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Review

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A Review of Bio Inspired Computing and its Applications

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ABSTRACT

Bio Inspired computation is the part of Artificial intelligence which was inspired by the biological behaviors of biological systems. Swarm intelligence is the collective behavior of an organized group in day-to-day life. Common examples of swarm intelligence include ant colony, bee colony, etc. and some are non-swarm intelligence like bat algorithm, etc. This study mainly focuses on application areas of various bio inspired computing based swarm and non-swarm intelligence. This review also discusses the newly developed algorithms. Specific application areas of such algorithms have been discussed in this research. This research highlighted the future scope of present algorithms.

Keywords: Optimization, Bio- Inspired computing, Swarm intelligence.

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1. INTRODUCTION

In Artificial Intelligence swarm intelligence or Bio-inspired computation is categorized as a subset. It is classified as fast growing area which was introduced by Gerado Beni and Jing Wang in 1989 in the area of robotic systems. Swarm Intelligence or Bio- Inspired computing can be described as the collective behavior of species available in Nature. Species like social insects as ants, bees and termites are executing the basic rules. The key approach to implement Bio- Inspired computation is problem - solving using nature inspired algorithms. Bio-Inspired computing techniques are adaptable, evolvable, redundant, extendable and innovative. In Bio- Inspired computation the swarm can adjust or self- organize according to the dynamic constraints. Swatting the assets' is a phrase used in many industries and organizations which aim to get as possible values from the existing values. A famous Aristotle quote in support is, ' The whole is more than the sum of the parts'. Every living thing in nature tries to survive according to the natural habitat. Optimal foraging policy is one such phenomenon learned from the living things. By nature all the living things are stochastic behavior. Optimizing the complex values is not an ordinary task. To do this so many algorithms were proposed by some authors. In this research, we are adopting nature-inspired algorithms for optimizing the best results. Nature inspired algorithms are categorized into two categories like swarm based and non- swarm based. When we are discussing about the swarm based algorithms like ant colony optimization, Bee colony, Firefly, glowworm, Lion, Monkey, Bat, Wolf etc.

2. RESEARCH METHODOLOGY

The research was conducted in multiple stages. Initially, some important algorithms are analyzed. Researchers have concentrated on those algorithms, which are not in popular, and needs for development. These algorithms were identified through some popular search engines like Google scholar using some keywords like swarm intelligence and non-swam intelligence, also studied from some well-known conference publications, proceedings and book chapters, etc. After collecting, the similar articles relating to the bio inspired computing the next stage is a literature review conducted in detail for each analyzed algorithm. Considering the methodology discussed above, we have identified major algorithms (Thirteen in number) which can be categorized into insect based, animal based and bird based algorithms that was shown in the figure under. Swarm based algorithms are collective in nature, such as ant colony, bee colony, glow worm, and firefly algorithms and animal based algorithms like Wolf, lion, monkey, bat and bird based algorithms like cuckoo search and flocks of birds etc.

have been discussed for their capacity and applications were conducted. Figure 1 shows the hierarchy of bio inspired computing algorithms for this study.

