Robust Path Planning of Swarm Robots using PSO assisted Bacterial Foraging

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Abstract

Swarm robots collaborating in groups offer various benefits and can execute a few undertakings that could be troublesome for a single robot. Regardless of headway in Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization Algorithm (BFOA) for ideal way arranging and formation control separately, their blend on swarm direction is unexplored. In this paper, we have proposed a novel transformative based calculation called, ”PSO assisted Bacterial Foraging” for the rushing of an automated swarm to a predefined focus with briefest way while sidestepping snags. Our calculation utilizes a blend of PSO for proficient and fast path selection and BFOA for keeping up the formation all through the direction. Experimental results show that intelligent switching of these two competing algorithms produce robust solution for dynamic path planning as well as formation preserving between the robots in presence of static obstacles keeping the trajectory path consistent.

1 Introduction

Over decades the regular wonders of swarming have summoned serious research interests in scientific and engineering fields. Such marvels can be seen in numerous distinctive animals [Derr and Manic, 2009], for example, herds of relocate feathered creatures,schools of reef fish. The aggregate gathering practices of these species are accepted to have certain focal points over individual ones, for instance, expanding the survival chances for the entirety amass under the risk from predators.

In a stationary circumstance (where obstacles are static), utilization of a group of robots to complete an errand has a few essential angles, for example, path planning, proficient robot correspondence, impediment evasion and so on [Arai *et al.*, 2002],[Sheng *et al.*, 2006]. Every robot is outfitted with sensors that can recognize neighboring agents and impediments inside a specific breaking point yet with some error [Liu *et al.*, 2003]. Proportionately, it can have a few methods for correspondence which can be utilized to discover the places of different robots inside this restrain so that appropriate formation with efficient path planning among the robots is conceivable to assemble. It is normal that position can be evaluated accurately. Every robot has the information about the position of all other agents in the group. As a general rule the robots, with inbuilt sensors can assess the route work with regard to every one of the impediments. Afterward if a robot detects more snags, this can be suited in the guide and the route capacity is recalculated.

Thusly, with a particular objective to fabricate the productivity of multi-robot systems, and to maintain a strategic distance between agent crashes amid mission, it is fundamental to develop a coordination technique among the robot in the swarm [Panigrahi *et al.*, 2014]. Coordination procedures for multi-robot systems describe how a gathering of homogeneous robots experience a domain without colliding with impediments or other robots along their ways [Roy, 2013],[Roy and Maitra, 2013]. Self-organizing [Balch and Arkin, 1998] structures are rash, they are not composed or controlled by any specialist or subsystem, and are directed by the individual exercises of the operators. The resulting association is totally decentralized and conveyed over all operators of the system. Gathering of self-sorting out robots look like swarms as they go over the earth, where each robot upgrade its position with the end goal that it could keep up a shielded partition from neighboring robots [Balch and Hybinette, 2000]. The swarms similarly change their pattern to suit the requirement for varieties in the working environment. This rule would permit the swarm fit into slender sections and to circumvent irritating hindrances. Moreover, with a specific objective it might be impossible for the swarm to overcome certain complex environment. There must be some reserve objective which needs to follow in unavoidable situation so that overall situation is overcome [10].

The rest of the paper is organized as follows: in section 2, we have discussed about the literature survey. The swarm robotic mathematical model as well as the self-organizing (neighboring based)formation control strategy are described in section 3. The problem is formulated in section 4. The overview of PSO assisted BFOA is defined in section 5. Section 6 includes the performace comparison along with some selective yet significant simulation results. Section 7 has concluded the present work.

