A Survey: Spider Monkey Optimization Algorithm

Neetu Agarwal[a], Kushboo Gupta [b], Shailesh Porwal [c], and Prof S.C. Jain[d]

[a,b,c,d] Rajasthan Technical University, Kota, India.

Abstract. Swarm intelligence is a one of the areas for evaluating the optimization states. Many algorithms have been developed by simulating the swarming behaviour of various creatures like ants, honey bees, fishes, birds and their results are found as very motivating for solving optimization problems. In this paper, a new approach for optimization is proposed by modelling the social behaviour of spider monkeys. Spider monkeys have been categorized as fission-fusion social structure based animals. The animals which follow fission-fusion social systems, initially work in a large group and based on need after some time, they divide themselves in smaller groups led by an adult female for foraging. Therefore, the proposed strategy broadly classified as inspiration from the intelligent foraging behaviour of fission-fusion social structure based animals.

Keywords: Nature Inspired Algorithm (NIA), Swarm intelligence and Spider Monkey Optimization (SMO)

1 Introduction

The name swarm is used for an accumulation of creatures such as ants, fishes, birds, termites and honey bees which behaves collectively. The definition given by Bonabeau for the swarm intelligence is any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies [7]. Swarm Intelligence is a meta-heuristic approach in the field of nature inspired techniques that is used to solve optimization problems. It is based on the collective behaviour of social creatures. Social creatures utilize their ability of social learning to solve complex tasks. Researchers have analysed such behaviours and designed algorithms that can be used to solve nonlinear, non-convex or combinatorial optimization problems in many science and engineering domains. Previous research [16] have shown that algorithms based on Swarm Intelligence have great potential to find a solution of real world optimization problem. The algorithms that have emerged in recent years include Ant Colony Optimization (ACO) [4], Particle Swarm Optimization (PSO) [16] , Bacterial Foraging Optimization (BFO) [14], Artificial Bee Colony Optimization (ABC) [8] etc. The necessary and sufficient properties for obtaining intelligent swarming behaviours of animals are self-organization and division of labour. Each of the properties is explained as follows:

1. **Self-organization**: Self-organization is an important feature of a swarm structure which results global level response by means of interactions among its low-level components without a central authority or external element enforcing it through planning. Therefore, the globally coherent pattern appears from the local interaction of the components that build up the structure, thus the organization is achieved by parallelly as all the elements act at the same time and distributed as no element is a central coordinator. Bonabeau et al. have defined following four important characteristics on which self-organization is based: [2]

   – **Positive feedback**: It is information extracted from the output of a system and reapplied to the input to promote the creations of convenient structures. In the field of swarm intelligence positive feedback provides diversity and accelerates the system to new stable state.
   – **Negative feedback**:Compensates the effect of positive feedback and helps to stabilize the collective pattern.
   – **Fluctuations**: Fluctuations are the rate or magnitude of random changes in the system. Randomness is often crucial for efflorescent structures since it allows the findings of new solutions. In foraging process, it helps to get-ride of stagnation.
   – **Multiple interactions**: provide the way of learning from the individuals within a society and thus enhance the combined intelligence of the swarm.

2. **Division of labour**: Division of labour is a cooperative labour in specific, circumscribed tasks and like roles. In a group, there are various tasks, which are performed simultaneously by specialized individuals. Simultaneous task performance by cooperating specialized individuals is believed to be more efficient than the sequential task performance by unspecialized individuals [6, 9, 16].

1.1 Optimization

In optimization of a design, the design objective could be simply to minimize the cost of production or to maximize the efficiency of production [16]. An optimization algorithm is a procedure which is executed iteratively by comparing various solutions still an optimum or a satisfactory solution is find. With the advent of computers, optimization has become a part of computer aided design activities. There are two distinct types of optimization algorithms widely used today.

1. **Deterministic Algorithms**: They use specific rules for moving one solution to other. These algorithms are in use to suite sometimes and have been successfully applied for many engineering design problems.
2. **Stochastic Algorithms**: The stochastic algorithms are in nature with probabilistic translation rules. These are gaining popularity due to certain properties which deterministic algorithms do not have.

