Analysis of search space in the domain of swarm intelligence

Vaishli P. Patel[1],Dr.Manoj Kumar Rawat[2], and Amit S. Patel[3]

[1] Department of Computer Engineering, Oriental University, Indore, Madhya Pradesh ,India
[2] Department of Computer Engineering, Oriental University, Indore, Madhya Pradesh ,India
[3] Department of Mechanical Engineering, Dharmsinh Desai University, Nadiad, Gujarat ,India
vaishalipatel02@yahoo.com,drmkrawat@gmail.com
aspatel.mh@ddu.ac.in

Abstract. The formulation and analysis of complex problems to get optimum solution is an emerging art which inspired new perspective in optimization world. Derived from biological system swarm intelligence algorithm attract many researcher due to its simplicity and adaptable nature with real life problem. But swarm algorithms suffer from its search process. Higher rate of exploitation may trap to pre-mature solution and higher rate of exploration slow down the process or may not true solution. In this paper we present detailed analysis and sorting of search strategies based on its property and structure to get optimum of exploration and exploitation for swarm algorithms. In our study we cluster majority of strategies in to information sharing and change in structure. In first part sharing of information is categorized by population initialization, population update and population control. In second part change in structure is categorized by modification in governing equation, hybridization and new topology. At last the analysis attempts to provide understanding for different strategies, current issues and future research for expert and researcher.

Keywords: Swarm intelligence, Exploration, Exploitation.

1 Introduction

Bio inspired algorithm which are replication of evolution and foraging pattern of different living entity exist on the world are broadly classified in two sub field: Evolutionary and swarm based algorithm.

Evolutionary algorithms are derived from the theory of survive in nature by increased population, progress, companion, mate selection and breeding. Genetic Algorithm, Differential Evolution, Evolution strategy are few among them.

Swarm algorithms are inspired from foraging process which exhibit social and cognitive behavior, decentralize and self-organized pattern of swarm. Particle swarm optimizer, artificial bee colony algorithm, glowworm swarm algorithm, firefly algorithm, cuckoo search algorithm, bat algorithm, grey wolf optimizer, Spider Monkey Optimization are the algorithms following swarm approach.

2 Complexity of Search Space in swarm intelligence

When meta heuristic algorithms are applied they surrounded with huge amount of data may be neighbor or far unknown region. And both data should be effectively analyzed to get optimum solution. It is also known as exploitation and exploration respectively. Higher rate of exploitation may converge process faster or pre-mature solution and lack of global solution. Higher rate of exploration slow down the process or may not true solution. Therefore it is important to find the technique which balance between local and global search process.

Whole search space is not homogeneous in terms of shape, distribution, dimension and property. It may be very with time or distance. It is difficult to optimize exploration and exploitation and get better solution. In last few decade many algorithms are developed to solve mention problem. Each have different initialization, governing equation, update strategy, fitness evaluation etc.

3 Literature Analysis

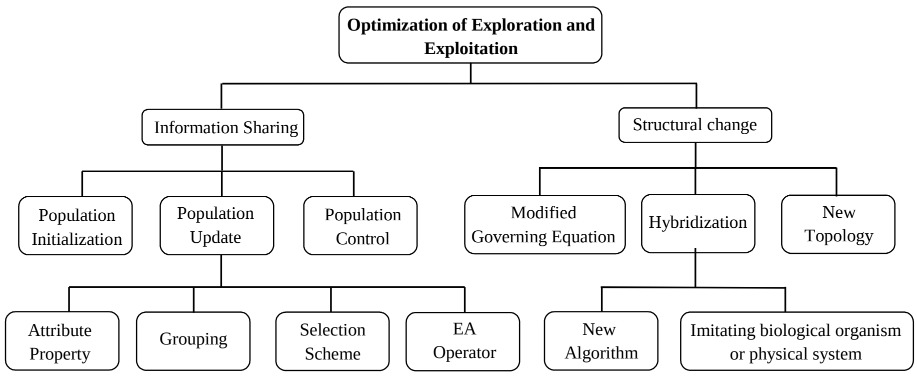

Fig. 1. Graphical depiction of sorting process for search strategies

After study of many research articles in this work we produced compressive review of search space analysis in swarm intelligence.