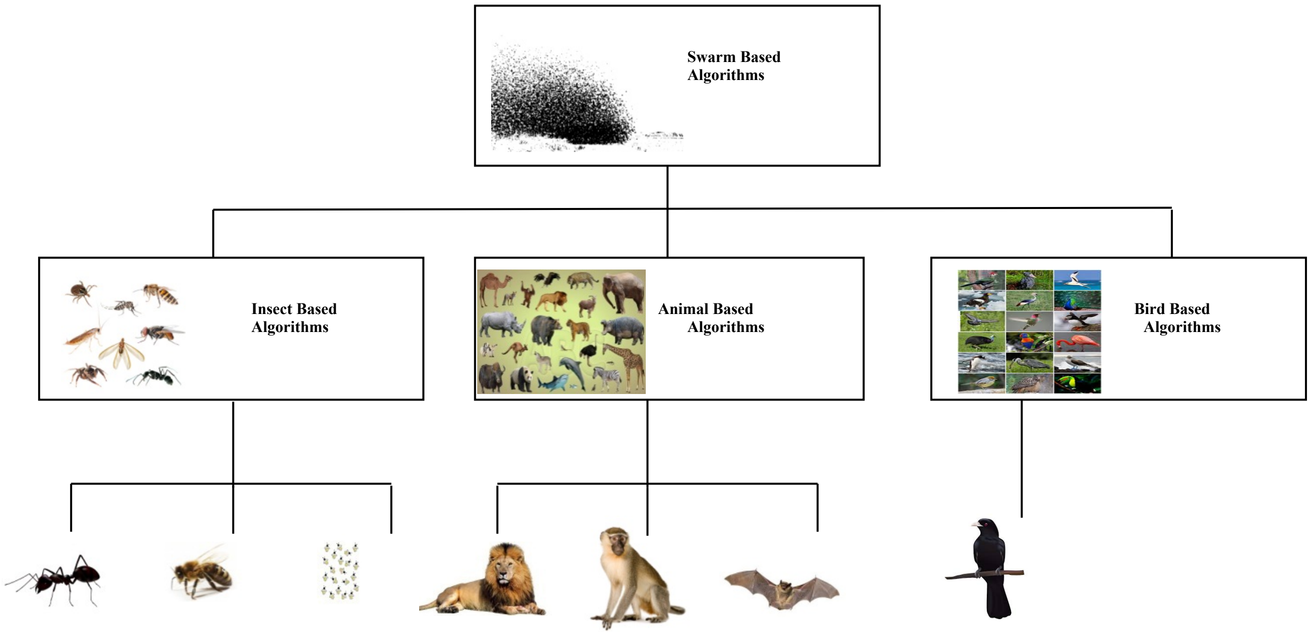

Figure 1. shows the hierarchy of Swarm intelligence

3. INSECT BASED OPTIMIZATION

3.1. Ant colony optimization

A. Basic Overview

Ant colony optimization algorithm was proposed by Colomi (1) and was based on the behavior of ants while searching food for themselves. Food searching is one task and optimizing the food is another task for ants. In order to communicate with each other during the food searching process, the ants use a chemical substance, i.e., the pheromone trail.

B. Application areas of Ant Colony Optimization

Application areas of ant colony optimization is Data mining, (2-4) clustering and classification by the ant colony (5-8). Artificial ant colony optimization is also involved to solve travelling salesman problem (9-13). The ant colony optimization is also participating in vehicular routing problems (14-16) along with this application areas the ant colony optimization is actively participated to solve job scheduling sequence (17-19) time table arrangement (19) telecommunication networking systems (20, 21) congestion control for MIMO detection (22), ant colony optimization extends in data composition by c means, economic dispatch problem, gaming theory (23, 24) social media approaches (24, 25) satellite control (25) etc.,

3.2. Artificial bee colony

A. Basic Overview

Artificial bee colony algorithms was proposed by Karaboga in 2005 (26) based on the foraging behavior of Honey bees. In this algorithm the behavior of honeybees were discussed with respect to their communication for nest site selection, mating, dance pheromone laying etc., based on which the algorithm was modified. The Artificial bee colony (ABC) algorithms optimize the results by conducting various iterations with the available alternate solutions to solve complex problems. In an Artificial bee colony, there are three types of honeybees: Employed bees, onlooker bees, and scout bees. An employed bee searches the food sources and informs to the onlooker bees. In the second stage, the onlooker bee verifies the results, i.e., food sources and selects the best food sources based on highest quality (fitness). The scout bees are translated from a few employed bees which abandon the food sources and search new ones. The employed bees always search the food sources and update their database with the new values for the onlooker bees and the onlooker bees make a decision for the best food source with the help of higher fitness function. In this case, if the bees are not getting good results, then the results are rejected or discarded and better results are re-searched.

