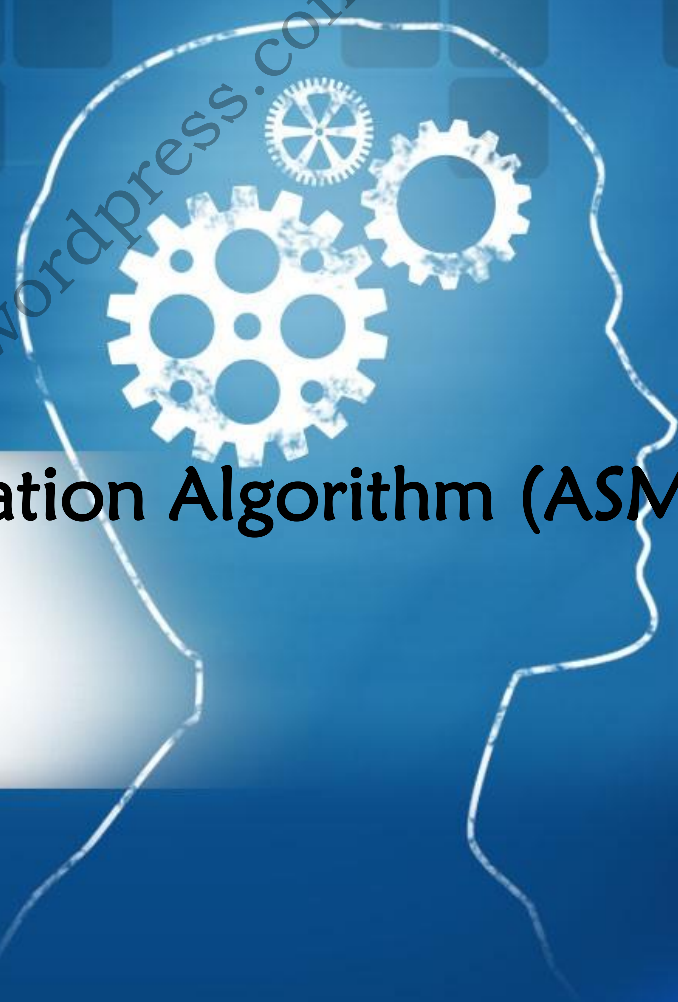
Ageist Spider Monkey Optimization Algorithm (ASMO)



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Outline

- Spider Monkey Optimization (SMO) algorithm
- Fission fusion social behavior
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About Spider Monkey

- Spider monkeys of the genus Ateles are New World monkeys in the subfamily Atelinae, family Atelidae.
- They are found in tropical forests of Central and South America, from southern Mexico to Brazil.

About Spider Monkey

- Spider monkeys live in the upper layers of the rainforest, and forage in the high canopy, from 25 to 30 m (82 to 98 ft).
- They primarily eat fruits, but will also occasionally consume leaves, flowers, and insects.
- Due to their large size, spider monkeys require large tracts of moist evergreen forests, and prefer undisturbed primary rainforest.
- Disproportionately long limbs and long prehensile tails make them one of the largest New World monkeys and give rise to their common name.

About Spider Monkey

- They can produce a wide range of sounds and will ``bark” when threatened; other vocalisations include a whinny similar to a horse and prolonged screams.
- Spider monkeys follow **Fission Fusion Social Structure (FFSS)** in which they form temporary small subgroups, whose members belong to large stable communities.
- These subgroups are lead by a *female leader* for searching food which split the subgroups when there is scarcity of food.
- Main group generally has around 50 members initially and subgroups have at least 3 members.

Spider Monkey Optimization (SMO) Algorithm

- Recent meta-analyses on primate cognition studies indicated spider monkeys are the most intelligent New World monkeys.
- Spider Monkey Optimization (SMO) algorithm is a new swarm intelligence algorithm proposed in 2014 by J. C. Bansal et. al.
- SMO is a population based method
- The social behavior of spider monkeys is an example of fission-fusion system.

Fission-Fission Social Structure

- The spider monkeys as a fission-fusion social structure (FFSS) based animals live in large community called unit-group or parent group , where each group contains of 40-50 individuals.

Fission-Fission Social Structure (Cont.)

- In order to minimize foraging competition among group individuals, spider monkeys divide themselves into subgroups.

- The subgroups members start to search for food and communicate together within and outside the subgroups in order to share information about food quantity and place.

Fission-Fission Social Structure (Cont.)

- The subgroups members not able to get enough food for group, female group leader (global leader) divided the group into smaller subgroups lead by female (local leader).

Fission-Fission Social Structure (Cont.)

- The parent group members search for food (forage) or hunt by dividing themselves in sub-groups (fission) in different direction then at night they return to join the parent group (fusion) to share food and do other activities.

Communication of Spider Monkeys

- Spider monkeys are travailing in different direction to search for food.
- They interact and communicate with each other using a particular call by emitting voice like a horse's whinny.
- Each individual has its identified voice so that other members of the group can distinguish who is calling.
- The long distance communication helps spider monkeys to stay away from predators, share food and gossip.
- The group members interact to each other by using visual and vocal communication

Behavior of FFSS Based Animal

- The group starts food foraging and evaluates their distance from food.
- Based on distance from the foods, group members update their positions and again evaluate distance from food sources.
- The local leader updates its best position with the group and if the position is not updated for a specified number of times then all members of that group start searching of the food in the different directions.
- The global leader updates its ever best position and in case of stagnation it splits the group into smaller size subgroups.

