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Swarm Optimization Techniques: *A survey*

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Abstract

Swarm intelligence is an artificial intelligence discipline, which concerned with the design of intelligent multi-agent systems by taking inspiration from the collective behaviors of social insects and other animal societies. Swarm intelligence optimization technique was introduced at 1989 by G. Beni and J. Wang in the global optimization framework as a set of algorithms for controlling robotic swarm. The aim of this paper is to provide one of the most important techniques to resolve the problems of improvement is the intelligence of the squadron, which is used in many applications in all areas. In this paper we also present the most important basic algorithms in this method to show the difference in each algorithm and which applications are suitable for it. Light was also shed on the bee's algorithm; important algorithm that was added in 2005.This survey will support the future research and development work as well as raising the awareness for presented approaches.

Keywords: *Particle swarm optimization, Ant Colony Optimization, artificial intelligent, Swarm intelligent.*

1. Introduction

Evolutionary algorithms (EAs) are the most commonly used population -based meta-heuristic methods. They are flexible to solve global optimization problem because they have a good abilities to perform a global geographic expedition and a local exploitation [116].

Swarm intelligence (IS), which is an artificial intelligence (AI) discipline, is concerned with the design of intelligent multi-agent systems by taking inspiration from the collective behavior of sociable insects such as ants, bees, and wasp, as well as from other animals being societies such as flocks of birds or schools of fish [1].

Therefore, Colonies of social insects have dazzled researchers for many years, and the mechanisms that govern their demeanor remained unknown for a long time . Even though each member of these colonies are non-sophisticated individuals, they are able to achieve complex mission in cooperation. Coordinated Colony behavior emerges from relatively simple actions or interactions between the colonies' individual members [1]. Many aspects of the collective activities of socialite insects are self-organized and study without a central monitoring.

Clustering denote the act of partitioning an unlabeled dataset into similar objects groups. Each group, called a 'cluster', contains objects that are similar between themselves and dissimilar to objects of other clusters. In the past few decades, cluster analysis has played a central role in a change of field of force ranging from engineering, computer sciences, life and medical sciences, to earth sciences, social sciences, and economics [2].

Swarm Intelligence (SI) has successfully been applied to a number of real world clustering problems [2]. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are two important and modern techniques of optimization [3]; Bee Colony Optimization (BCO) was added to them in 2005. The main properties of the collective behavior can be express as follows:

Homogeneity: Every member in a flock has the same behavioral model. The flock moves without a leader, even though temporary leaders seem to appear.

Locality: for each bird only the nearest flock mates has effect on its motion. Vision is considered to be the most important senses for flock organization.

Collision Avoidance: avoid colliding with nearby flock mates.

Velocity Matching: attempt to correspond velocity with nearby flock mates.

Flock Centering: attempt to stay close to nearby flock mates.

The capability of Particle Swarm Optimization (PSO), heuristic technique for lookup of optimal solutions based on the conception of swarm, to efficiently face classification of multiclass database instances. PSO reveals itself very effective in facing multivariable problems in which any variable takes on real values.

The main methodologies of swarm intelligence like PSO, ACO and BCO, Are linked to Artificial Life in general, and with bird flocks, ant colonies and bee’s colonies in swarm theory specially. ACO is one of the most important techniques for approximate optimization. PSO is an approach to problems whose solutions can be represented as a point in n-dimensional solution space [4], while BCO is a specialization to Swarm Intelligence activity (SI) where the workers/members/agents to the group are honey bees. The bee system is a monetary standard example of organized team work, well-coordinated fundamental interaction , coordination, labor partition , simultaneous task carrying into action , specialized individuals, and good communication.

The paper is structured as follows: Section 2 describes ACO. Section 3 presents ACO algorithm. While in section 4 most famous application of ACO presented. And in section 5 presents ACO advantages and disadvantages. Section 6 talked about PSO, Also PSO algorithm presented in section 7 ,while PSO applications was presented in section 8, and PSO advantages and disadvantages were got in section 9. The BCO described in section 10, the BCO algorithm presented in section 11, As for section 12 it displays BCO applications, which Followed by section 13 showing BCO advantages and disadvantages. An analysis of ACO, PSO and BCO, and they common Problems were presented in Section 14 and section 15 respectively. The conclusion and future work were addressed at section 16.And as usual the last section for the paper references at section 17.