B. Applications areas of Ant Colony Optimization

Application areas of the Artificial bee colony is involved in various problem solving approaches such single objective numerical value optimizer, cluster approach in global optimization (26), (27-29). The abc has been also utilized for the (30, 31) and for cluster approach in (31) global optimization (32) participated in (33), (34) the abc is also participated for (35) and participated in various raking problems in wireless sensor networks further it can be witnessed for multi-dimensional problems for both single and multi-objective problems evaluation and differential evolution problems.

3.3. Firefly

A. Basic Overview

Firefly algorithm was proposed by (36) based on the behavior of fireflies. Firefly algorithm is a metaheuristic algorithm which gives better results comparative than the other swarm based algorithms. This algorithm works with the behavior of fireflies, how they are attracting for finding mates, finding prey or only for mutual communication with the help of bioluminescence or flashing signals. In this algorithm all, the fireflies are unisex only. The attractive rate is calculated by the brightness how much they are emitting. According to the problem requirement, we are selecting fireflies randomly in the first step. After this step, the results are verified by the fitness function defined for the each firefly selected randomly. The iteration continues until to find similar fireflies relating to the problem domain. During this process, the number of iterations is predefined. One of the major advantages of this firefly algorithm is conjunction with other algorithms to obtain the best outcome.

B. Applications areas of Fire fly Optimization

Application areas of this algorithm are for (37) and (38, 39), for mixed variable optimization(39) and (40, 41). The firefly algorithm can also participated in (42-44) (45), the fireflies also participated (46-48). firefly algorithm also involved for (49, 50). Apart of all the above firefly algorithm (51). Along with this firefly along with cuckoo participated for (52).

3.4. Glow warm

A. Basic Overview

Glow warm swam optimization was developed based on the behavior of glow warms (53). The glow warms are communicating others with the help of chemical substance called luciferin emission that helps them flow glow emission. The increasing of emission leads to the good results. As per the artificial glow warm optimization initially in a swarm glow warms are selected randomly, which they are self-potential. In second step, the glow warms are moving towards the high intensive warms and calculates the direction based on the objective function defined to each glowworm at the current location. In this case each glow worm compare its potentiality with the other glowworms in the neighborhood and changes the traversal direction if the desired results are available or else it can continue by its own results. This process is continued until the said glowworm reaches its convergence results and in this optimization also the iterations are predefined.

B. Application areas of Glow Worm optimization

Application areas of glow warm optimization includes (54), (53),. The glow swarm optimization algorithm involves for (55), (56). The glowworm swarm optimization extends the participation for (53) also participated in optimal power flow based for three phase is landed micro grids (57).

4. ANIMAL BASED ALGORITHMS

4.1. Bat algorithm

A. Basic Overview

The bat algorithm is a metaheuristic algorithm developed based on the echolocation behavior of bats (58). This algorithm that helps to solve single objective and multi-objective optimization problems. In this, the bats are emitting the echo with different wavelength and loudness to attract the prey. It changes the frequency according the search and it was intensified by a random walk. This process will continue until any obstacle found. This technique enables bats to evaluate the perfect location of any object or prey. In this, the bats will estimates the distance of the prey and adjusting the flight velocities, intensity of the cry. Vector algebra is the mathematical tool for calculation of the problem. With single iteration, the bat will calculate whether the prey is nearer or not. According to that bat will increase the frequency and decrease the loudness. Although the bat algorithm is restricted to continuous problems, a binary version of bat algorithm was introduced to address discrete decision making (59) there are so many studies have conduced which involves classical bio- inspired like neural networks (59).