SMO Algorithm : Major Steps

- SMO is trial and error collaborative iterative process.
- SMO process consists of six phases:

1. Local Leader Phase (LLP)
2. Global Leader Phase (GLP)
3. Local Leader Learning Phase (LLLP)
4. Global Leader Learning Phase (GLLP)
5. Local Leader Decision Phase (LLDP)
6. Global Leader Decision Phase (GLDP)

Initialization of The Population

- Initially, *SMO* generates a uniformly distributed initial population of N spider monkeys where each monkey $SM_i (i = 1,2, \ldots, N)$ is a D-dimensional vector.

- Each spider monkey SM corresponds to the potential solution of the problem under consideration. Each SM_i is initialized as follows:

$$SM_{ij} = SM_j^{min} + U(0,1) \times (SM_j^{max} - SM_j^{min})$$

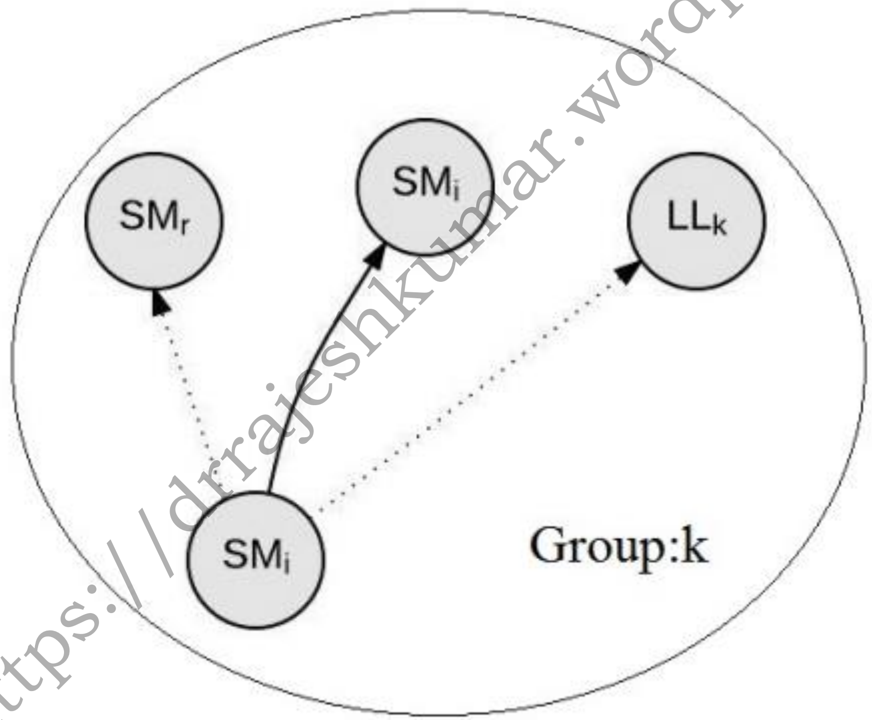
Local Leader Phase (LLP)

- In this phase, each SM modifies its current position based on the information of the local leader experience as well as local group members experience.

- The position update equation for i^{th} SM (which is a member of k^{th} local group) in this phase is:

$$SM_{ij}^{new} = SM_{ij} + U(0,1) \times \left(LL_{kj} - SM_{ij}\right) + U(-1,1) \times (SM_{rj} - SM_{ij})$$

Local Leader Phase (LLP)



Algorithm: LLP

Algorithm 1 Position update process in Local Leader Phase:

for each $k \in \{1, \dots, MG\}$ **do**
  for each member $SM_i \in k^{th}$ group **do**
    for each $j \in \{1, \dots, D\}$ **do**
      if $U(0,1) \geq pr$ **then**
        $SM_{ij}^{new} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1) \times (SM_{rj} - SM_{ij})$
      else
        $SM_{ij}^{new} = SM_{ij}$
      end if
    end for
  end for
end for

Global Leader Phase (GLP)

- In this phase, all SM's update their position using experience of global leader and local leader members experience.

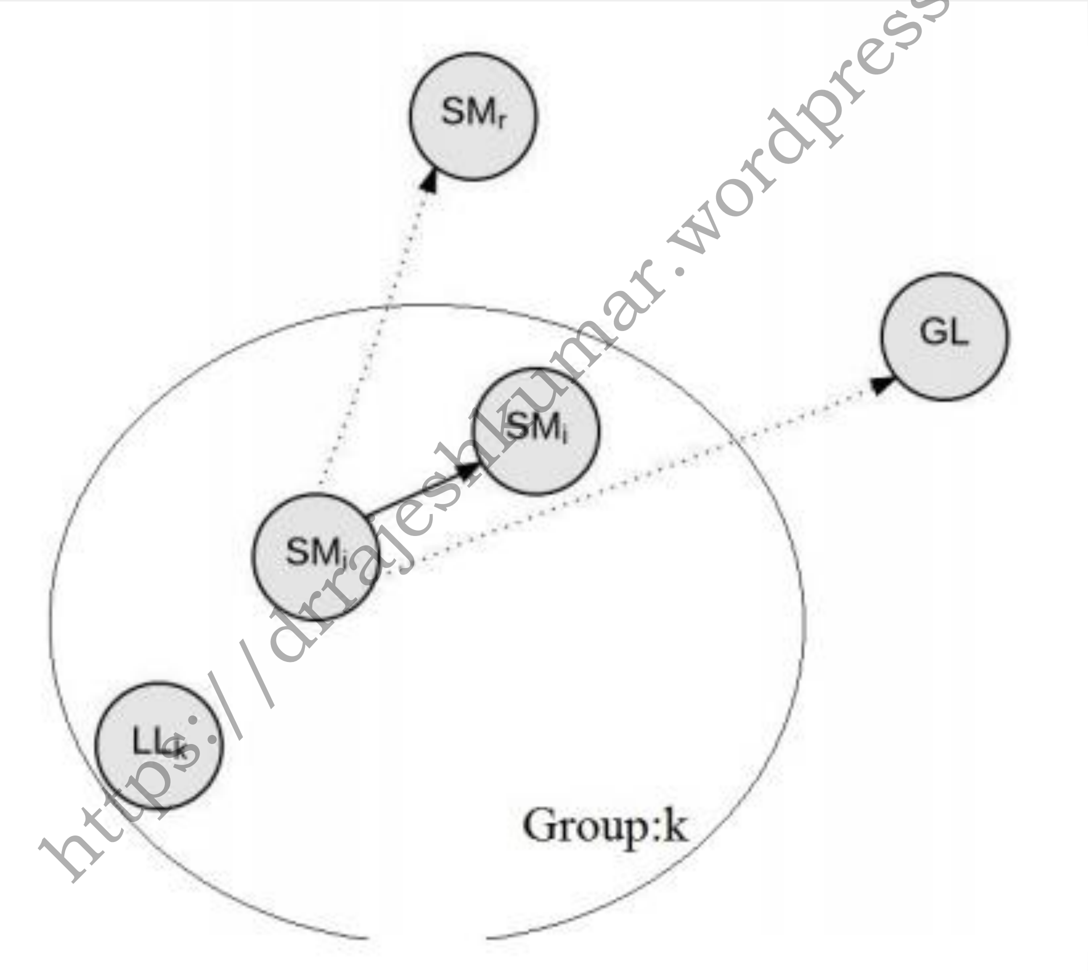
- The position update equation :