2. Ant Colony Optimization

Ant Colony Systems or the basic idea of a real ant system is illustrated in Figure1. There is a path along which ants are walking (for example from food source A to the nest E, and vice versa, see Figure1 (a)). Suddenly an obstacle appears and the path is cut off. So at position B the ants walking from A to E (or at position D those walking in the opposite direction) have to decide whether to turn right or left (Figure1(b)). The choice is influenced by the intensity of the pheromone trails left by preceding ants. A higher level of pheromone on the as shown in Figure1

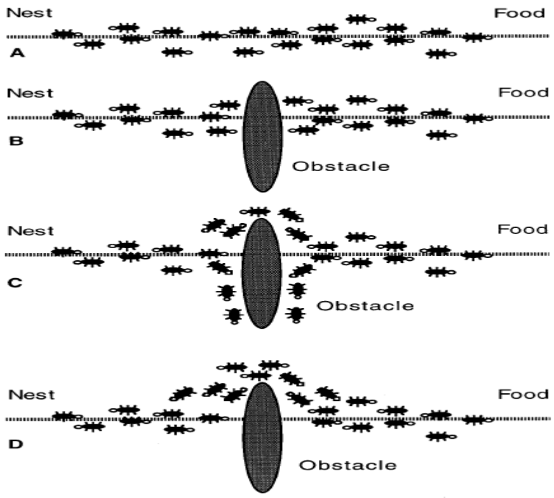

Figure1. Ant Colony Systems

Figure1. (A) Real ants follow a path between nest and food source. (B) An obstacle appears on the path: ants choose whether to turn left or right with equal probability. Pheromone is deposited more quickly on the shorter path. (D) All ants have chosen the shorter path [5].

3. ACO algorithm

Algorithm (1): the ant colony optimization for combinatorial optimization problems [V.Maniezzo, et al,1994].

```
Set parameters, initialize pheromone trials.
While (termination condition not met) do
        {
                Construct Ant Solutions
                Apply Local Search (% optional)
                Update Pheromones
        }
End while
```

Construct Ant Solutions: Partial solution extended by adding an edge based on stochastic and pheromone considerations.

ApplyLocalSearch: problem-specific, used in state-of-art ACO algorithms.

When ants construct a tour they locally increase the amount of pheromone on the visited edges by a local updating role.

$$P_{ij}^{k} = \begin{cases} \dfrac{\tau_{ij}^{k}}{\sum_{l \in N_i^k} \tau_{il}^{k}} & \text{if } j \in N_i^k \\ 0 & \text{if } j \notin N_i^k \end{cases}$$

Where N_i^k is the neighborhood of ant k when in node i.

UpdatePheromones: increase pheromone of good solutions; decrease that of bad solutions (pheromone evaporation).

after all the ants have finished their own round, a global updating rule is applied to modify the pheromone amount on the paths that belong to the best ant tour found until now.

$$\tau_{ij} \leftarrow (1-p)\tau_{ij}, \ \ \forall (i,j) \in A$$

4. A representative selection of ACO applications

Table 1. ACO applications

Problem	Authors	Reference
Traveling salesman problem(TSP)	Dorigo, Maniezzo, and Colorni Dorigo and Gambardella St¨utzle and Hoos	[7, 8, 9] [10] [11]
Quadratic assignment problem (QAP)	Maniezzo Maniezzo and Colorni St¨utzle and Hoos	[12] [13] [11]
Scheduling problems	St¨utzle den Besten, St¨utzle, and Dorigo Gagn´e, Price, and Gravel Merkle, Middendorf, and Schenk Blum (resp., Blum and Sampels)	[14] [15] [16] [17] [18, 19]
Vehicle Routing Problems (VRP)	Gambardella, Taillard, and Agazzi Reimann, Doerner, and Hartl	[20] [21]
Timetabling	Socha, Sampels, and Manfrin	[22]
Set packing	Gandibleux, Delorme, and T'Kindt	[23]
Graph coloring	Costa and Hertz	[24]
Shortest supersequence problem	Michel and Middendorf	[25]
Sequential ordering	Gambardella and Dorigo	[26]
Constraint satisfaction problems	Solnon	[27]
Data mining	Parpinelli, Lopes, and Freitas	[28]
Maximum clique problem	Bui and Rizzo Jr	[29]
Edge-disjoint paths problem	Blesa and Blum	[30]
Cell placement in circuit design	Alupoaei and Katkoori	[31]
Communication network design	Maniezzo, Boschetti, and Jelasity	[32]