B. Applications areas of BAT Optimization

Application areas of Bat algorithm which includes (60) for (61), (62). Bat algorithm also involves to solve multi-objective problems in (63), (64). Bat algorithm has also participated for solving (65)(Bat algorithm based scheduling), for solving (66) (Bat algorithm for mutation), required computation time will increase when the number of multilevel thresholds are growing (2), for global optimization BBA(A binary Bat Algorithm (67) introduces for future selection (68).

4.2. Monkey

A. Basic Overview

To solve global numerical optimization problems Monkey based algorithm is one of the best algorithm to solve such type of problems. In this algorithm the adoption of monkeys behaviors when they are climbing mountains. The monkeys algorithm will follow the three processes climb process, watch-jump process and somersault to achieve the desired results. To find the best value or best results on availability data sets if the monkey will reach to the top of the mountain it will start the climbing process and change the location when the current results are not satisfying the desired results and so. If found the best results comparative than the previous the monkey will apply watch jump process. This iterative process continues until the monkey will not reach the desired goal or destination. After iterations of climb and watch jump process each monkey will find local maxima to its initial state. In order to locate a yet higher mountaintop it is obvious for each monkey to somersault to a new search domain this is called somersault process. After abundant repetitions of climb process, watch-jump process and somersault process the monkey is reported an optimal solution.

B. Applications areas of Monkey Optimization

Applications areas of (69) for (70), (71). The monkey algorithm is also participate with (72), (73, 74), for solving numerical optimization problems based on fission- fusion behavior of monkeys with spider monkey optimization (74), Monkey based algorithm can also (75), clustering the popular data analysis in data mining, monkey algorithm involves with hybridization for optimal clustering analysis (76) for effective structural health monitoring optimal sensor placement is the integral component, monkey algorithm hybridized with artificial fish swarm intelligence (2), for hybrid power systems optimization monkey algorithm (77) involves to solve problem. In mathematics for real- parameter optimization based on exploration and exploitation a modified or improvised monkey algorithm (78) involves to solve the problems above mentioned, this algorithm involves for optimizing uncertain structural systems subject to earth quake ground motions (79).

4.3. Lion based

A. Basic Overview

Lions are most socially wildcat species. Lions are strong sexual dimorphisms in both social behavior and appurtenance. In lion based optimized algorithm the initial population was formed randomly and categorized in two groups named nomads and residents. Residents live in a group called Pride. Nomads behave sporadically in singular or in pairs. According to this algorithm, each lion in the population moves towards better placed called solution. In resident group, usually females are hunting in randomly and the rest of them are moving according to the group. Any weak Lion found it has to be eliminated and this process was done by the strongest lion either killing or general death. The above process is done until the lions may not get good results i.e., the destination.

B. Applications areas of LION Optimization

Applications of Lion algorithm are employed (80), (81). (82), the ant lion colony optimization algorithm also finds the solution for classical engineering problems (82). The ant lion optimization also involves in multi agent methodology for integrating the process and scheduling for defining guidelines in Global Initiative for Chronic Obstructive Lung Disease (83), (84).

4.4. Wolf

A. Basic Overview

It is one of the recent meta heuristic algorithm by Simon fong (85). Wolf algorithm is based on the behavior of wolfs for hunting. Wolfs are dividing the task and update their current locations with the better locations. If the new location is better than the current location then the wolf jump to the new location and make its as a current location. This process will repeats until all the wolf's are satisfied with the results, i.e., food. Based on the behavior of wolf colony algorithm was designed. These algorithms are more superior than the current bio- inspired algorithms.

B. Applications areas of Wolf Optimization

Applications of the wolf based algorithm is used for optimizing the search conditions (86), for un inhabited combat air vehicle path planning the wolf colony search algorithm has participated (87) wolf colony algorithm also involves in fault system estimation problem on power systems (88), in optimal operation of hydro power station (89), a grey wolf optimizer in multi-layer perceptions (90) for effective cheap method for improving the performance of metaheuristics. Evolutionary population dynamics and grey wolf optimizer (91).