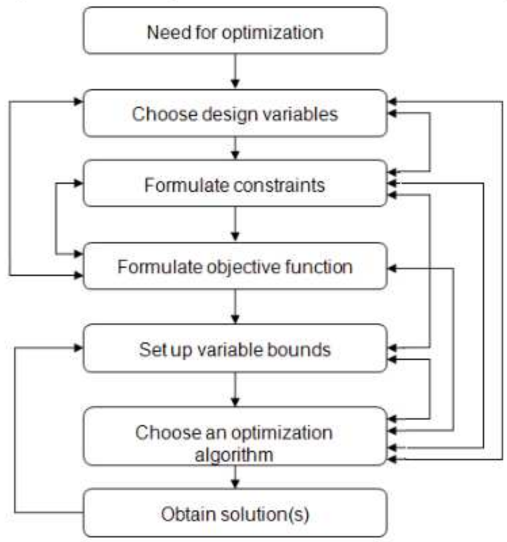

Fig. 1: Flow chart of the optimal design procedure

2 Natures Inspired Algorithms

In recent years Nature-inspired algorithms have attained gross to resolve complex problems of real world such as NP complete and NP hard problems and numerous complex optimization functions whose absolute solution does not exist. Nature inspired algorithm [20], inspired by nature, is a stochastic approach wherein an individual or a neighbors interacts with each other intellectually to explain complicated preexisting mechanisms in an efficient manner. NIA is focused mainly on evolutionary based algorithm and swarm based algorithm.

2.1 Evolutionary Algorithms

Evolutionary algorithm is a computational standard motivated by Darwinian Evolution [15]. Evolution computing is the general term for a domain of problem resolving methodologies based on biological evolution principles. The evolutionary algorithms which are further categorized into three subcategories namely genetic algorithms, genetic programming,evolutionary strategies and differential evolution algorithm.

2.2 Swarm Intelligence

Swarm intelligence assets in unlocking optimization problems considering collaborative nature of self-sustaining creatures like bees, ants, monkeys [2, 8, 3] whose

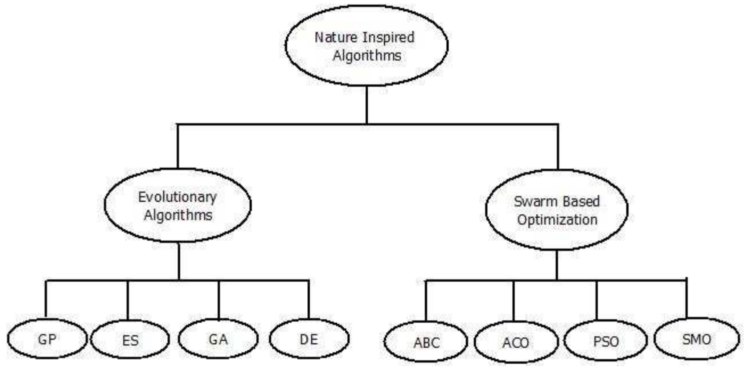

Fig. 2: Nature Inspired Algorithms for Optimization

food-gathering capabilities and civilized characteristics have been examined and simulated [5]. The algorithm based on swarm intelligence which are further categorized into three subcategories namely particle swarm optimization, ant colony optimization and artificial bee colony optimization.

3 Spider Monkey Optimization (SMO) Technique

SMO is a subclass of swarm intelligence, proposed by Jagdish Chand Bansal et al., in the year 2014 [4]. SMO is a food foraging based algorithm, considering nature and social frame work of spider monkeys. Fission-Fusion social system relates to social configuration of spider monkey. Many researchers have been studied that SMO algorithm is good at exploration and exploitation but there is possibilities of further improvements.
Here, a populous, consistently dictated by a female, is fragmentized into tiny clusters for seeking, chiefly food and they are buddy up to 40 to 50 singular who rift into small groups in search of food who again are headed by a female. In case she fails to meet the objective (food finding), further subdivides, again succeeded by a female, replicating the process until reach the food. For recent updates in their positions, various steps are undertaken: inspection of probing of wide search space and picking or electing of superlative practical results [10].

