International Journal of Engineering & Technology, 7 (4.6) (2018) 4-8

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

A Future Perspective Survey on Bio-inspired algorithms based self-organization techniques for GA

Santhoshini Banda, U. Sri Lakshmi, P. Victer Paul*

Department of Computer Science and Engineering, Vignan Foundation for Science, Technology and Research, Guntur, AP, India
**Corresponding author E-mail:victerpaul@gmail.com*

Abstract

Genetic algorithms (GAs) are the most important evolutionary computation technique that is used to solve various complex problems that involve a large search space. To have a performance improvement over GA the concept of Hybrid genetic algorithms that were inspired by the biological behavior of different living beings was put to use to solve the NP-completeness problems. In this paper, a survey on the various recent working HGA with bio-inspired algorithms that exhibits self-organization behavior is performed. This paper discusses the various Biological self-organization behaviors and the generalized self-organization behaviors that are used to solve combinatorial optimization problems. This paper helps the scholars and researchers to have a better understanding on the bio-inspired based self-organization techniques for Genetic algorithm so that they can formulate new algorithms based on existing SO techniques.

Keywords: *genetic algorithm, self-organization, evolutionary computing, bio-inspired, survey*

1. Introduction

1.1 Optimization

In computational science, the process of selecting the best alternative from the given set of alternatives is called the process of "optimization". In order to get the optimum solutions or unconstrained maxima, minima for continuous or differentiation functions, this traditional Optimization technique is used. Even though there is a limitation of scope for implementation of classical methods in practical applications that are not differentiable or continuous, yet most of the numerical techniques and advanced techniques are formed by basis of classical techniques which are most useful for practical problems. To process the input adjustments, device characteristics, for finding maximum or minimum output result, in the mathematical process also, Optimization techniques are implemented. The input variables: The cost function, the objective function is called the process or function. There are two major classifications of optimization.

Exact optimization: For the formation of branching and an exhaustive search, we generally take exact methods. Heuristic methods are the effective exploitation of problem structure. The advantage of problem structure is taken by exact methods.

Stochastic optimization: For maximizing or minimizing the values of multiple input parameters which are subjected to randomness in mathematical, statistical function, is processed by stochastic optimization. Involving chance or probability is called the word stochastic. In sales, service, finance, manufacturing, business /analytics and in communications also stochastic processes are implemented. In probability, like the water level predicting in a reservoir based on rainfall distribution at random level, usage of water, randomly variable traffic but constantly available bandwidth communication networks dropped connections also stochastic processes are always involved [14,16,17]. Based on predictable and exact input values, outcome occurs (or fail to occur), deterministic processes never involve in probability otherwise, in contrast.

Simulated Annealing includes this kind of stochastic optimization techniques: From annealing in metallurgy has come from the name and inspiration, techniques involved. To reduce their defects, to increase the size of its crystals by controlled cooling of a material, in heating. Hill Climbing: To find a local optimum it is good (By considering a neighboring solution, a solution cannot be improved) yet, to find the best optimal solution, it is not guaranteed (the global optimum) among all solutions which are possible (search space). Swarm algorithms: collection behavior in decentralized, self-organized systems, which are based on Artificial Intelligence (AI) techniques. Interaction with each other and the environment are generally made up of agents. Evolutionary Algorithms: Evolution of species are inspired by the evolutionary algorithms. A feasible solution to the problem is the population of the individual. A fitness function is characterized by each individual. A better solution can be obtained by higher fitness. For the new generation, to reproduce offspring by parents are based on their fitness.

There are also several variants have been developed based on evolutionary algorithms. Among these variants genetic algorithms are most widely and most effective used variant for combinatorial optimization. They are also used in, simulated annealing, Quantum annealing, Reactive search optimization (RSO), Random search, Stochastic tunneling and parallel tempering.

1.2 Genetic Algorithm

A genetic algorithm has the evolutionary computation research which is most popular techniques. The fixed length bit string used the representation in the traditional genetic algorithm as given in the figure 1. An individual's particular feature is assumed to rep-

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resent each position in the string, solution feature expressed by the position's value. "A structural features solution collection which has little or no interaction" is evaluated by the string usually. In biological organisms, genes draw directly the analogy. An entity which is structurally independent of other genes is represented by each gene. A bit-string crossover, that are two strings used as a parent and by swapping a sub-sequence between two individual forms a new individual uses the main reproduction operator. Bit-flipping mutation, a new offspring string is formed by flipping a single bit in the string is another popular operator [11-15].

Other operators which are varied are also developed, which are less frequently used. The main difference between different operators is the introduction of new information into the population is there or not. For example, the mutation does, but crossover does not. The string can be manipulated by constrained all operators with the structural interpretation of genes in a consistent manner. Let us take an example, swapping between parents in which two genes sat at the same location on two strings, based on their values may not be combined. Based on their fitness values, parents are being selected from individuals traditionally, and parents are replaced by the offspring. For example, N offspring have been generated that replace the next generation parents, if N parents are selected.