5. BIRD BASED OPTIMIZATION

5.1. Cuckoo search

A. Basic Overview

In 2009 , Yang and Deb proposed cuckoo search algorithm inspired by the behavior of cuckoo bird which was a meta heuristic approach (36). The algorithm was based on the behavior of cuckoo's breed paratism. Cuckoo search is strengthen by levy flights rather than the isotropic. It is a population based algorithm to solve complex non- linear problems, brood paratism means it lays eggs in another bird nest like crow in India. Cuckoo generally searches the crow's nest regularly for laying eggs. For this its searches the best nest for laying eggs. After laying the eggs by cuckoo the eggs were hatching by the crow. Alien eggs are detected by crow then the eggs are thrown away from the nest or a bonded. In cuckoo search optimization, the cuckoo will select the nest randomly and calculates the best nest according the fitness function or objective function according to the problem domain.

B. Applications areas of Cuckoo Seach Optimization

Applications of cuckoo search includes for selecting optimal matching parameters in milling operations (92), cuckoo search involves in feed forward neural network training (93), for structural design optimization of vehicle components (94), for solving travelling sales man problem (95), the basic cuckoo search algorithm has been modified and utilized for unconstrained optimization problems (96), for satellite image segmentation in multi-level thresholding (97), the cuckoo search algorithm have been improved for global optimization (98), the hybridized cuckoo with fuzzy for solving multi-objective scheduling problem (99), parameter estimation for chaotic systems using cuckoo search algorithm (100).

6. FEATURE SCOPE OF BIO INSPIRED ALGORITHMS

Tremendous research has been conducted and so many application areas proposed in this preset review article with adequacy of references. Mainly the algorithms are ant colony, bee colony and firefly algorithm from the insect based category, bat based from the animal category of Bio-inspired computing. We also reviewed the current algorithms like lion, wolf and glow warm etc., these algorithms are not much more utilized in application areas comparative than the previously discussed algorithms, because they are newer. Further, this research also focused on bird based algorithms like cuckoo and its application areas. Future research will concentrate on the above algorithms that are not popular or newer. Further, the feature also concentrates on the outcome of the available algorithms to fulfill the domain requirements. Future research can also emphasis for hybridization of the above algorithms with genetic algorithm, neural networks etc.,

7. CONCLUSION

This study gives the detailed review about the bio inspired computing based algorithms which include Insect Based, Animal Based and Bird based algorithms. It is clear that in this study, some of the few algorithms like an ant colony, Artificial Bee colony, Bat, Lion and Cuckoo optimization algorithms are very famous and well having plenty of publications participated in so many application areas. These algorithms have been participating in so many engineering domains like automobile engineering, mechanical engineering, electrical engineering, etc. In this review, the authors also reported the less popular algorithms like glow warm, lion and wolf etc.

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CONFLICT OF INTEREST

The authors declared no potential conflicts of interests with respect to the authorship and/or publication of this paper.

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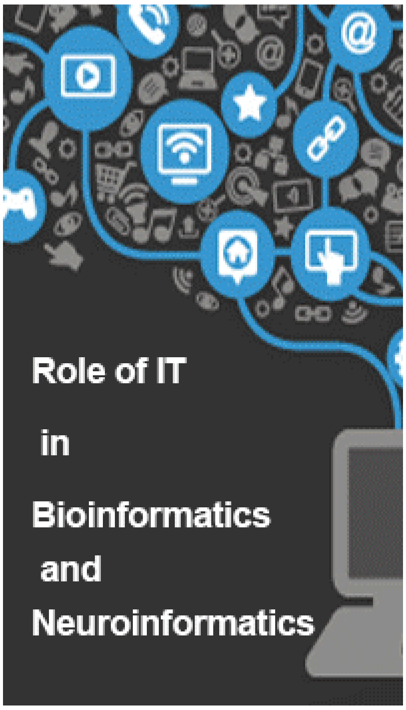

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