$$SM_{ij}^{new} = SM_{ij} + U(0,1) \times \left(GL_j - SM_{ij}\right) + U(-1,1) \times (SM_{rj} - SM_{ij})$$

- Positions of SM_i are updated based on the probabilities $prob_i$:

$$prob_i = 0.9 \times \frac{fitness_i}{\max\_fitness} + 0.1$$

Global Leader Phase (GLP)



Algorithm: GLP

Algorithm 2 Position update process in Global Leader Phase (GLP) :

for $k = 1$ to MG **do**
    $count = 1$;
    $GS = k^{th}$ group size;
    while $count < GS$ **do**
        for $i = 1$ to GS **do**
            if $U(0,1) < prob_i$ **then**
                $count = count + 1$.
                Randomly select $j \in \{1 ... D\}$.
                Randomly select SM_i from k^{th} group s.t. $r \neq i$.
                    $SM_{ij}^{new} = SM_{ij} + U(0,1)(GL_j - SM_{ij}) + U(-1,1)(SM_{rj} - SM_{ij})$.
            end if
        end for
    if i is equal to GS **then**
        $i = 1$;
    end if
    end while
end for

Global Leader Learning (GLL) Phase

- In this phase, the global leader is updated by applying the greedy selection in the population (the position of the SM having best fitness in the population is selected as the updated position of the global leader).

- The **Global Limit Count** is incremented by 1 if the position of the global leader is not updated.

Local Leader Learning (LLL) Phase

- In this phase, the position of the local leader is updated by applying the greedy selection in that group i.e., the position of the *SM* having best fitness in that group is selected as the updated position of the local leader.

- If the fitness value of the new local leader position is worse than the current position then the **Local Limit Count** is incremented by 1.

Local Leader Decision (LLD) Phase

- If the local leader position is not updated for specific number of iterations which is called **Local Leader Limit (LLL)**, then all the spider monkeys (solutions) update their positions randomly or by combining information from Global Leader and Local Leader based on *pr*.

$$SM_{ij}^{new} = SM_{ij} + U(0,1) \times \left(GL_j - SM_{ij}\right) + U(0,1) \times (SM_{ij} - LL_{kj})$$

Algorithm: LLDP

Algorithm 3 Local Leader Decision Phase:

for $k = \{1 \ldots MG\}$ **do**
  if $LocalLimitCount_k > LocalLeaderLimit$ **then**
    $LocalLimitCount_k = 0$
    $GS = k^{th}$ group size;
    for $i \in \{1 \ldots GS\}$ **do**
      for each $j \in \{1 \ldots D\}$ **do**
        if $U(0,1) \geq pr$ **then**
          $SM_{ij}^{new} = SM_j^{new} + U(0,1) \times (SM_j^{max} - SM_j^{min})$
        else
          $SM_{ij}^{new} = SM_{ij} + U(0,1) \times \left(GL_j - SM_{ij}\right) + U(0,1) \times (SM_{ij} - LL_{kj})$
        end if
      end for
    end for
  end if
end for

Global Leader Decision (GLD) Phase

- If the global leader is not updated for a specific number of iterations which is called **GlobalLeaderLimit (GLL),** then the global leader divides the (group) population into sub-populations (small groups).

- The population is divided into two and three subgroups and so on till the maximum number of groups MG.

Algorithm: GLDP

Algorithm 4 Global Leader Decision Phase**:**

If $GlobalLimitCount > GlobalLeaderLimit$ **then**

  $Global\ LimitCount = 0$

  if $Number\ of\ groups < MG$ **then**

    Divide the population into groups.