2 Literature Survey

Organically enlivened arrangements mimic productive groupings of animals in nature, for instance, rushing winged animals, scavenging bugs, tutoring fish, and swarming bumble bees. These sorts of developments regularly apply in self-arranging standards [Gazi, 2005]. In a self-association calculation, the judgments of fragments are left hazy, and these parts are required to mastermind themselves until they shape a system that has the pined for helpfulness. In [Yoshioka and Namerikawa, 2008], the paper portrays arrangement control procedures with Virtual Structure (VS) for multi-vehicle frameworks. A few control laws are presented for organized multi vehicle framework keeping in mind the end goal to accomplish VS accord, VS running and VS rushing with impact shirking. The asymptotic soundness of the controller is likewise demonstrated. In [Su *et al.*, 2009], the creators demonstrate that the Olfati-Saber [Olfati-Saber, 2006] rushing calculation still enables all the educated operators to move with the pined for relentless speed, and a clueless specialist to in like manner move with the same looked for speed if the educated operators can affect it now and then in the midst of the progression. Numerical reproduction demonstrates that a little no of educated operators can realize most of the specialists to move with the looked for speed and the greater the educated gathering is the more noteworthy piece of operators will move with the fancied speed. In the situation where the virtual pioneer goes with a differing speed, a proposed acclimation to the Olfati-Saber calculation [Olfati-Saber, 2006] shows that the consequent count engages the asymptotic after of the virtual pioneer. That is, the position and speed of the focal point of mass of all operators will focalize exponentially to those of the virtual pioneer. The united rate is also given. In [Tanner *et al.*, 2003], control law for crash evasion and union of a swarm is determined. In [Lei *et al.*, 2008], creators utilize swarm rushing control technique to execute Reynolds biods demonstrate among the multi-robots. A stable running con trol law with the assistance of chart theoretic approach is ascertained to build up a craved shape, while every one of operators' speeds and positions merge to the same. Reenactment in Player/Stage shows that proposed procedure can be productively connected to multi-robot arrangement control issue.

Contribution: In the paper [Roy *et al.*, 2016], formation control strategy is built in view of 'attraction-repulsion' technique. The proposed controller is droved by two understood transformative systems, to be specific, Bacterial Foraging Optimization Algorithm (BFOA) and Particle Swarm Optimization (PSO). We observe some intriguing outcomes; mechanical swarm when left by BFOA accomplishes strict formation all through the adventure, however with expanding multifaceted nature of the earth, the effectiveness of the framework diminishes. While the framework delivers least path length with no arrangement when left by PSO. The above perceptions propel us to develope a fusion methodology for repaying the above issues.

The success rate of BFOA (56%) to reach to the desired location is very less when compared with PSO (100%). But BFOA promises strict formation throughout the trajectory while PSO declares shortest path. *The fusion of BFOA and PSO produce higher success rate than BFOA but formation in most of the journey is not maintained.* To develop all requirement, we switch PSO and BFOA intelligently, namely *PSO assisted BFOA* for increasing the accuracy and efficiency. It guarantees higher success rate than BFOA, lower path length, and maintains formation (most of the journey). We also present an extensive statistical analysis and simulation results to differentiate the performance of PSO and BFOA.

3 Swarm Mathematical Model

Let there be total N identical swarm in a 2D plane, then dynamics of each agent(considering point-mass) can be described by [Liu and Passino, 2004];

$$\dot{x}_i^{(1)} = x_i^{(2)}, ..., \dot{x}_i^{(N-1)} = x_i^{(N)} \tag{1}$$

$$\dot{x}_i^{(n)} = u_i; i = 1, 2, ..., N \tag{2}$$

where $x_i^{(m)}$ is the m^{th} derivative and u_i is the control input of i^{th} agent. The relative position vector between i^{th} and j^{th} agent can be expressed as $x_{ij} = x_i - x_j$.

Consider the interaction between agent-to-agent and agent-to-obstacle are "attraction-repulsion" type. Attraction function [Gazi and Passino, 2002] depicts that each agent wants to maintain a constant distance to every other neighbors for achieving grouping and cohesion whereas repulsion function is for avoiding inter-agent and agent-obstacle collision. Attraction function can be represented as $-k_p^i x_{ij}$ ($k_p^i > 0$ is the strength of attraction) and repulsion function [Gazi and Passino, 2002] can be represented by k_r^i $exp(\frac{-0.5||x_{ij}||^2}{{r_s^i}^2})x_{ij}$ ($k_r^i > 0$ is the magnitude of repulsion, $r_s^i > 0$ is the repulsion region). Then the control input for each agent can be defined by;

$$\begin{aligned} u_i &= -m_i k_p^i e_{pi} - m_i k_v^i e_{vi} \\ &+ m_i k_r^i \sum_{i \neq j}^{N} exp(\frac{-0.5||e_{pi} - e_{pj}||^2}{{r_s^i}^2}) * (e_{pi} - e_{pj}) \end{aligned} \tag{3}$$

where k_p^i, k_v^i are position and velocity attraction gains, $e_{pi}(= x_i - \bar{x})$ and $e_{vi}(= v_i - \bar{v})$ are the position and velocity error of the i^{th} agent from the average position and velocity of the swarm respectively.