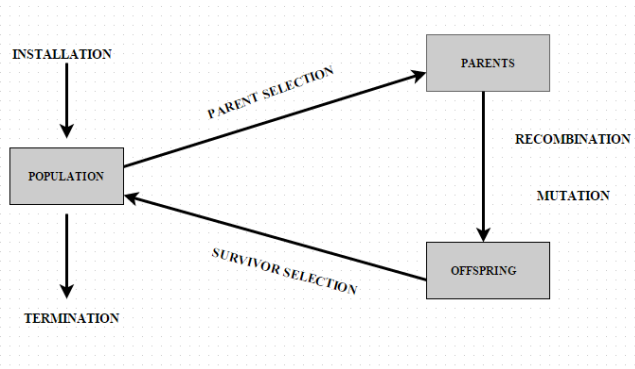


Figure 1 steps in GA in recent years

1.3 Performance improvement of GA

The input of this algorithm is set of possible solutions of the problem. A fitness value is assigned to each solution or individual which denotes how good a solution is. For example, we can take the final report of students in any school. If student's performance is good in examination then his final report will be good and he will be promoted to next class. On the other hand, those, who have bad marks and worst report, will not be promoted to next class. Similarly, in case of the genetic algorithm, the individual with good fitness value will reproduce next population and the least fit members have fewer chances to be selected for reproduction. Each solution in search space is represented by chromosome and each chromosome represented by a string of bits (string of 1's and 0's). There are three operators in GA which are used to generate new population from parent population: selection, crossover, mutation. Selection operator selects chromosomes for production based on its fitness value. Highly fitted chromosomes are more times likely to be selected than less fitted ones.

With some advantages, GA has also some drawbacks like

•The rate of convergence is not so good.

•Due to limited population size, a genetic algorithm may sample bad representatives of good search regions and good representatives of bad regions.

•Huge evaluation of generation and population are time-consuming.

A review is presented on the hybrid genetic algorithm, their effectiveness, and efficiency with various techniques. Any local search method can be merged with GA by two ways. In first we can use GA operator to find initial variables for local search and in the second we can use local search on initial population and then perform a global search using GA. GA and its operators are used to find initial population for traditional optimization method. Thus a long trial and error process is avoided which is a drawback of traditional algorithm. This hybrid genetic algorithm is proved to be more effective than traditional algorithms. GA and HGA are proved to be effective for space layout and optimization problems. Designing becomes very difficult with large data so we have to use the ability of computer in designing. GA is a soft computing technique like neural network and fuzzy system which is used to enable computer with human-like thinking capability.

2 Performance Improvement of GA

2.1 Hybrid GA

A significant interest in hybrid algorithms received. To solve a real-world problem which is being increased in recent years. In order to produce the hybrid within a framework which reaps the best, other techniques can be incorporate with the genetic algorithms from the combination.

A genetic algorithm provides only convergence without optimality, unlike various search and optimization techniques. So, It is not well defined of the choice of when to stop the genetic algorithms. When no better chromosome is not identified in 50 generations, the genetic algorithm process can be stopped. Differentiate fitness measures among different chromosomes will be provided by GA but provides no guarantee of optimality which is the major disadvantage in the usage of GA. There is always lurking of the better chromosome as there is no guarantee of optimality.

In order to find the optimal chromosome in a region, the Local search mechanism is coupled with the GA typically. Among the various good regions, chromosomes can be picked by using a hybrid algorithm. In order to find the number of regions which are expected to find, search space can be known initially. Unless and till these regions can be found when we run the GA repeatedly. As before, in most practical problems, the search space shape is not known. With some regularity, we have to repeat the GA with a systematic approach to find the best chromosomes.

2.2 Different techniques of Performance Improvement in GA

2.2.1 Stage improvements [2]

To maintain the genetic diversity, Genetic operators are used in genetic algorithms. In the process of evolution, there is a necessity of genetic diversity or variation. In the natural world, genetic operators are analogous that occurs.

Reproduction – on population, Reproduction is the first mechanism usually. In order to produce offspring among the population, the selection of chromosomes to be done as parents to crossover. To create new offspring, the best ones have to be survived. Selection operators are also known as reproduction operators. Roulette, wheel selection, rank selection, Boltzmann selection, steady-state selection and tournament selection are commonly used methods to crossover for parents in the selection process of chromosomes.

Crossover – In order to produce offspring (new chromosome) after combining two chromosomes, the crossover is the genetic operator for that. Based on the user definable crossover probability, crossover occurs during evolution. Among the parent chromosomes selection of genes done by crossover to create a new chromosome (offspring).