Follow Table 1. ACO applications

Problem	Authors	Reference
Bioinformatics problems	Shmygelska, Aguirre-Hern´andez, and Hoos	[33]
	Moss and Johnson	[34]
	Karpenko, Shi, and Dai	[35]
	Shmygelska and Hoos	[36]
	Korb, St¨utzle, and Exner	[37]
	Blum and Y´abar Vall`es	[38]
Industrial problems	Bautista and Pereira	[39]
	Blum, Bautista, and Pereira	[40]
	Silva, Runkler, Sousa, and Palm	[41]
	Gottlieb, Puchta, and Solnon	[42]
	Corry and Kozan	[43]
Continuous optimization	Bilchev and Parmee	[44]
	Monmarch´e, Venturini, and Slimane	[45]
	Dr´eo and Siarry	[46]
	Socha and Dorigo	[47]
	Socha and Blum	[48]
Multi objective problems	Guntsch and Middendorf	[49]
	Lop´ez-Ib´a˜nez, Paquete, and St¨utzle	[50]
	Doerner, Gutjahr, Hartl, Strauss, and Stummer	[51]
Dynamic (or stochastic) problems	Guntsch and Middendorf	[52]
	Bianchi, Gambardella, and Dorigo	[53]
Music	Gu´eret, Monmarch´e, and Slimane	[54]

5. Advantages and Disadvantages of the Ant Colony Optimization

Table 2. ACO advantages and disadvantages

Advantages	Disadvantages
1. Inherent parallelism 2. Positive Feedback accounts for fast detection of best solutions. 3. easy to implement on a basic level(few parameters) 4. fast in finding near optimal solutions in comparison to classical approaches	1. Coding is not straightforward 2. Research is experimental (try and error) rather than theoretical 3. Time to convergence uncertain and unknown (but convergence is guaranteed!)

6. Basic Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is one of swarm intelligence algorithms that detect a solution to an optimization problem in a search space, or model and estimate social behavior in the presence of objectives. The PSO algorithm was first represented in 1995 by James Kennedy and Russell C. Eberhart. Since 2006, three successive standard PSO versions have been put on line on the Particle Swarm Central [55], namely SPSO 2006, 2007, and 2011.

7. PSO Algorithm

Algorithm (2): the Particle swarm for combinatorial optimization problems.

For each particle
{
Initialize particle
}
For each particle DO
{
Calculate fitness value
If (the fitness value is better than the best fitness value (pBest) in history)
set current value as the new pBest
}
Choose the particle with the best fitness value of all the particles as the gBest
While (maximum iterations or minimum error criteria is not attained)
For each particle DO
{
Calculate particle velocity according equation (1)
Update particle position according equation (2)
}

$$V_i^{k+1} = w\,V_i^k + C_1 rand_1() \times \left(P_{Best_i} - S_i^k\right) + C_2\ rand_2() \times \left(G_{Best} - S_i^k\right) \quad (1)$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (2)$$

Where,

w is inertia weight and is usually decreasing linearly from 0.9 to 0.4 throughout the simulation.

v_i^{k+1} is the velocity of i at iteration k,
s_i^{k+1} is the current position of i at iteration k,

C1 and C2 are positive constants and rand1 and rand2 are uniformly distributed random number in [0, 1].

P_{Best_i} is the i^{th} Particle personal best. And G_{Best} is the is the global best for all Particles.

The velocity vector is range of [-Vmax, Vmax]. In Velocity updating eq. (1), eq. (2) terms that create new velocity are:

Inertia term (w), forces the particle to move in the same direction as before by adjusting the old velocity.

Cognitive term (Personal best P_{Best}), forces the particle to go back to the previous best position.

Social Learning term (Global Best $G_{Best)}$, forces the particle to move to the best previous position of its neighbors.