3.1 Neighbors Based Formation Control

Formation control is a coordinated control for a fleet of robots so that they maintain a desired spatial pattern throughout entire journey [Roy and Maitra, 2013]. The robots can move together without collision and form certain pattern/formation to perform the task better. Control of dynamics of individual members of the formation so that the formation shows the desired motion characteristics as a whole. The control input for maintaining a certain formation is well known neighbor-based law [Roy, 2013], decribed by

$$u_i = -\sum_{j \in N_i} \sum_{m=0}^{N-1} k_m (x_i^{(m+1)} - x_j^{(m+1)}) \tag{4}$$

where $k_0, ..., k_{(n-1)}$ are the nonzero feedback gains. Combaining the euqations (3) and (4) constitute the control law for the overall system.

4 Problem Formulation

To evaluate the next positions of each member of the swarm from their current positions in a given environment with static obstacles, the following approximations is made to validate the path planning problem.

- Robots are of the same model and satisfy non-slipping and pure-rolling constraints.
- The present location of each agent is known with respect to the given frame of reference.
- Each agent can exchange necessary information via communication equipment.

Let $f_g(x_i^t)$ is the fitness function that determines the distance of i^{th} agent from target zone (x_g) at t instances which can be expressed as for N agents;

$$f_g(x^t) = \sqrt{\sum_{i=1}^{N} ||x_i^t - x_g||^2} \tag{5}$$

Let $f_o(x_i^t)$ is the fitness function corrosponds to the hindrance's location and neighbor's-agent position. Consider $d_{i'j'}$ is the distance between i^{th} and j^{th} agent's next position. Then the constrants that the agent will not hit its kin is given by [Chakraborty *et al.*, 2008]; $d_{i'j'} - 2r_s > 0$. Then $f_o(x^t) =$

$$\sum_{i'=1}^{N} \sum_{j'=1, i \neq j}^{N} (max(0, (d_{i'j'} - 2r_s)))^2 + \sum_{i=1}^{N} (\frac{f_{ob}}{d_{i,obs}}) \tag{6}$$

where $d_{i,obs}$ is the distance of the nearest obstacle from the i^{th} agent and $f_{ob}(= 6200)$ is the scale factor in our experiment.

For successful formation control, $F(x_i^t)$ should be minimized for various values of gains (equation 4). Therefore, the overall fitness function can be written as;

$$f = f_g(x^t) + f_o(x^t) + F(x^t) \tag{7}$$

which needs to be minimized based on the current positions of the robots with respect to their target zone, constrained by neighbor-agents/obstacles in their trajectory and formation breaking to avoid such obstacles and inter-agent collision.

5 PSO assisted Bacterial Foraging Optimization Algorithm

BFOA [Roy, 2013] is a meta-heuristic inspired from the foraging behavior of E. coli bacteria; in the nature once a bacteria reaches to the desired location, it should attract the others so that the whole swarm converge to the same. The main advantage of this technique is formation control i.e. throughout the trajectory they maintain a specific formation. On the other hand, PSO [Roy and Maitra, 2013] is another search method which is able to enhance the performance of the system with optimum result. The key idea of PSO assisted BFOA consists of combining these two approaches together in which PSO ensures a fast convergence towards optimal path solution and BFOA is acting to maintain the formation throughout the trajectory.

PSO assisted BFOA Algorithm

Figure 1 represents the flowchart of our proposed algorithm. The deatils is written below;

Step 1: Parameter Initialization: Initialize the no of agent in the swarm, initial position of each agent, goal position, no of particles in PSO and no of bacteria in BFOA.

Step 2: Path Selection: The bacteria search for the shortest path in the environment from the start point to goal position with formation control strategy. This step is divided into two parts; first part is responsible to minimize/maximize the fitness function and second part is responsible for evaluating the optimum value of the gains.

1st part: BFOA is started to minimize the goal function and to maximize the obstacle function.

2nd part: Attraction gain, formation gain, velocity damping gain, repulsion gain are evaluated based on the current fitness value.

Step 3: Path Updating: Next position and velocity of every agent is updated depending on the previous step. But often the swarm is unable to cross obstacles with maintaining formation. In such situation the system has to break the formation to evade the obstacle (which is the demerit of BFOA).

Step 3.1: Obstacle Avoidance using PSO: If goal is not reached and previous position of the each agent is same as the next position, then it can be concluded that BFOA has failed. In such condition, PSO is started for some random duration to avoid the obstacle. This algorithm is divided in three part:

1st part: PSO is used to minimize the goal function and to maximize the obstacle function.

2nd part: Attraction gain, velocity damping gain, repulsion gain are evaluated.

3rd part: According to the value of the previous step, the next position and velocity is updated for each agent in the swarm.