Mutation – Mutation occurs after the completion of crossover. Based on the user definable mutation probability, usually set a

fairly low value (0.01) which is a good selection during evolution mutation occurs. From its initial state, one or more gene values can be altered in a chromosome.

2.2.2 Self-Organization

External influence is not imposed in self-organizing which is a dynamic process. There will be an influence on the behavior of the low-level individual in the population when there an interaction among individuals occur in a direct way to produce the common pattern in self-organizing. To avoid getting trapped from local optimum and to avoid the premature convergence, self-organizing and genetic algorithms are combined.
The combination of the self-organizing and genetic algorithm are function optimizer which gives different parameter such as population size, crossover probability, and mutation probability. The population, crossover, and mutation affect the performance of GA. Kwon Jeong and Jang lee propose the multimodal function optimization that improves the performance by adapting the population size, crossover and mutation operator through GA itself. In combined SOM and GA have the possibilities to find the many local optima instead of one global optimum. SOM holds well in non-linear mapping for large search space.

2.2.3 Local search technique

Optimization problems that are computationally hard can be solved by the Local search which is a meta-heuristic method. In order to find the solution which maximizes the criterion among various candidate solution, the Local search can be used. Until and unless an optimal solution is found or a time bound is elapsed, Local search algorithm moves from solution to solution by applying local changes in the search space (space of candidate solutions).
To target among various different manners, most problems in terms of search space can be formulated.
Starting from the candidate solution to neighbor solution in an iterative way, the local search algorithm can be implemented. It is possible only we define the search space in a neighborhood relation. For example, By differing the one node, the neighborhood of a vertex cover of another vertex cover. By evaluating the variable, usually, the neighbors of a truth assignment are the truth assignments by differentiating only for Boolean satisfactory. There will be various different neighborhoods defined for the same problems. Referring the k component of the solution as k-opt can be involved with the neighborhood by changing the local optimization.
For each candidate solution, has more than one solution typically; based on the information about the solutions in the neighborhood of current one, by the choice of one to move to others is called local search. Metaheuristic takes the name hill climbing by maximizing the criterion locally when the choice of the neighbor solution. At a locally optimal point, in the neighborhood when there are no improving configurations present, local search is stuck. Simulated annealing, reactive search optimization on memory-less stochastic modifications, iterated local search, on memory, based on iterations more complex schemes can be cured by restarting the local-optima problem. On the basis of time-bound local search can be terminated. In a given number of steps, improvement of the best solution found by the algorithm is not done, then another common choice is to be terminated. Anytime algorithm is local search: Before ending at any time even though if it is interrupted also, a valid solution can be returned. Hill climbing, gradient methods, simulated annealing, genetic algorithms, local search issues ate the optimization methods and local search techniques.

3. Self-Organization in Genetic Algorithm

Based on the total knowledge of the problem and its parameters, development of self-organizing genetic algorithm (SOGA) can be done. The objective of the GA is to discover the ideal result which is close to the objective capacity of the optimization problems with expansive pursuit space.
The traditional GA comprises of a few stages and among those, initialization stage is to be considered as exceptionally essential, where the nature of the introductory results at the beginning stage is to be chosen. Traditionally, the population instantiation is performed by random introduction systems, which might likewise deliver the bigger amount of most exceedingly bad individuals. Then again, actuated models of population seeding procedures lead the overdue accomplishments of the fitness capacities with poor meeting qualities.

3.1 Generalized self-organization:

SO is a runtime decision making and it is initiated by the internal activities. In SO, the participating chromosomes exchange information among each other to produce the common model that can affect the quality of the other individuals in the population. SO plays a vital and effective role in solving complex problems with large search space.

3.1.1 Self Organizing Map

The primary purpose of SOM is to convert the chromosome pattern into one or more dimension of the discrete map. This conversion is done flexibly in the order of its topology. The chromosome neurons are selected as different input stimuli or categories of input patterns during the learning process. The position of the best neurons is considered as ordered and the coordinate of the input as a lattice. As a result, the SOM is formed with the required topographic map of patterns.
For unsupervised learning, the system learns to create its classification of the input patterns with any outside influence. To accomplish this, it can be assumed that the member individuals can be defined by the patterns share the common features and the system has the ability to learn from those input chromosome patterns. One f the interesting category of unsupervised learning is competitive learning that resultant output chromosome contends with each other and with the final only one is reminded at a time. This final neuron is referred as a winner neuron.