  else

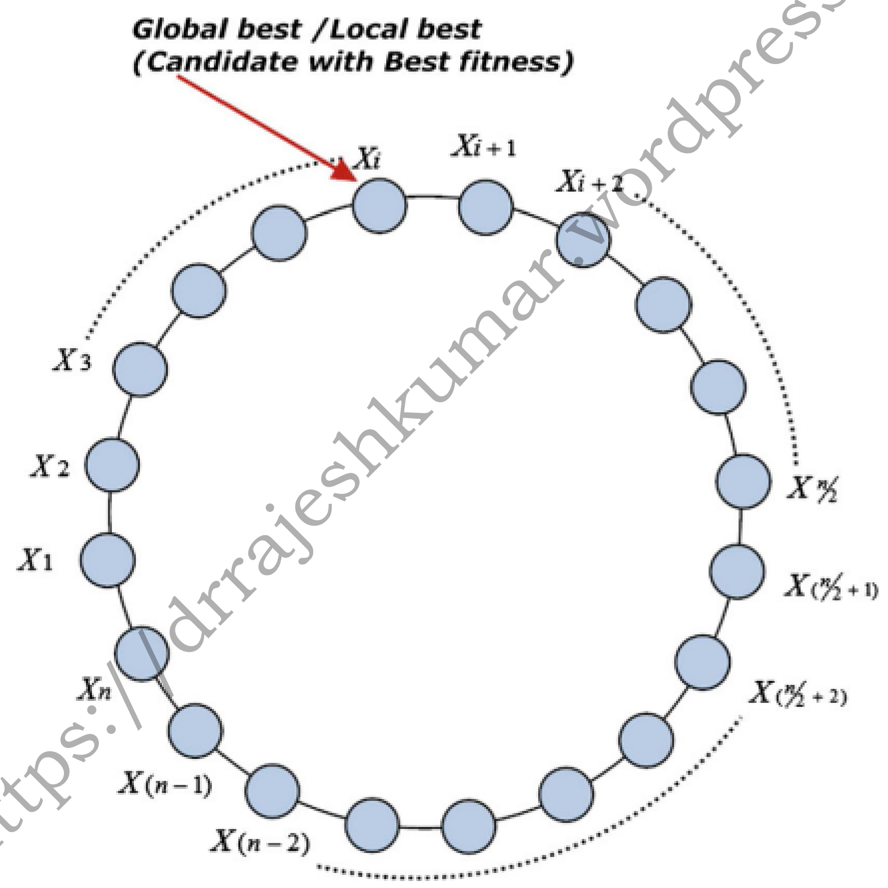
    Combine all the groups to make a single group.

  end if

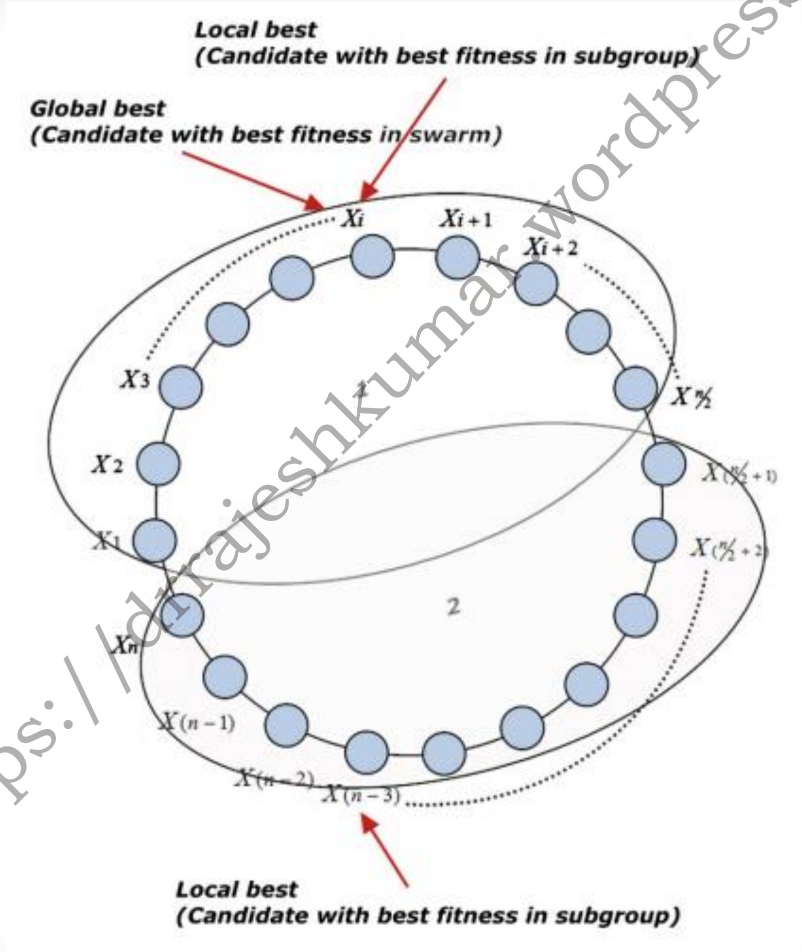
  Update Local Leaders position.