8. PSO Applications

Table 3. A representative selection of PSO applications

Problem	Authors	Reference
Traveling salesman problem	Onwubolu and Clerc	[56]
Flowshop scheduling	Rameshkumar,Suresh and Mohanasundaram	[57]
Task assignment	Salman, Imtiaz and Al-Madani	[58]
Neural networks	Kennedy, Eberhart, and Shi	[59]
	Mendes, Cortez, Rocha, and Neves	[60]
	Conradie, Miikkulaninen and Aldrich	[61]
	Gudisz and Venayagamoorthy	[62]
	Settles, Rodebaugh and Soule	[63]
Bioinformatics	Correa, Freitas and Johnson	[64]
	Georgiou, Pavlidis, Parsopoulos and Vrahatis	[65]
Industrial applications	Katare, Kalos and West	[66]
	Marinke, Matiko, Araujo and Coelho	[67]
Reactive power and voltage control	Yoshida, Kawata, et. Al	[68]
PID controller	Gaing	[69]
Biomedical image registration	Wachowiak et. Al	[70]
Floor planning	Sun, Hsieh, Wang and Lin	[71]
Quantizer design	Zha and Venayagamoorthy	[72]
Power systems	Venayagamoorthy	[73]
Clustering analysis	Chen and Ye	[74]
	Madeeh N. Al-Gedawy	[97]
Constraint handling	Pulido and Coello	[75]
	Liang and Suganthan	[76]
Electromagnetic applications	Mikki and Kishk	[77]
Multiobjective problems	Moore and Chapman	[78]
	Coello and Lechuga	[79]
	Fieldsend and Singh	[80]
	Hu and Eberhart	[81]
	Parsopoulos and Vrahatis	[82]
	Li	[83]
Dynamic problems	Carlisle and Dozier	[84]
	Hu and Eberhart	[85]
	Eberhart and Shi	[86]
	Carlisle and Dozier	[87]
	Blackwell and Branke	[88, 89]
	Jason and Middendorf	[90]
	Parrott and Li	[91]
	Li, Blackwell, and Branke	[92]
Music	Blackwell and Bentley	[93]

9. PSO Advantages and Disadvantages

Table 4. PSO advantages and disadvantages

Advantages	Disadvantages
• It can be applied into scientific, research and engineering use. • PSO has no overlapping and mutation calculation. • Search can be carried out by the speed of the particle. • during the development of several generations, only the most optimist particle can send information to the other particles, and then speed of the re-searching become very fast. • The calculation in PSO is very simple.	• Method easily suffers from the partial optimism. This causes the less exact at the regulation of its speed and direction. • The basic PSO method does not produced good results on problems related to scattering and non-coordinated systems. The examples of such problems are as the solution to the energy field and the moving rules of the particles in the dynamic environment.

10. Bee Colony Optimization (BCO)

A colony of honey-bees can extend itself over long distances (more than ten km) and in multiple directions simultaneously to exploit a large number of food sources [94].

The basic idea behind BCO is to habitus the multi agent system (colony of artificial bee) that will search for good solutions of various combinatorial optimization problem , exploring the rule used by honey bee during nectar collecting process. Artificial bee colony usually consists of a small individuals number , but nevertheless, BCO principle is gathered from the natural systems. Artificial bees investigate in the search Area looking for the feasible solution . In order to reach the best possible solutions, autonomous artificial bees collaborate and central selective. Using collective knowledge and selective information sharing, artificial bees concentrate on the more promising areas and slowly abandon solutions from the less promising ones. Piecemeal, artificial bees collectively generate and/or improve their solutions. The BCO search is running in repetitive until satisfy some predefined stopping criterion [95].

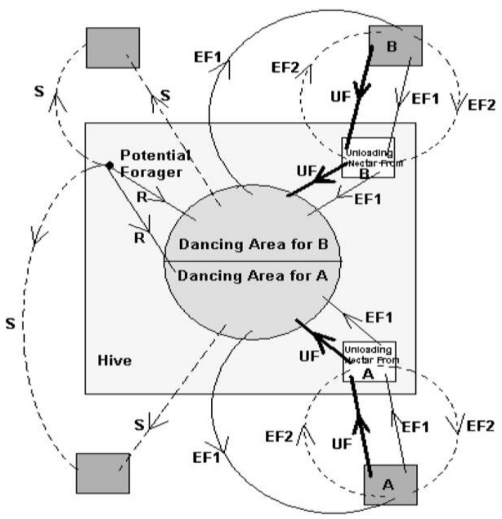

Figure 2. Behaviour of honeybee foraging for nectar [96].

