is 0.2 and the p_{one} is 0.8 in the original BSO-OS paper [34]. A brief comparison of parameters between BSO and BSO-OS algorithms is listed in Table III.

IV. Brain Storm Optimization: Future Directions

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 different real-world problems.

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

- Theoretical analysis is important in brain storm optimization algorithms, such as theoretical aspects of BSO algorithms and analysis and control of BSO parameters.

Algorithm 5: The **New individual update** Operation

New individual generation: randomly select one or two individual(s) to generate new individual;
if *random value $rand$ is less than a probability $p_{elitist}$* **then** /* generate a new individual based on elitists */
  if *random value $rand$ is smaller than a pre-determined probability p_{one}* **then**
    generate a new individual based on one randomly selected elitist;
  else
    two individuals from elitists are randomly selected to generate new individual;
else /* generate a new individual based on normal */
  if *random value $rand$ is less than a pre-determined probability p_{one}* **then**
    generate a new individual based on one randomly selected normal;
  else
    two individuals from normal are randomly selected 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;

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. For example, the new grouping strategy, and/or the parallelized and distributed realizations 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, data mining techniques, machine learning methods, or other mathematical optimization methods.
- Utilizing BSO algorithms on different kinds of optimization problems, such as multiple/many objective optimization, constrained optimization, discrete optimization, dynamic optimization, large-scale optimization, and other computationally intensive optimization problems, *etc*.
- More real-world applications should be solved via the BSO algorithm, such as data analysis, big data analytics, wireless sensor network, *etc*.

V. 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

TABLE III
A BRIEF COMPARISON OF PARAMETERS BETWEEN BSO AND BSO-OS ALGORITHMS

Type	Name	Meaning
Common	x_i	The ith dimension of solution $\mathbf{x}$
	$\xi(t)$	Step size function
	t	Iteration number
	T	Maximum number of iteration
	S	Population size: the number of solutions in a population
	D	Number of decision variables
BSO	$p_{\text{generation}}$	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
BSO-OS	p_{elitist}	Pre-determined probability, which is used to determine the elitist group or normal group will be chosen in new individual generation
	p_{one}	Pre-determined probability, which is used to determine a new individual being generated by one or two "old" individuals

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. A comprehensive survey of developments and applications of BSO algorithm has 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. Based on the developments of brain storm optimization algorithms, different kinds of optimization problems and real-world applications could be solved.

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