end if

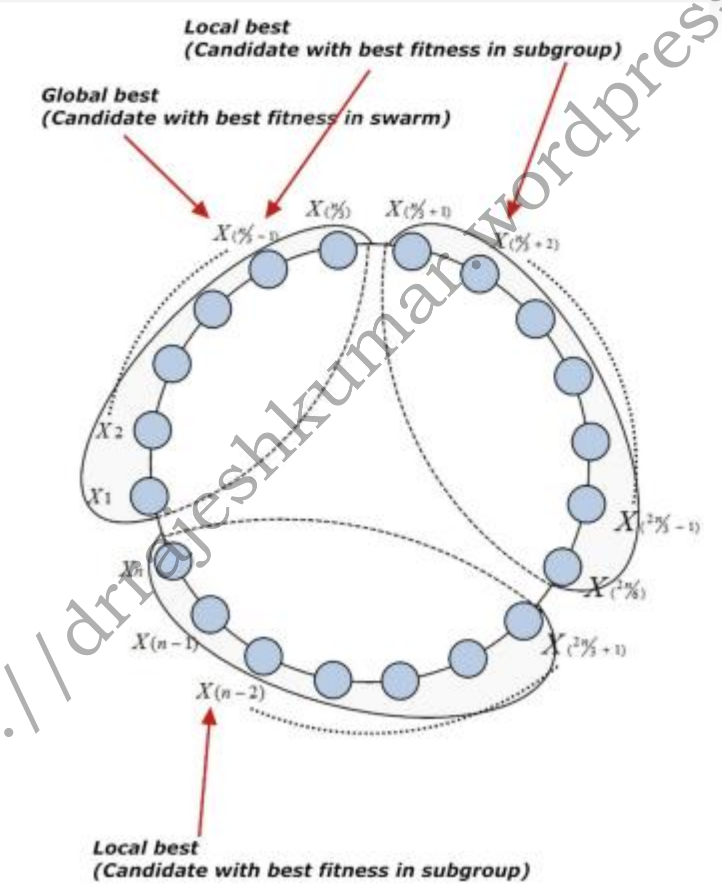
Single Group



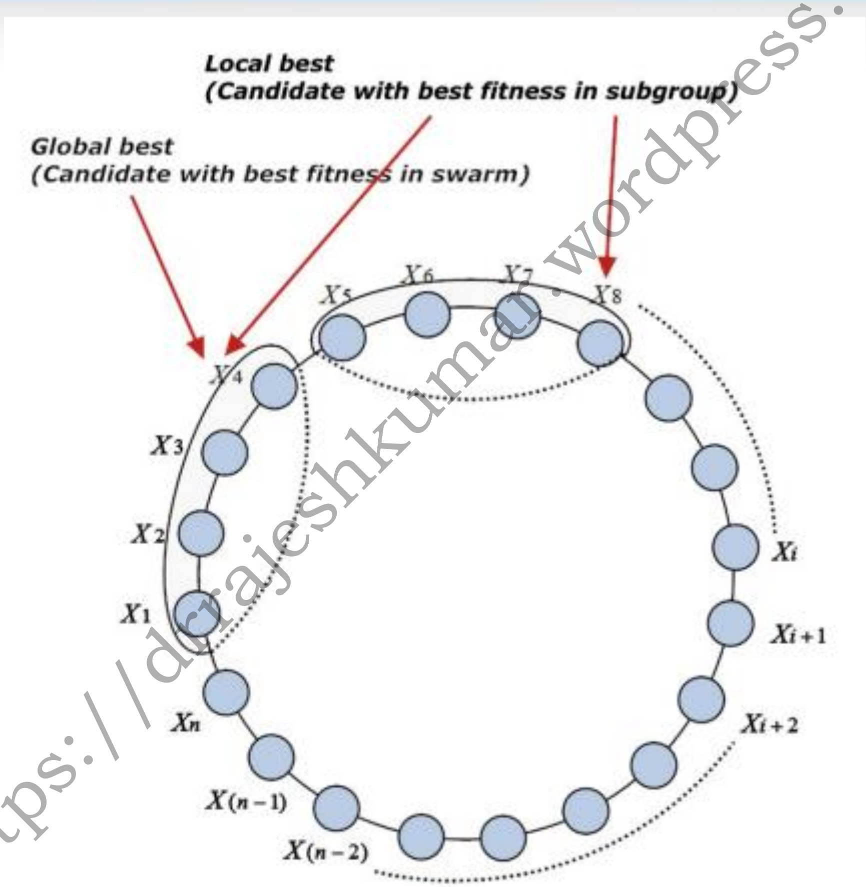
Swarm Divided Into Two Group



Swarm Divided Into three group



Minimum Size Group



Control Parameters in SMO

Four Control Parameters in SMO:

1. *Local Leader Limit* : $D \times N$
2. *Global Leader Limit* : $\in [\frac{N}{2}, 2 \times N]$
3. the maximum group MG : $\frac{N}{10}$
4. perturbation rate pr : $\in [0.1, 0.9]$

Example

Objective function:

$$\min(f(x_1, x_2)) = (x_1 - 1)^2 + (x_2 - 2)^2$$

Subject to $-4 < x_1, x_2 < 4$

Initialization

- Initial population (N) = 5
- Dimension (D) = 2
- Number of groups = 2
- pr = 0.5
- Population Generate SM_i :

	Initially	$\boldsymbol{f}_{\mathbf{i,0}}$
$SM_{1,0}$	(1,0)	4
$SM_{2,0}$	(-1,1)	5
$SM_{3,0}$	(3,-1)	13
$SM_{4,0}$	(2,2)	1
$SM_{5,0}$	(-2,3)	10

Objective Function Value

	Initially	$f_{i,0}$
$SM_{1,0}$	(1,0)	**4**
$SM_{2,0}$	(-1,1)	5
$SM_{3,0}$	(3,-1)	13
$SM_{4,0}$	(2,2)	**1**
$SM_{5,0}$	(-2,3)	10

$$f_{0,avg} = 6.6 \; and \; f_{0,min} = 1$$

Local Leader Phase (LLP)

	Initially	$f_{i,0}$		$SM_{ij}^{new} = SM_{ij} + U(0,1) \times (LL_{kj} - SM_{ij}) + U(-1,1)(SM_{rj} - SM_{ij})$	SM_{ij}^{new}
$SM_{1,0}$	(1,0)	**4**	SM_1^{new}	$(1,0) + 1[(1,0) - (1,0)] + 1[(-1,1) - (-1,0)]$	$(-1,1)$
$SM_{2,0}$	(-1,1)	5	SM_2^{new}	$U(0,1) < pr$	$(-1,1)$
$SM_{3,0}$	(3,-1)	13	SM_3^{new}	$(3,-1) + 1[(1,0) - (3,-1)] + 1[(1,0) - (3,-1)]$	$(-2,1)$
$SM_{4,0}$	(2,2)	**1**	SM_4^{new}	$(2,2) + 1[(2,2) - (2,2)] + 1[(-2,3) - (2,2)]$	$(-2,3)$
$SM_{5,0}$	(-2,3)	10	SM_5^{new}	$U(0,1) < pr$	$(-2,3)$