Fig.1 shows the general strategies for optimization between exploration and exploitation. It is done either by structure modification or information exchange. In information exchange it is further divided based on which strategy is applied: population distribution, update or control. Algorithm structure can be modified by updating governing equation, hybridization with new algorithm or with new topology.

3.1 Information Sharing

Swarm population is dynamic in nature to find better food source, mates, pray or for mutual communication. During this behavior they share information locally or globally. In another words solution search space is updated with new data and characteristic with time and space which is decentralized in nature. In this work we document the algorithms which utilized different sharing mechanism to optimize the local and global information. Based on analysis we divided the sharing mechanism in to population generation, updates and control

Population generation

In swarm intelligent based algorithm initial population play major role in optimum solution. Because of insufficient data, less diversification, randomness and non-uniform distribution of population may cause the solution to be struck premature convergence or fully diverge and may be no solution. In this section we present different mechanism for better population generation.

Table 1. Summary of methods to generate initial population

Autors/Years	Algorithm	Method to generate initial population
Fengli Zhou[1]	PSO-DE-GABC	New positions are created surrounding the random particle to improve divergence and global best to improve convergence.
Om Prakash Verma[2]	Firefly algorithm	To improve convergence rate opposition based learning is used during initialization. Position of each candidate is updated in different dimensions by dimension based approach.
Dipayan Guha [3]	Grey wolf optimization	Quasi opposition based learning theory.
Yugal kumar[4]	ABC	K-means algorithm.
Parham Moradi[5]	ABC	Logistic maps
Dongping Tian [6]	PSO	Logistic maps
Wang ChunFeng[7]	ABC	Good point set theory.
Ali Asghar Heidari[8]	GWO	Oppositional based learning
Zhiyu Zhou[9]	GWO	Differential evolution algorithm
Rehab AliIbrahim[10]	GWO	Chaotic logistic map and the opposition based learning
Xiaolian Liu[11]	GWO	Inverse Parabolic Spread Distribution

Population update

Due to dynamic nature of swarm new information (position, fitness, local or global best) is generated with best or worst solution. But it is meaningless until we not get right information at the right time. In literature researcher proposed varieties of strategies to utilize right data at right time to come out from local convergence or to explore global optimum. According to our finding we divide update rule in further four sub class: Population attribute, Grouping, Selection scheme and Evolutionary algorithm (EA) operators.

Population attribute

In this part best or worst information available from personal, neighbor, historical or new data is shared with other candidate to find optimum solution.

Table 2. Summary of attribute

Year/Authors	Algorithm	Attribute
Tran Dang Cong[12]	ABC	Use current, global and random property of data.
Chao Gan[13]	BA	Local search will be disturbed to find global best
Zhennao Cai [14]	GWO	Random local search and random global search
Yongquan Zhou[15]	Monkey algorithm	Cooperation process
Qiang Tu [16]	GWO	Global-best around the current best solution and Cooperative strategy
Vijay Kumar[17]	GWO	The each grey wolf learn from movement of sun
LongWen[18]	GWO	Personal historical best position and the global best position.
Ran Cheng[19]	PSO	Use any better particles in the current swarm instead of historical best.
Anping Lin[20]	PSO	Cooperative archive
Eman Saad [21]	ABC	Use previous knowledge gained by predecessor
Hema Banati[22]	BA	Best neighbour.
Longwang Yue[23]	Ant colony	Penalty strategy based on worst solution
Mohammed A. Awadallah[24]	ABC	Fittest food sources
Selcuk Aslan[25]	ABC	Nondeterministic behaviours of the employed bees.
Hong-Jun Wang [26]	Ant Colony Algorithm	Property of best ant and the worst ant
M.K.A. Ariyaratne [27]	Firefly algorithm	Determine poor iterations to improve the exploration property.
Zhang[28]	Firefly algorithm	Local and global best solutions are used to direct attractive search process. To avoid worst solution evading mechanism is used
LijinWang[29]	Cuckoo search	Apply solution-based and a fitness-based similar metrics to find the nearest neighbour solutions which is used to generate new solution.
Rahib H. Abiyev [30]	Monkey algorithm	One and all component perturbation process
MoumitaPradhan[31]	Grey wolf optimization	Property of hunting behaviour and social hierarchy
Hailun Xie[32]	Firefly Algorithms	Property of high similarity of firefly and relocation in different direction
Mingfu He [33]	PSO	Cooperation mechanism
Wen Long[34]	GWO	Property of random individual