Step 3.2: If obstacle is avoided: If the obstacle is avoided using PSO then the algorithm is shifted to step 2 and continue until goal point is reached.

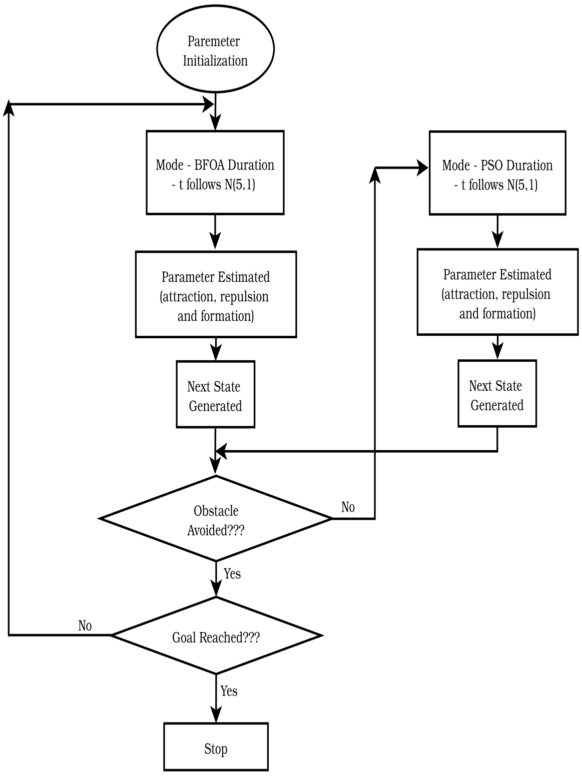

Figure 1: PSO assisted BFOA flowchart.

6 Results and Discussions

In this section, the simulation results are presented to evaluate performance of the proposed algorithm with different environment and complexities. Each simulation is repeated for 30 times to record the length of generated path that corresponds to best or optimal solution.

6.1 Simulation Results of the Proposed Method

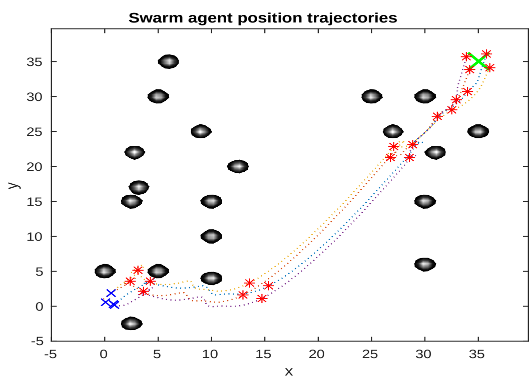

Figure 2: Swarm Trajectory of PSO assisted BG.

Figure 2 represents the simulation result of PSO assisted BFOA. Initially the trajectory of each agent is estimated by BFOA to ensure strong formation. At t = 2.23 sec the swarm is forwarding with a "square" formation. With this specific pattern they are able to avoid obstacle until t = 9.46 sec. Then a typical situation arrive, where strict formation is unable to evade hindrances. In such case, PSO starts automatically. At t = 11.17 sec the strict formation breaks and the swarm easily avoid the snags. After avoiding it, BFOA will start again. The whole system is converged to the previous formation and reached to the desired location at t = 15.15 sec. Here the main advantage is that with the effectiveness of PSO, the success rate is increased to 100%. Moreover, the whole system is able to move to the desired location with proper formation in most of the time.

6.2 Path Length Comparison

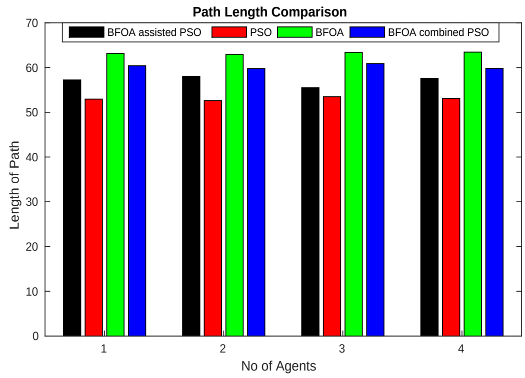

Figure 3: Path Length Comparison of Different Algorithms.