New $SM_{i,1}$

	Initially	$f_{i,0}$		SM_{ij}^{new}	$f_{0,new}$	$SM_{i,0}$
$SM_{1,0}$	(1,0)	4	SM_1^{new}	$(-1,1)$	5	(1,0)
$SM_{2,0}$	(-1,1)	5	SM_2^{new}	$(-1,1)$	5	(-1,1)
$SM_{3,0}$	(3,-1)	13	SM_3^{new}	$(-2,1)$	10	(-2,1)
$SM_{4,0}$	(2,2)	1	SM_4^{new}	$(-2,3)$	10	(2,2)
$SM_{5,0}$	(-2,3)	10	SM_5^{new}	$(-2,3)$	10	(-2,3)

Calcultion of $prob_i$

$$prob_i = 0.9 \times \frac{min\_fitness}{fitness_i} + 0.1$$

	Initially	$f_{i,0}$		SM_{ij}^{new}	$f_{0,new}$	$SM_{i,0}$	$f_{i,0}$	$prob_i$
$SM_{1,0}$	(1,0)	4	SM_1^{new}	$(-1,1)$	5	(1,0)	4	0.325
$SM_{2,0}$	(-1,1)	5	SM_2^{new}	$(-1,1)$	5	(-1,1)	5	0.28
$SM_{3,0}$	(3,-1)	13	SM_3^{new}	$(-2,1)$	10	(-2,1)	10	0.19
$SM_{4,0}$	(2,2)	1	SM_4^{new}	$(-2,3)$	10	(2,2)	1	1
$SM_{5,0}$	(-2,3)	10	SM_5^{new}	$(-2,3)$	10	(-2,3)	10	0.19

Group Leader Phase

	$SM_{i,0}$	$SM_{ij}^{new} = SM_{ij} + U(0,1) \times (GL_j - SM_{ij}) + U(-1,1)(SM_{rj} - SM_{ij})$	SM_{ij}^{new}
$SM_{1,0}$	(1,0)	(1,0) + 1[(2,2) − (1,0)] + 1[(−1,1) − (1,0)]	(0,3)
$SM_{2,0}$	(−1,1)	(−1,1) + 1[(2,2) − (−1,1)] + 1[(−2,1) − (−1,1)]	(1,2)
$SM_{3,0}$	(−2,1)	(−2,1) + 1[(2,2) − (−1,1)] + 1[(1,0) − (−2,1)]	(5,1)
$SM_{4,0}$	(2,2)	(2,2) + 1[(2,2) − (2,2)] + 1[(−2,3) −(2,2)]	(−2,3)
$SM_{5,0}$	(−2,3)	(1,0) + 1[(2,2) − (1,0)] + 1[(1,1) −(1,0)]	(6,1)

Objective Function Value after first iteration

	$SM_{i,0}$	$f_{i,0}$		SM_{ij}^{new}	$f_{0,new}$	$SM_{i,1}$	$f_{i,1}$
$SM_{1,0}$	(1,0)	4	SM_1^{new}	(0,3)	2	(1,0)	2
$SM_{2,0}$	(−1,1)	5	SM_2^{new}	(1,2)	0	(-1,1)	0
$SM_{3,0}$	(−2,1)	10	SM_3^{new}	(5,1)	17	(3,1)	5
$SM_{4,0}$	(2,2)	1	SM_4^{new}	(−2,3)	10	(2,2)	1
$SM_{5,0}$	(−2,3)	10	SM_5^{new}	(6,1)	26	(2,1)	2

$$f_{0,avg} = 2 \; and \; f_{0,min} = 0$$

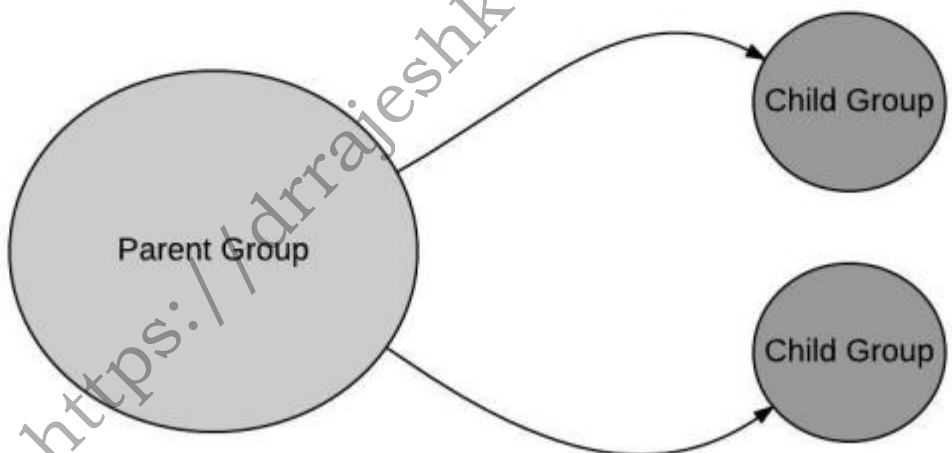
Problems With SMO

- In the original SMO algorithm, the position of each spider monkey is updated depending upon the position of another randomly selected spider monkey in LLP and GLP.
- This update is irrespective of whether the position of randomly selected monkey is better or not
- This leads to low convergence rate further causing high rate group breaking and merging.

ASMO is developed !