Table 3. Summary of attribute

Year/Authors	Algorithm	Attribute
Rohit Salgotra[35]	Cuckoo search algorithms	Division of population and division of generations.
Manju Sharma[36]	PSO	Statistical property of dataset is used for velocity limits
R.Murugan[37]	Bat algorithm with artificialbee colony	Property of individual's directional information, habitat selection and self-adaptive compensation.
Fadl Dahan[38]	ACO	Quality of the rest of the solutions.
Abhijit Banerjee[39]	Firefly algorithm	Short term memory in terms of last location and light intensity
Supriya Dhabal [40]	Cuckoo Search Algorithm	Global best solution is used to replace old one
Mengchu Tian[41]	Firefly algorithm	Property of optimal firefly used to improve others
R.Murugan [37]	Bat algorithm with ABC	Aging level of the individual's best solution.
Divya Kumar K.K. Mishra[42]	ABC	Property of covariance information

Population Grouping

In this part whole population is divided in to number of subgroup based on different criteria and each sub group has same property. Information extracted from each group is used for future improvement of the solution.

Table 4. Summary of grouping criteria

Year/Authors	Algorithm	Grouping Criteria
Eman Saad [21]	CB-ABC	Best solution from history and self-adaptive information
Laizhong Cui [43]	ABC	Convergence and diversion population
Xifan Yao [44]	IDABC	Based on value of fitness function
Avinash Sharma [45]	Ageist Spider Monkey Optimization	Levels of ability to interact and to track changes in the environment

Selection Scheme

Selection scheme is the tool to balance between exploration by promoting random unknown region and exploitation by selecting better individual. In this section we explain different selection scheme proposed in literature.

Table 5. Summary of selection criteria

Year/Authors	Algorithm	Selection Scheme
Ahmet Babalik [46]	ABC	Utilize objective values instead of fitness value in greedy selection process
Changsheng[47]	ABC	Replace greedy selection process with Deb's constrained handling method
Subhodip Biswas [48]	ABC	Greedy scheme of positional perturbation
Xiaojing Li[49]	ACO	Node random selection mechanism
Mohammed Azmi Al-Betar[50]	Bat Algorithms	Six selection mechanisms global best, proportional, exponential, random, linear and tournament rank
Ali Asghar Heidari [8]	Grey wolf	Greedy selection mechanisms
Mohammed A. Awadallah [24]	ABC	Four selection schemes: global-best, exponential, tournament and linear rank
BinWu [51]	Glow worm	Greedy selection mechanisms
Ammar Mansoor Kamoona[52]	Cuckoo search	Greedy selection mechanisms

EA Operators

To optimize local and global search process EA algorithm use crossover and mutation operators. Crossover operator swaps the part of data string with other and mix final solution to enhance exploitation. Mutation change part of data string randomly to enhance diversity or exploration. In literature researchers propose variety of EA operators and its modification to find optimum result, following table show the brief review of EA operators used in bio inspired algorithm.

Table 6. Summary of EA Operators

Year/Authors	Algorithm	EA Operators
LijinWang [29]	Cuckoo search	Probabilistic mutation strategy
D. Tian [53]	PSO	Gaussian mutation strategies
Guoqiang Liu [54]	PSO	Gaussian chaotic mutation operators.
Xiaohui Yan [55]	ABC	Crossover operator
Manju Sharma [36]	PSO	Mutation operator
Manju Sharma [56]	PSO	Polygamous crossover operator. Parameters of cross over operator are updated dynamically.

Table 7. Summary of EA Operators

Year/Authors	Algorithm	EA Operators
YanXia [57]	PSO	Probabilistic mutation operator is applied on historical best position.
Hossein Sharifipour [58]	ACO	Gaussian mutation with (1+1) ES algorithm
Leila Eskandari [23]	ACO	Mutation of the global best and personal best of each solution.
Shilei Lyu[59]	Bat Algorithm	Mutation mechanism with loudness parameter to control local and global search
Mengchu Tian [41]	Firefly algorithm	Adaptive mutation
Asma M. Altabeeb [60]	Firefly algorithm	Partially matched crossover operator (PMX). Two mutation strategies are applied based on random selection and swapping.
Judhisthir Dash [61]	Cuckoo Search	Mutation operator of differential evolution technique.
Min Cao[62]	ACO	Roulette wheel algorithm of genetic algorithm

Population control

To balance exploration and exploitation researcher introduced control parameter which regulate the search process in different phases. In this section we list some of the parameter strategy to control the search process.