Table 1: Path Length Comparison

Environments	PSO	BFOA	Fusion	Proposed Method
Free Space	48.27	49.07	48.72	48.24
Low Complex	51	54.29	53.55	52.40
High Complex	56.6	60.75	59.32	57.05

To evalute the effcetiveness of our proposed controller, we compare the performance with other controller stated in [Roy *et al.*, 2016] as well as the fusion of these two techniques. Figure 3 and Table 1 represent the comparison study in term of path length. In the obstacle-less environment, our proposed controller produces optimal result than others in every situation. However, PSO guarantees shotest path length in all other situation (low obstacle zone and high obstacle zone), whereas BFOA guarantees strict formation but large path length throughout the journey.

6.3 Formation Comparison

In this work, our main objective is higher effciency in terms of formation control and goal-reached accuracy. Goal-reached accuracy is already accumulated in the previous section. This section includes the formation comparison with different tecniques. Agents to be in strict formation, should always maintain a strategic distance from its neighbors. So at t^th instances the formation (FE) between all agent can be represented by;

$$FE = \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} ||x_i^t - x_j^t||_2 \tag{8}$$

On the off chance that strict formation is kept up, then standard deviation (STD) of FE will create most reduced score comparatively most astounding score acquired when no arrangement is kept up. If there should arise an occurrence of BFOA, as strict arrangement is keep up all through the adventure, the STD of FE deliver a score of 1.98. For PSO, the score is about 20.67. For fusion case, nearness of hindrances will break the formation. So in that situation, the score is about 10.33. In any case, for PSO assisted BFOA, arrangement is kept up until their is an unavoidable tangles. Here, the score is 3.12 which depicts the formation accuracy for proposed controller.

To ensure formation, BFOA is better choice whereas optimal path length is guaranteed by PSO. Switching between this two techniques is proposed to ensure optimal path length as well as formation. From the table itself it has been seen that everything is ensured with our proposed method. Path length is slightly greater than PSO but less than BFOA and fusion, similarly formation is also ensured most of the time.

6.4 Performance Evalution

The formation coefficients of all agents for PSO and BFOA are compared for analysis. Initially a statistical similarity for each agent is compared using analysis of variance (ANOVA) [Hines *et al.*, 2008]. *BFOA formation coefficient* and *PSO formation coefficients* for each agent are tested for null hypothesis H_0 : coefficient does not vary across agents. It is observed that all agent behaviors are same for both cases.

Table 2: ANOVA Results for formation Coefficient

		Degree of Freedom (DF)	Sum of Square (SS)	Mean Square (MS)	F_0
PSO Formation	*Agent*	9	0.0025	2.7e-4	1.12
	Residuals	9990	2.48	2.5e-4	NA
BFOA Formation	*Agent*	9	0.08	9.3e-3	1.3
	Residuals	9990	71.38	7.1e-3	NA

The variation between the agents is less which is confirmed by ANOVA results (Table 2). Hines et al. [Hines *et al.*, 2008] offers detailed insight of ANOVA in chapter 12. Table 2 uses standard notation as in [Chowdhury *et al.*, 2015], gives ANOVA results for the tests that includes relevant data, i.e. degree of freedom (DF), Sum of Squares (SS), Mean Square(MS) and F statistic (F_0). F_0 is the ratio of two MS. It is well known that both MS values follow chi-square distribution [Chowdhury *et al.*, 2015]. F_0 is the ratio of two chi-square variable, so it follows F-distribution. Hence if H_0 is true, F_0 should follow F distribution with degree of freedom (9, 9990). Then the calculated value of F_0 is used to reject H_0 at significance level α, if $F_0 > F_{\alpha,9,9990}$. Now for our case we choose $\alpha = 0.01$. Since $F_{0.01,9,9990}$ = 2.41; this gives $F_0 < F_{0.01,9,9990}$. So we cannot reject H_0 and conclude that BFOA formation coefficients do not vary significantly across agents. Tukey HSD test also shows that no significant difference in mean across agents.

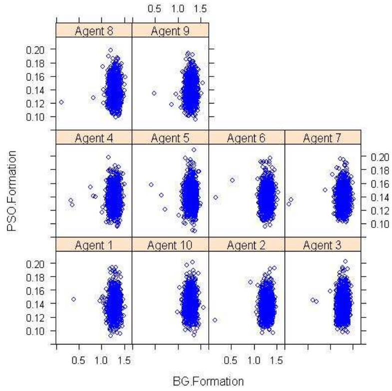

Figure 4: Comparison of PSO and BFOA Formation.