3.1 Steps of SMO technique

SMO technique is based on population repetitive methodology. It consists of seven steps. Each step is described below in a detailed manner:

1. **Initialization of Population**: Originally a population comprised of N spider monkeys signifying a D-dimensional range M_i where i=1,2,...N and i

represents i^{th} spider monkey. Each spider monkey (M) exhibits possible results of the problem under consider. Each M_i is initialized as below:

$$M_{ij} = M_{minj} + R(0,1) \times (M_{maxj} - M_{minj}) \tag{1}$$

Here M_{minj} and M_{maxj} are limits of M_i in j^{th} vector and R(0,1) is a random number (0,1).

2. **Local Leader Phase (LLP)**: This phase relies on the observation of local leader and group mates, M renew its current position yielding a fitness value. If the fitness measure of the current location is larger than that of the former location, then M modifies his location with the latest one. Hence i^{th} M that also exists in k^{th} local group modify its position.

$$M_{newij} = M_{ij} + R(0,1) \times (LL_{kj} - M_{ij}) + R(-1,1) \times (M_{rj} - M_{ij}) \tag{2}$$

Here M_{ij} define i^{th} M in j^{th} dimension, LL_{kj} correlate to the k^{th} leader of local assembly location in j^{th} dimension. M_{rj} defines r^{th} M which is randomly picked from k^{th} troop such that $r \neq i$ in j^{th} dimension.

3. **Global Leader Phase (GLP)**: This following phase initiates just after accomplishing LLP. Depending upon the observation of global leader and mates of local troop, M updates their location. The position upgrade equation for GLP phase is as follows:

$$M_{newij} = M_{ij} + R(0,1) \times (GL_j - M_{ij}) + R(-1,1) \times (M_{rj} - M_{ij}) \tag{3}$$

Here GL_j poises for global leader's location in j^{th} dimension and j=1,2,3,...,D defines an arbitrarily chosen index. M_i modify their locus considering probabilities $Pr_i^{\prime}s$. Fitness is used to calculate probability of a specific solution, with various methods such as

$$Pr_i = 0.1 + (\frac{fitness_i}{fitness_{max}}) \times 0.9 \tag{4}$$

4. **Global Leader Learning (GLL) Phase**:Here greedy selection strategy is applied on the population which modifies the locus of global leader i.e. the location of M which has best fitness in the group is chosen as the modified global leader location. Also its is verified that global leader location is modifying or not and in case not then GlobalLimitCount(GLC) is increased by 1.
5. **Local Leader Learning (LLL) Phase**:Here, local leader locus is modified by implement greedy selection in that population i.e. the location of M which has best fitness among the entire group is chosen as the latest location of local leader. Afterwards, this modified local leader location and old values are compared and LocalLimitCount (LLC) is increment by 1.
6. **Local Leader Decision (LLD) Phase**: Here, updating of local leader location is done in two ways i.e. by arbitrary initialization or by mixing information obtained via global and local leader, if local leader location is

not modified up to a precalculated limit named as LocalLeaderLimit through equation based on perturbation rate (p).

$$M_{newij} = M_{ij} + R(0,1) \times (GL_j - M_{ij}) + R(0,1) \times (M_{ij} - LL_{kj}) \qquad (5)$$

Clearly, it is seen in equation that modified dimension of this M is fascinated towards global leader and oppose local leader. Moreover, modified M's fitness is determined.

7. **Global Leader Decision (GLD) Phase**:Here, global leader location is examine and if modification is not done up to precalculated iterations limit named as GlobalLeaderLimit then division of population in small group is done by local leader. Primarily population division is done in two classes and further three, four and so on until the upper bound called groups of maximum number (GM) is reached. Meanwhile, local leaders are selected using LL method for newly formed subclasses.