Table 8. Summary of control strategy

Year/Authors	Algorithm	Control Strategies
Shin Siang Choong[63]	ABC	Modified Choice Function: Weight of the exploration and exploitation is adaptively control during different phase of search process.
Mingfu He [33]	PSO	Damping factor: The least optimal solution from history is decided to drop or reinitialized.
Ahmet Babalik [46]	ABC	Modification rate: To change more than one parameter during update phase.
Hailun Xie [32]	Firefly Algorithms	Attractiveness coefficient is replaced with a randomized control matrix
Wen Long[34]	Grey wolf	Nonlinear control parameter strategy.
Akash Saxena [64]	Grey Wolf Optimizer	Search process is governed by truncated sinusoidal function instead of linearly decrease function.
Bo Yang [65]	Cuckoo search	To analyse the current and historical information Speed Factor and Aggregation factor are used, further to effectively utilize this information scale conversion factors is used.
Hojjat Rakhshani [66]	Cuckoo search	Reinforcement learning to swap between snap (global search) and drift modes (local search).
M.A.H. Akhand [67]	Spider Monkey	Swap Sequence and Swap Operators based operations

Table 9. Summary of control strategy

Year/Authors	Algorithm	Control Strategies
Chao Gan[13]	Bat algorithm	Stochastic inertia weight: Property of random variable is used to update inertia weight. Pulse rate: optimize local and global search Loudness: acceptance or rejection of a new solution
Qiang Tu[16]	Grey wolf	Dispersion rate: Which have self-adjusting property to govern population from early stage of iteration (local search) with increased number of iteration (Global search)
Vijay Kumar[17]	Grey wolf algorithm	Prey weight: To change parameter dynamically. Astrophysics strategy: To change movement of population in elliptical orbit.
LongWen[18]	GWO	Nonlinear adjustment strategy
Anping Lin[20]	PSO	The comprehensive learning probability is updated dynamically by quality of solution.
Hema Banati [22]	Bat Algorithm	Step size: More precise steps Search weight factor: To control step size with progression of algorithm.
Dongping Tian[53]	PSO	The sigmoid-based acceleration coefficients with Slowly varying and regular varying function.
Qi Liu[68]	Bat algorithm	Time factor: A non-linear decreasing function depends on iterations.
Manju Sharma[36]	PSO	Inertia weight is updated by some constant value
YanXia[57]	PSO	Simplex neighbourhood search strategy
Shilei Lyu[59]	Bat Algorithm	Step-control mechanism: Count effect of individual and group, Further adaptively change with group fitness and iterations.
Mengchu Tian[41]	Firefly algorithm	Optimal firefly strategy: Affect movements of other fireflies.
M.R. Ramli [69]	Bat Algorithm	Dynamic dimension size
Kaiping Luo [70]	Ggrey wolf optimizer	Modified weight-based formula: Used to dynamically estimate the location.
Gulnur [71]	Bat Algorithm	Weight coefficient: To minimize effect of best position in new solution.
Min Cao [62]	ACO	Simulation experiment : To find optimal parameter
Abhijit Banerjee[39]	Firefly algorithm	Adaptive mechanism to update parameter based on iteration and intensity of solution
Supriya Dhabal[40]	Cuckoo Search	Levy's distribution updated as function of current and maximum iteration
Sandeep Kumar[72]	Spider monkey	Parameter perturbation rate is updated exponentially in place of linearly
Xiaolian Liu[11]	GWO	Dynamic parameter update: Function of lower and upper limit of solution.
Shubhendu Kumar Sarangi[73]	Cuckoo search	Step size update: function of current fitness value
Manoj KumarNaik[74]	Cuckoo search	Step size update: function of fitness value and current position.
Shubham Gupta[75]	GWO	Random walk: Cauchy distribution is used to draw step size

3.2 Change in structure

In previous discussion we present information sharing to improve search process but there are other ways to improve search process by modified governing equation, hybridize with new algorithm or implementing new topology.

Modified governing equation

Each algorithm has different governing equation with different mathematical property. Which can be further improved by introducing new parameter, merge with other formula or by adding new mathematical steps. In this section we introduced the work done in the equation modification.