11. BCO Algorithm

In ABC algorithm, there are three groups of bees: employed bees (For every food source, there is only one employed bee), onlookers and scouts (bee of an abandoned food source).

Algorithm (3): BCO algorithm [96]

Initialize

REPEAT

Move the employed bees onto their food sources and determine their nectar amounts.

Move the onlookers onto the food sources and determine their nectar amounts.

Move the scouts for searching new food sources.

Memorize the best food source found so far.

UNTIL (requirements are met)

As other social foragers, bees search for food sources in a way that maximizes the ratio *E/T* (where *E* is the energy obtained and *T* is the time spent for foraging). In the case of bee swarms, *E* is proportional to the nectar amount of food sources discovered by bees and the bee swarm works to maximize the honey being stored inside the hive. In a maximization problem, the goal is to find the maximum of the objective function $F(\theta)$, $\theta \in R^p$. Assume that θ_i is the position of the i^{th} food source; $F(\theta_i)$ represents the nectar amount of the food source located at θ_i and is proportional to the energy $E(\theta_i)$. Let $P(c) = \{ \theta i(c) \mid i = 1, 2, . . ., S\}$ (c: cycle, *S*: number of food sources around the hive) represent the population of food sources being visited by bees. As mentioned before, the preference of a food source by an onlooker bee depends on the nectar amount $F(\theta)$ of that food source. As the nectar amount of the food source increases, the probability with the preferred source by an onlooker bee increases proportionally. Therefore, the probability with the food source located at θi will be chosen by a bee can be expressed as

$$P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)} \quad (1)$$

After watching the dances of employed bees, an onlooker bee goes to the region of food source located at θ_i by this probability and determines a neighbor food source to take its nectar depending on some visual information, such as signs existing on the patches. In other words, the onlooker bee selects one of the food sources after making a comparison among the food sources around θi. The position of the selected neighbor food source is calculated as the following:

$$\theta_i(c+1) = \theta_i(c) \pm \emptyset_i(c) \quad (2)$$

$\emptyset_i(c)$ is a randomly produced step to find a food source with more nectar around θi. $\emptyset(c)$ is calculated by taking the difference of the same parts of $\emptyset_i(c)$ and $\emptyset_k(c)$ (k is a randomly produced index) food positions. If the nectar amount $F(\theta i(c + 1))$ at $\theta i(c + 1)$ is higher than that at θi(c), then the bee goes to the hive and share her information with others and the position θi(c) of the food source is changed to be θi(c + 1), otherwise θi(c) is kept as it is. Every food source has only one employed bee. Therefore, the number of employed bees is equal to the number of food sources. If the position θi of the food source i cannot be improved through the predetermined number of trials ''limit'', then that food source θi is abandoned by its employed bee and then the employed bee becomes a scout. The scout starts to search a new food source, and after finding the new source, the new position is accepted to be θ_i.

12. BCO Applications

Table 4. A representative selection of BCO applications

Problem	Authors	Reference
Complex Transportation Problem	D. Teodorovic and M. Dell	[98]
Routing Protocol MANET	D. Chaudhary	[99]
Fault Based Test Suite Prioritization	A. Kaur and S. Goyal	[100]
Sudoku Puzzles	J.A. Pacurib, G.M.M. Seno and J..P.T.	[101]
Problem Solving Mechanism	P.Navrat, T. Jelinek, and L. Jastrzembska	[102]
Engineering Optimization	X. S. Yang	[103]
Numerical Optimization	D. Karaboga and B. Akay	[104]
Accident Diagnosis	M. S. Oliveira, R. Schirru and J. A. C. C. de Medeiros	[105]
Maximum Satisfiability Problem	D. Teodorovic	[106]
Travelling Salesman Problem	L. P. Wong, M. Y. H. Low and C. S. Chong	[107]
Multi- Dimensional Knapsack Problem	P. N. Nhicolaievna and L. V. Thanh	[108]
Developing Optimization Algorithm	G. Leguizamon and Z. Michalewicz	[109]
Generalized Assignment Problem	I.Alaya, C.Solnon and K.Ghedira	[110]
Constrained Problem Optimization	P.C. Chu and J.E. Beasley	[111]
Advisory System	S. M. Saab, N. K. T. El-Omari and H. H. Owaied	[112]
Numerical Assignment Problem	B. Lu1, L. Özbakır and P. Tapkan	[113]
Job Shop Scheduling	N. Stanarevic, M. Tuba, and N. Bacanin	[114]
Pairwise Test Sets Generation	M. S. P. Babu1and N. T. Rao	[115]