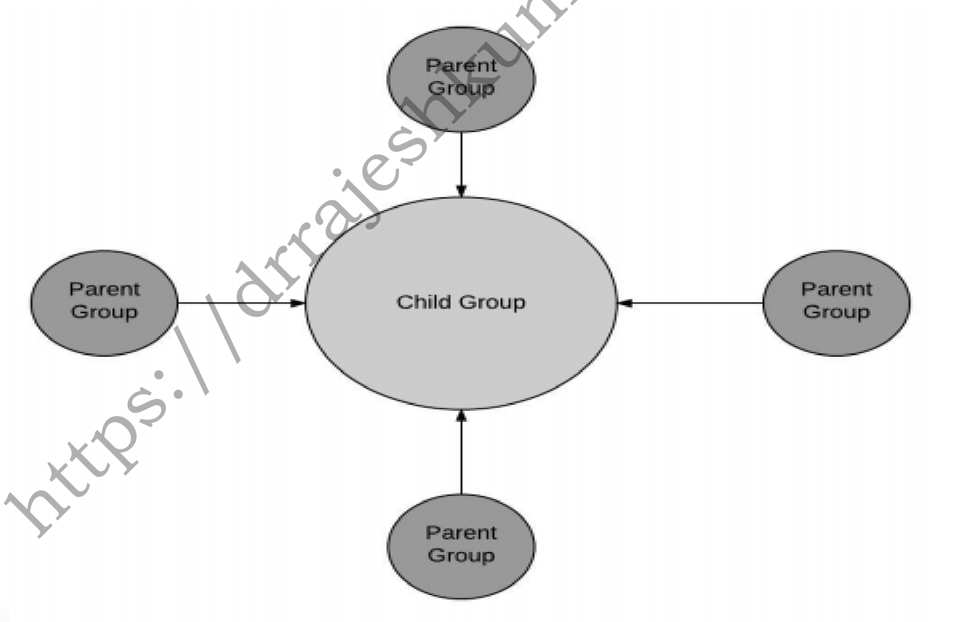
Local Leader Decision (LLD) Phase

- If a Local-Leader's position is not up dated for a predetermined number of iterations then that local leader can decide to break up its group into 2 halves . This can be seen as replicating the fission process in the spider monkey swarm.



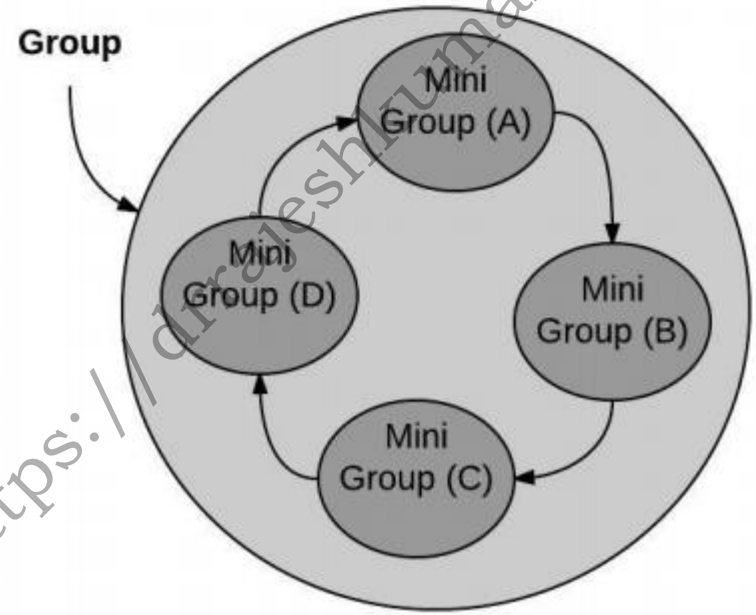
Global Leader Decision (GLP) Phase

- If the Global-Leader's position is not up dated for a predetermined number of iterations then that global leader can decide to merge all the groups together. This can be seen as replicating the fusion process in the spider monkey swarm.