The pseudo-code of the SMO algorithm is as follows:-

(1) Define Population, LocalLeaderLimit, GlobalLeaderLimit, Perturbation rate.
(2) Determine fitness (each individual distance from sources of food)
(3) Apply greedy selection to choose global and local leaders.
while Termination condition is not met **do**
  (i) To hit target, new locations for group population is formulated with the help of self experience as well as local and group population experience, using Local Leader Phase (LLP).
  (ii) Relied on fitness value of group members, employ greedy selection strategy.
  (iii) Assess probabilities Pr_i for all companions using equation (4).
  (iv) Generate new locations for each group companions, chosen by Pr_i, by self experience, global leader experience also consider experience of group member using Global Leader Phase (GLP).
  (v) Greedy selection method is applied to modify global and local leaders locations of entire groups.
  (vi) Any local leader of a group, if fails to modify her locus within LocalLeaderLimit then deflect that specific group companions for further foraging using Local Leader Decision (LLD) Phase.
  (vii) Any global leader if fails to modify her locus within GlobalLeaderLimit then she diversifies group into subgroups by Global Leader Decision Phase with the minimum threshold of each groups size being 4
end while

Algorithm 1: Spider Monkey Optimization (SMO)

4 Current research areas in SMO

Researchers have been continuously working to improve the efficiency and accuracy of SMO Algorithm. Table 1 shows a brief review of SMO modifications.

Table 1: Advances in Spider Monkey Optimization

S.No.	Modification and Description	Yr/Ref.
1	Modified position update based spider monkey optimization	2014 [10]
2	Self adaptive Spider Monkey Optimization	2014 [9]
3	Modified Monkey Optimization Algorithm for solving optimal reactive power Dispatch Problem	2015 [12]
4	Fitness based Position Update in SMO	2015 [11]
5	Spider Monkey Optimization: A Novel Technique for Antenna Optimization	2015 [1]
6	Tournament Selection based Probability Scheme in Spider Monkey Optimization Algorithm	2016 [6]
7	Multilevel Thresholding Segmentation approach based on Spider Monkey Optimization Algorithm	2016 [13]
8	A Novel Binary Spider Monkey Optimization Algorithm for Thinning of Concentric Circular Antenna Arrays	2016 [19]
9	Ageist Spider Monkey Optimization algorithm	2016 [18]
10	Power law-based local search in spider monkey optimisation for lower order system modelling	2016 [17]

In 2014, Sandeep Kumar et al. [10] proposed "Modified Position Update in Spider Monkey Optimization Algorithm". This given paper introduces a position update technique in SMO and modifies both local leader and global leader phase. The proposed algorithm tested over benchmark problems and results showed that it has given better results for unbiased problems under consideration.

In 2015, Sandeep Kumar et al. [11] proposed "Fitness Based Position Update in Spider Monkey Optimization Algorithm". In this paper, a new strategy to update position of solution during local leader phase using fitness of individuals. The proposed algorithm was named as Fitness based Position Update in SMO (FPSMO) algorithm as it updates position of individuals based on their fitness. The anticipated strategy enhanced the rate of convergence. The planned FPSMO approach tested over nineteen benchmark functions and for one real world problem so as to establish superiority of it over basic SMO algorithm.

In 2016, A. Sharma et al. [18] proposed "Ageist Spider Monkey Optimization algorithm". In this paper, a spider monkey group consists of member from every age group is considered. The agility and swiftness of the spider monkey differs on the basis of their age groups.

In 2016, Ajay Sharma et al. [17] proposed "Power law-based local search in spider monkey optimisation for lower order system modelling". This proposed paper represents a better solution for lower order system modelling using spider monkey optimisation (SMO) algorithm to reach a better approximation for lower order systems and reflects mostly original higher order systems characteristics. Moreover, a strategy for local searching, namely, power law-based local search was integrated with SMO. The proposed strategy is named as power law-based local search in SMO (PLSMO).

5 Conclusion

Natures inspired techniques have presented remarkable solutions to the optimization problems in various fields. Spider Monkey Optimization is one of the Swarm based nature inspired algorithm that is capable of delivering optimal results for complex real life optimization problems. This paper presents a survey on the basic version of SMO as well as various variants of SMO algorithm for achieving optimization in different domains. Futuristic approaches may use the concept of algorithm for even better optimization results with less timing requirements.

6 Future Scope

SMO is designed to have both the exploration of the possible solutions and exploitation to reach the best solution in a balanced way such that the optimal result is achieved in remarkable considerable time. Still, there is always a scope for improvement. From Future perspective, researchers may focus on achieving even higher exploration and convergence rates through global and local leader phases using more probabilistic approaches. In future, this algorithm concept may also be used in solving optimization requirements of different engineering fields and other real life problems.

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