Table 10. Summary of Modified governing equation

Year/Authors	Algorithm	Equation Modification
Guopu Zhu[76]	PSO	ABC equation is modified by global best from PSO
Tarun Kumar Sharma[77]	ABC	ABC equation is modified by the local and global best from PSO
Nafiseh Imanian [78]	ABC	New solution derived from global , local best and velocity equation of PSO
Zakaria N. Alqattan[79]	ABC	Velocity equation of PSO is embedded with onlooker phase
XuChen [80]	ABC	ABC updated with Fireworks explosion search
M.R. Ramli[69]	Bat Algorithm	Velocity equation is enhanced by inertia weight which is function of velocity and speed.
BinWu[51]	glow worm swarm	ABC and PSO are combined to developed new movement formula.
Aref Yelghi[81]	firefly algorithm	Firefly attractiveness is replaced with tidal Force formula
Prabhat R.Singh [82]	Monkey Optimization	Local leader phase is modified by the Nelder–Mead method.
Ali Asghar Heidari [8]	grey wolf optimizer	Equation of motion is modified by levy flight which is function of random decreasing stability index
Anping Lin[83]	PSO	PSO search equation is combined with global learning component with linearly updated control parameters with function of acceleration coefficient and inertia weight.

Hybridization

This section discusses hybridization approaches for solving limitation of search process. Typically, the hybrid algorithm borrowed structures from the other nature-inspired algorithms or Imitating biological organism or physical system. The hybridization of algorithms combine strength and lessen their limitation.

Hybridize with new algorithm

Table 11. Summary of Hybridization

Year/Authors	Algorithm	Hybridization
Mohammed El-Abd[84]	ABC-SPSO	Component-based: PSO is combined with ABC component to enhance personal best.
N.Baktash[85]	PSABC	Fitness value of ABC is optimize by PSO
Oğuz Altun[86]	PSO-ABC Chain	Two Phases: ABC and PSO are used to find personal best. Parameters are optimized by Cuckoo Search.
L.N. Vitorino[87]	Adaptive Bee and PSO	ABC is perform when PSO trap to convergence
ZhiyongLi [88]	PSO-ABC	Local search phase of PSO is combined with global search phases in ABC for the global optimum.
Asgarali Bouyer [89]	ICMPKHM	Combined K Harmonic Means clustering algorithm with an improved Cuckoo Search and PSO.
Rajeev Goel[90]	ACO and firefly	The initial population of firefly is obtain through ant
Vinita Jindal[91]	Ant Particle Optimization	Comparison based: Ant colony and PSO work separately to find their best solutions. And among them best solution found as global best.
K. M. Dhanya[92]	Crow Search-Ant Colony	Relay-based technique: output of one algorithm assign as input to another.
Boris K. Lebedev[93]	Ant and Bee Colony	Swap based: Ants and bees exchange their function.
Messaoudi Imane[94]	Bat algorithm	Tabu search is used to select new solution in bat algorithm.
Mb Saraswathi[95]	Cuckoo Search-Bat Algorithm	Local output of Cuckoo search algorithm is assign to bat algorithm to find global optimum solution.
R.Murugan[37]	Bat algorithm with ABC	Recombination method: First phase is BA, the second is onlooker bee and the last is scout bee phase
Víctor Yepes[96]	Glow worm and simulated annealing	Every glow worm movement is optimized by SA
Ibrahim Berkan[97]	Firefly and PSO	Condition based: If particle fitness is improve it is handled by FA otherwise by PSO.
María-Luisa[98]	Artificial ants and fireflies	Parameters Control: parameter of ant algorithm is tuned by FA.
Alifia Puspaningrum [99]	Cuckoo Optimization and HSA	Recombination method: First stage is cuckoo search, Second stage is harmony search
Judhisthir Dash[61]	Cuckoo Search PSO	New particle of PSO are produced by Lévy flight
S.V. Konstantinov [100]	GWO and Bees Algorithm	Search process of Grey Wolf Optimizer and the Bees Algorithm are combined.