3.2 Bio-Inspired Self-Organization Techniques in GA

3.2.1 Self-Organizing Genetic Algorithm for Multiple Sequence Alignment

A problem can be optimized and solved by using a Genetic algorithm (GA) which can be applied to multiple sequence alignment (MSA). A process which is essential in molecular sequence analysis is multiple sequence alignment. In Bioinformatics, the important task is to align three or more nucleotide simultaneously in a sequential manner. The nucleotide can be replaced with an amino acid. Incorporation in many structures and function prediction methods from the sequence are considered to be an important application. Phylogenetic analysis and phylogenetic tree which was inferred by MSA was relatively close to the construction of MSA. Crossover and mutation can be implemented by two new operators suggested by SOGA.
An appropriate crossover point was selected by SOCO operator and from this, the corresponding rate was determined. The representation of a chromosome into a binary form was converted by the proposed mutation operator (Self-Organizing Binary shuffler) and this converted binary form of chromosome performs mutation until the termination occurs.

3.2.2 Self Organization in grey wolf algorithm

In nature, the leadership hierarchy of grey wolves can be represented by the Grey wolf algorithm. Alpha, beta, delta, and gamma are the four major classification categories in the grey wolves.

Alpha can be considered as the fittest solution, beta can be considered as a second fittest solution, Delta as the third fittest solution in the grey wolves' algorithm. Alpha guides the hunting process in the grey wolf algorithm. Occasionally, beta and delta take participation in the hunting. Based on the Best search agent, the best solutions which are first can be saved and obligation of other positions updating can be done by other agents. Based on their position, grey wolf algorithm can be applied in the exploration process. In order to search, we can diverge from each other and converge to attack the prey. The Best Three individual solutions like alpha, beta and delta can be founded after in the population set. By usage of self-organization method, based on the three fittest solutions can be arranged by the other individuals in the generation. Among the three best fittest solutions, Identification of common pattern can be done by self-organization technique. By calculation of each individual fittest weights, recognition of common patterns can be done and other individual's arrangement can be formulated by the intermediate table in the generation. Replication of element position can be alerted by using an intermediate table to self-organize the individuals. In order to enhance the performance of the genetic algorithm, the position of each individual can be replicated.

3.2.3 Krill herd algorithm

Krill individuals herding behavior inspired the krill herd algorithm. The objective function for the krill moment is said to be the minimum distance of each individual krill from the food and from the highest density of the herd. The krill individual position closer to the best fitness is changed by the defined motions in a frequent way. The individual presence, foraging activity, and random diffusion induce the time-dependent positions of the individual movement. A local and global optimizer has the first two actions. Krill herd algorithm's notable efficient results were due to parallel work of two global and local strategies. Searching process can be improved by adding the self-organization methodology as the third action. Fitness is defined by the distance between each krill individuals from the highest density and food.

4. Future Perspective Bio-Inspired Self-Organization Techniques

4.1 Social spider Optimization technique

Most of the insects that are present exhibit certain cooperative systems that incorporate a self-organizing behavior. One such insect is the Social spider [7] which consists of two main components: its members and communal web. The members of the social spider are classified into two categories based on their gender that is as males and females. The social spiders based on their gender exhibits different evolutionary functions which show their cooperative behavior. Since social spiders live as groups they tend to have social interactions for which they require a communication channel. This communication channel is provided to them by their communal web. This biological behavior of spiders to interact socially can be considered as a self-organization technique that can be used in solving various complex problems.

4.2 Group mosquito host-seeking algorithm

A swarm of mosquitoes when they tend to seek for a host, they get divided into three groups namely the producer group, the scrounger group and the dispersed group. Every mosquito near the host based on the intensity of carbon dioxide [6] and a smelling substance along with the radiated heat. Based on the radial distance between the mosquito and the host the fitness value of the mosquito is determined. The mosquito with high fitness value form the producer group and they tend to reach the host before every other group. Whereas, the scrounger group mimics the activities of the producer group and it reaches the host after the producer group. This biological behavior of group mosquitoes [5] can be considered as a self-organization behavior as different mosquitoes groups themselves based on their fitness value and this can be used to frame an algorithm that can solve the complex problems like the traveling salesperson problem.

4.3 Bumblebee colony optimization algorithm

The foraging behavior of bumblebees [8] has three phases that are the employed bee, the onlooker bee, and the scout bee. The employed bee and the onlooker bee go in search of the local neighborhood in search of food sources. The scout bee phase is where the bumblebees identify the exhausted food sources, abandon them and further look for new sources. Since the bumblebees have local interactions between them to form the different phases of foraging activity, this behavior of bumblebees is used for solving combinatorial optimization problems.

5. Conclusion

Hybrid genetic algorithms that exhibit self-organization behavior tends to find optimal solutions that are better and faster than the ones that are obtained using classic genetic algorithms. In traditional genetic algorithms, the probability of ending up with local optima or premature convergence is very high. By including the self-organization process to the classical genetic algorithm the flaws faced in GAs are avoided. These various self-organization techniques in HGA that are needed to solve combinatorial optimization problems are studied and discussed in this paper. This future perspective oriented survey thus helps the researchers to understand the existing SO in HGA techniques and thus frame newer bio-inspired Self-organization algorithms.

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