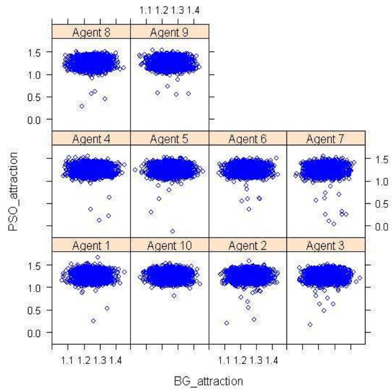

Figure 5: Comparison of PSO and BFOA attraction.

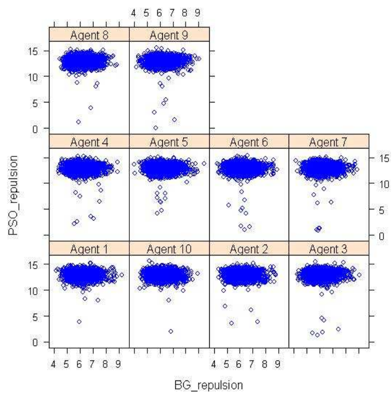

Figure 6: Comparison of PSO and BFOA repulsion.

Figure. 4, 5, 6 show the comparative difference of PSO and BFOA. Most of the formation coefficients of PSO agents are in the range 0.1 to 0.2 where as for BFOA, it is in the range of 1.0 to 1.5. This is responsible for lack of formation in PSO compared to BFOA. Similarly for attraction and repulsion coefficient for PSO and BFOA (Table 2) ANOVA shows that agents (in respective case) are similar in behavior. Hence these coefficients can be compared using their mean for each case. Figure. 5 shows less variation for attraction coefficient for PSO and BFOA. In few instances, the value of attraction coefficients for PSO are below 1. Agents in either case have attraction coefficient values in the range 1.0 to 1.5. So it can be concluded that nature of attraction is similar for either case.

Now to compare repulsion, Figure. 6 represents the coefficient variation for PSO and BFOA. Significant difference can be observed in the coefficient values. Most of the repulsion coefficients of PSO are in the range 10 to 15 where as for BFOA it is in the range of 4 to 9. Thus, we can conclude that PSO can handle repulsion more seriously whereas BFOA is responsible for formation.

Based on the above results BFOA maintains formation where as PSO sacrifices formation to avoid obstacle. The main idea of PSO-assisted BFOA is come to ensure formation maintaining as well as capable of avoiding obstacles.

6.5 Convergence Analysis of the Proposed Controller

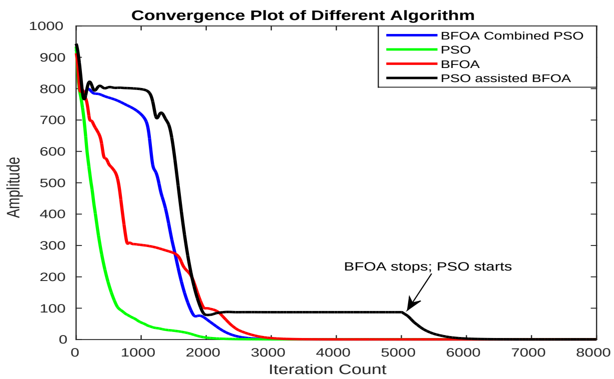

Figure 7: Convergence Plot of Different Algorithms.

Authors tried different algorithms in similar condition for comparative analysis. Figure 7 displays convergence time (iteration count) for each algorithms. BFOA demonstrates highest convergence timing because of the strict formation all throughout the trip, for PSO, the fitness value converges firstly due to shortest path with no formation while fusion produce higher convergence than PSO and lower convergence than BFOA. Whenever swarm stalls out, the convergence plot will keep up a steady esteem (which is represented by the dark horizontal bit of Fig. 7). In such condition, BFOA can't drive the swarm to the objective area. Right then and there, PSO will begin to drive the group to the coveted zone by breaking the formation which decrease the convergence timing for ensureing higher achievement rate than BFOA.

7 Conclusions

In this paper, we introduce PSO assisted BFOA, a new hybrid evolutionary approach to solve global path planning problem with obstacle avoidance in static environment. In our case, lowest path length and formation maintaining are the primary objectives. BFOA alone is unable to fulill it. Using PSO we sacrifice formation only when obstacles cannot be avoided while maintaining formation. This leads to a new hybridize evolutionary method called *PSO assisted BFOA*. Our extensive simulation results conclude that integration these two methods is helpful to fulfill the above criterion. The implementation of PSO assisted BFOA on a real-world robotic platform can be done to demonstrate and effectiveness of our proposed method. Future work can include to study the performance of the same technique in dynamic obstacles contidion.

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