13. BCO Advantages and Disadvantages

Advantages	Disadvantages
1. strong robustness. 2. fast convergence. 3. high flexibility. 4. fewer setting parameters.	1. Premature convergence in the later search period. 2. The accuracy of the optimal value which cannot meet the requirements sometimes

14. Analysis of ACO , PSO and BCO

The ACO is deduced from the caducity behaviors of ant colonies. At the essence of these behaviors the indirect communication between the ants enables them to find short paths between their slit and food sources. This property of real ant colonies is utilized in ACO algorithm to solve, discrete optimization problems. The PSO technique designed on the social behaviors observed model is animals or insects; PCO has gained increasing celebrity between researches as a strong and efficient technique for solving complex and population n based random optimization problems. Both the ACO and PSO algorithm are the data clustering algorithms by simulate swarm behavior. While the ACO is more applicable for problems where source and goals are first known and deterministic. At the same time PSO is a clustering algorithm in the domain of mutli-objective, dynamic optimization and restriction processing. The ACO is more impleminted for problems that needs layers of results and PSO is applicable for problems that are fuzzy are nature. All these features of the ACO and PSO are clear in the following applications. Several versions of BCO have been developed to solve various industrial and engineering problems efficiently. It has also expanded its applications to include a wider range of optimization problems, whether persistent or interoperability, among this applications Biological Applications, Job Shop Scheduling Problems, Designing Cellular Manufacturing Systems and Printed Circuit Board Assembly.

15. ACO , PSO and BCO Common Problems

15.1. Efficiently Solves NP hard Pro blems:

Routing: TSP (Traveling Salesman Problem), Vehicle Routing and Sequential Ordering. Assignment: QAP (Quadratic Assignment Problem), Graph Coloring, Generalized Assignment, Frequency Assignment and University Course Time Scheduling. Scheduling: Job Shop, Open Shop, Flow Shop, Total tardiness (weighted/non-weighted), Project Scheduling and Group Shop. Subset: Multi-Knapsack, Max Independent Set, Redundancy Allocation, Set Covering, Weight Constrained Graph Tree partition, Arc-weighted L cardinality tree and Maximum Clique. Other: Shortest Common Sequence, Constraint Satisfaction, 2D-HP protein folding and Bin Packing. Machine Learning: Classification Rules, Bayesian networks and Fuzzy systems.

Network Routing: Connection oriented network routing, Connection network routing and Optical network routing

Convenience of realization, properties of low constraint on the continuity of objective function and joint of search space, and ability of adapting to dynamic environment, make PSO be applied in more and more fields. Some PSO applications: Electronics and electromagnetic, Signal, Image and video processing, Neural networks, Communication networks…

15.2. Recent Developments in SI Applications

1. U.S. Military is applying SI techniques to control of unmanned vehicles
2. NASA is applying SI techniques for planetary mapping
3. Medical Research is trying SI based controls for nanobots to fight cancer
4. SI techniques are applied to load balancing in telecommunication networks
5. Entertainment industry is applying SI techniques for battle and crowd scenes

16. Conclusions and Future Work

ACO, PSO and BCO are three different swarm optimization methodologies. All were able to offer the best solutions to evolutionary computation problems. ACO have a better ability to solve shortest path problems. While PSO excels in problems of the type that needs to exchange and share capacity but also its flexibility exceeds other improvements; Whilst BCO will be the best choice for problems with nature of organized team work.

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