Table 12. Summary of Hybridization

Year/Authors	Algorithm	Hybridization
Wen Long[101]	GWO and cuckoo search	Cuckoo algorithm is used to generate new solution of wolf algorithm.
Ebenezer Daniel[102]	GWO	Parameters Control: Parameters of GWO are optimized by cuckoo search algorithm.
Prashant J. Gaidhane [103]	GWO and ABC	Information sharing strategy of bees is applied to wolf.
Xinming Zhang[104]	Biogeography-Based Optimization and GWO	Single-dimensional and multi-dimensional strategy is used to hybrid two algorithm
Rehab AliIbrahim[10]	Grey Wolf Optimizer	GWO local search is improved by DE operator
DaqingWu[105]	DM-PSO-ABC	Recombination method: First stage is dynamic multi swarm PSO, Second stage is CABC, Third stage is PSO global model.
Mustafa Servet Kiran[106]	PSO- ABC	After recombination of PSO and ABC solution obtain is given to PSO and ABC as the global best and neighbour food source for onlooker bees.
P. Amudha[107]	ABC-PSO	Cooperation strategy: One part of population process by PSO and other is by ABC. Further achievement of one part is shared with other.
Zichen Zhang[108]	Cuckoo search and differential evolution	Cooperation strategy: One group process by CS and other is DE. Both are combined to share individual information.
Fadl Dahan[38]	Dynamic Flying Ant Colony Optimization	3-Opt algorithm is hybridize with FACO to reduce the chances of local minimum
Gulnur [71]	Bat Algorithm	Modified Bat algorithm is hybrid with Differantial Evolution Algorithm
Qi Liu[68]	Bat algorithm	BA has been hybridized with external optimization algorithm
Mohammed[109]	Island bat algorithm	The strategy of island model is adapted for bat-inspired algorithm

Imitating biological organism or physical system

New solution is generated by imitating the biological organism or physical system exhibit on the earth. This may include behavior, interaction or survival phenomena of living entity or any fix rule govern the physical system. In the following paragraph we present recent work done in the literature.

Table 13. Summary of Biological organism or Physical system

Year/Authors	Algorithm	Biological organism or Physical system
Krishn Kumar Mishra[110]	Direction Aware PSO with Sensitive Swarm Leader	Basic human qualities: Maturity, leader, awareness, follower's relationship and leadership are combined with PSO
Yongquan Zhoua[111]	Symbiotic organism search algorithm	Biological interaction: mutualism, commensalism and parasitism phase

New Topology

Different topology follows different rule and structure to solve problem. Property of topology can be used to find search solution with different perspective. This section present different topology used in swam intelligence for effective search result.

Table 14. Summary of new topology

Year/Authors	Algorithm	New Topology
Noosheen Baktash[112]	Cellular PSO-ABC	Cellular automaton: Population is distributed to different cell and best of solution obtain from each cell is exchange with other.
Wenping Zou[113]	ABC and Von Neumann topology	Von Neumann topology: Rectangular lattice topology is used to share best solution with neighbours.
Anping Lin[83]	PSO - ring topology	Ring topology
Junkai Ji[114]	ABC with scale-free networks	Topology of scale free network
Chao Lu[115]	Cellular GWO	Cellular automaton

4 Current problems and future opportunities

In our study we find that balance between exploration and exploitation play major role in success of any swarm inspired algorithm. Many researchers proposed good solution but still there are challenging issue. Based on that we conclude some open problem and future direction.

Population generation

Swarm algorithms are more sensitive to generation of initial population. Small changes to initial population can change problem entirely. In literature most of the methods are surrounded to chaotic or opposition based learning. But in future new method should be developed based on new statically property, nonlinear distribution, numerical method, simulation technique which compatible with surrounding environment.

Population Update

In our finding population is updated based on data attribute, grouping, Selection scheme and EA operators. In future different attribute should be find out based on inherent property of data. Grouping may be combined with clustering for clear understanding of data. Selection scheme should be adaptive or automatic and data dependent and advanced EA operators can be applied.

Population Control

It is find out that most of the strategies are based on constant parameter update, in future automatic parameter tuning may be good domain to emerge.

Change in structure

It is found that in modification of governing equation most of formulations are based on formula borrow from other algorithm. It is recommended that in future other novel parameter, formula or step from biological system, physical law, chemical process, mathematical rule or any real life application should be applied.

Hybridization

It is prove that hybridization of different algorithm come with new opportunities. It is recommended that recent developed algorithm in swarm intelligence should be learned and based on its property other compatible algorithm should be combine.

New Topology

In literature few researcher try to developed algorithm structure with new topology. This is still active research area. New topological structure from other domain should be investigated and applied to swarm algorithms.

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