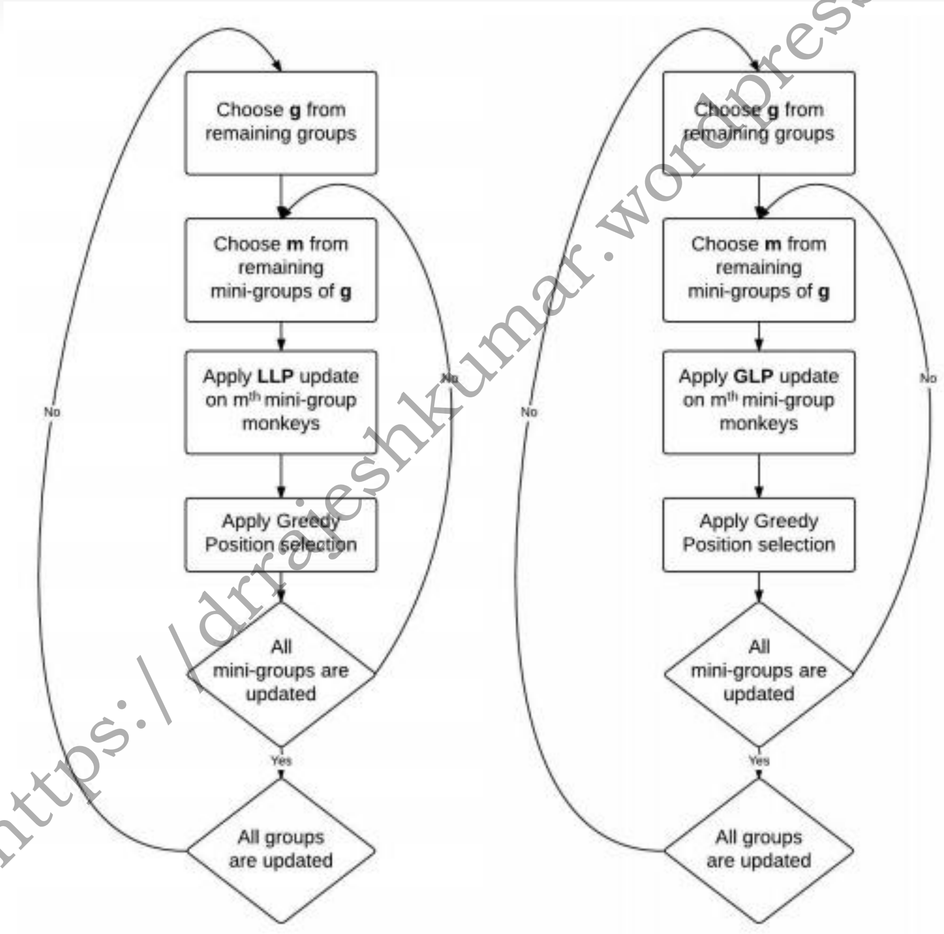


Age Based Sub division

- Each group is further divided into multiple mini-groups on the basis of the age of the individual monkeys to replicate the difference in the physical abilities of the individual monkeys.



Age based LLP and GLP update

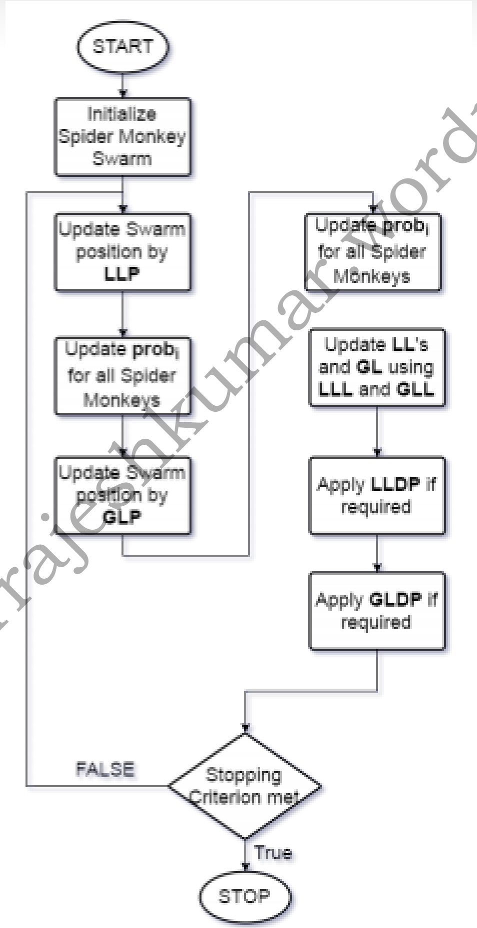


Advantage of Age based Sub division

- By doing so the slower/older groups would gain from the information gained by the faster groups during the LLP and GLP position up date.

- This enables them the chance to choose better random monkeys for updating their position thus improving the convergence of the overall algorithm.

Overall ASMO algorithm



Example

Objective function:

$$f(x_1, x_2) = (x_1 - 5)^2 + (x_2 - 2)^2$$

$$\min\big(f(x_1, x_2)\big) = 0 \; at \; x_1 = 5 \; and \; x_2 = 2$$

Iteration=Initial

	x_1	x_2	f
1	3.9119	0.2291	31.5541
2	3.4557	4.3762	8.0315
3	6.1716	5.2035	11.6350
4	9.7900	0.8466	24.2748
5	3.9716	5.8186	15.6391
6	9.5872	9.5511	78.0609
7	2.3959	8.0942	43.9200
8	5.8313	6.2626	18.8610
9	2.7949	4.3316	10.2988
10	9.3439	3.1406	20.1706
11	**3.9119**	**0.2291**	**4.3199**
12	9.9202	9.3949	78.8935

Iteration=1

	x_1	x_2	f
1	4.5700	2.5567	0.4948
2	3.4557	4.3762	8.0315
3	4.5297	3.2526	1.7903
4	4.5002	0.1946	3.5093
5	3.9716	5.8186	15.6391
6	5.8495	9.5511	57.7406
7	2.7661	8.0942	42.1290
8	5.8313	6.2626	18.8610
9	**4.5700**	**2.5567**	**0.4948**
10	5.4015	3.3942	2.1049
11	3.9119	0.2291	4.3199
12	6.2083	0.0174	5.3907

Advantages over other algorithms

- Better convergence rate due to subdivision based position update.
- Fission-Fusion based social structure enables the algorithm to easily avoid the local minima.
- Only two hyper-parameters to be adjusted in terms of iteration limits to break or merge the groups.

Comparison with other Algorithms

	DE	ASMO	LdDE	ILABC	SSG-PSO	ECLPSO
Sphere	30	**0.00E+00**	5.68E-14	7.54E-43	**0.00E+00**	**1.00E-96**
Elliptic	30	**0.00E+00**	6.23E-14	8.61E-39	**0.00E+00**	**8.41E-92**
Ackley	30	**2.18E-14**	3.26E-11	**2.77E-14**	**1.25E-14**	**3.55E-15**
Rosenbrock	30	8.27E+00	1.87E+00	**1.01E-01**	6.90E+00	2.75E+01
Rastrigen	30	**0.00E+00**	3.21E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**
Griewank	30	**0.00E+00**	2.11E-02	3.64E-13	**0.00E+00**	**0.00E+00**
Schwefel 2.22	30	**2.25E-86**	4.34E-08	6.02E-23	9.33E-22	2.02E-31
Schwefel 1.2	30	1.29E-01	**3.74E-09**	8.92E+01	4.16E+01	5.62E+01
Shifted Rosenbrock	30	1.26E+01	3.27E+00	8.34E-01	**2.64E-13**	3.42E+01
Shifted Rastrigen	30	**0.00E+00**	4.91E+00	0.00E+00	1.22E+01	**0.00E+00**
Wilcoxon test	p		0.273	0.0781	0.4375	0.0313
	h		1	0	0	1

Thank You