# Coordinated Multi-Robot Movement for Highly-Constrained Exploration Operations Using a Hybrid Algorithm Combining Levy Flight and Particle Swarm Optimization

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## Nomenclature

| | | |
|---|---|---|
| $s$ | = | Stepsize calculated from levy flight movement |
| $\beta$ | = | levyflight parameter for stepsize generation |
| $V_{i,j}$ | = | Velocity of $j^{th}$ robot in $i^{th}$ direction |
| $w$ | = | Inertia factor in Particle Swarm Optimization(PSO) |
| $p_w$ | = | Cognitive factor in PSO |
| $n_w$ | = | Social factor in PSO |
| $t$ | = | Time step |
| $X_{i,j}$ | = | Position of $j^{th}$ robot in $i^{th}$ direction |
| $L\_theta_j$ | = | Levy heading of $j^{th}$ robot |
| $Plbx_j$ | = | Local best position of $j^{th}$ robot in x direction |
| $Plby_j$ | = | Local best position of $j^{th}$ robot in y direction |
| $Pgbx_j$ | = | Global best position of $j^{th}$ robot in x direction |
| $Pgby_j$ | = | Global best position of $j^{th}$ robot in y direction |
| $R\_theta_j$ | = | Inter-robot repulsion heading of $j^{th}$ robot |
| Dj | = | Resultant distance of remaining robots in cluster |

## I. Introduction

There has been an increase in interest to use multiple autonomous robots for exploration tasks in these modern days, because of its many potential advantages. For instance, in Urban Search and Rescue (USAR) operations, the use of robots could prevent humans from exposure to noxious gases and harmful particulate clouds in unpredictable environments; an example is scenarios where one needs to search for victims in a post-disaster office building setup. Multiple robots are preferred to single robots due to the ability to distribute tasks to cover larger areas in shorter search times and also due to the potential for robustness, flexibility, and scalability of the teams. In large area explorations, a cooperative search strategy among robots can decrease the path overlaps by robots, increasing the search efficiency. These strategies can be applied to heterogeneous groups of robots, such as multiple ground vehicles like rovers combined with UAVs to search these areas. Other potential applications for multi-robot area exploration include lunar and planetary exploration tasks in an unknown environment, of great interest to space scientific community.

Particle Swarm Optimization (PSO) is an adaptive population-based method in which the behavior of the particles is a combination of social and cognitive behaviors over iterations and is an effective technique for collective robotic search problems [21]. PSO enables the robots to travel in trajectories to converge on the target location. In the past, Particle Swarm Optimization (PSO) has been used for many multi-robot search operations due to its flexibility and

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easy adaptability [11-12][14-17]. There are many adaptations made to basic PSO to suit the robotic search scenarios versus the particle search. The author in [9] clearly stated about the modifications to basic PSO to suit robot applications like the continuous movement of robots, limitations on movement of robot, considerations on size of robot compared to point sized particles in PSO, calculation of fitness function value in real-world is different to that of PSO, robot collision with obstacles and restrictions on information shared.

However, even after these adaptations, there are assumptions made to suit different scenarios and simplify the problem statement. We have identified four common assumptions to real-world scenarios made in the past studies on PSO based multi-robot searching: assumptions based on information of search area, assumptions on how the position of the robot is determined in the search space, restrictions on the communication system, and assumptions on level of information of target position. The first one is based on information about the area to be explored. A multi-robot search in [11][16][19][21] conducted experiments on the known search area before the start of exploration. Studies in [12][15][17] are based on unknown search space with obstacles, these studies are conducted on limited boundary environment while not knowing the position of obstacles in the search space. However, ant study given an unknown size of the search area is still in the early stages of development[15]. Our study is meant to develop an algorithm that can even work in an environment with no initial information on the size of the environment and produce optimal search efficiency in scenario with no information on obstacles. The second assumption is about the global positioning system of the robot in the search area. Most PSO based search algorithms assume they have perfect knowledge of the position of every robot in the environment at any point in time[12][15-16][17-19]. Very few works of literature worked on the lack of a robot's global position[9][11]. In this current study, the algorithm developed can work independent of information about the position of robot globally. The third assumption is based on the restriction on communication systems and the amount of information shared. In PSO based search algorithms in the past have no restrictions on communications[16][19][21]: robots can communicate among themselves and to the central station at any point in time to share the information of their local best position with all other robots and to determine the global best position within the search space. This type of centralized coordination gives better efficiency[16][18] but in most real-world cases, not all robots will have wide communication abilities, especially indoors; even in cases where it is possible, adding this capability can significantly increase the cost of the mission. Authors in [9][12] studied in limited communication scenarios. The current study deals with this scenario, where robots can only communicate with other robots only within a certain radius and there is no central station to monitor the robot movement. The fourth assumption is about the information about the target being searched. Most of the PSO based robotic search algorithms need to know the position of the target or some kind of information about the target, where the target can emit some signal which can be detected by the robot from long distances[9]. Ref.s [12][11] assumed they can detect the target when they're at a certain distance from the target, using camera or distance sensors to determine the target. To solve this last problem, in the case of a lack of target information, we need to look at what other algorithms can give us. Random walk algorithms are flexible but they tend to be highly inefficient. However, Levy Flight (LF) algorithms [10] are used often where the area of exploration is large and the distribution of targets is sparse. This paper considers these assumptions and discusses a hybrid algorithm, combining the LF and PSO, developed for efficient coordinated searching in these constrained conditions.

In order to deal with problem of restricted communication and lack of information about the search space, target position and position of robot, we attempt to come up with a novel multi-robot searching strategy, which is a hybrid of Levy Flight (LF) and PSO. This algorithm uses LF behavior as a cognitive term and inter-robot repulsion as a social component in basic PSO. Co-operation strategies for robots are well defined for increased search efficiency in most of the real-world search operations, where the size of the search area is initially unknown. Preliminary test simulations have been performed of multiple robots in a closed room without obstacles and seem to be working fine with this hybrid algorithm strategy. In the final paper, we plan to expand the test scenarios to the larger building floor environment with obstacles and other complex boundary conditions.

This paper is set-up in the following sequence. In Section II we discuss background information for the paper, which includes levy flight and the mathematical equivalent of power-law, and basic PSO and its adaptation to multi-robot scenarios. In Section III we explain the methodology of the novel hybrid algorithm, which is a combination of PSO and levy flight; this is meant for searching tasks in an unknown obstacle-rich environment with no boundary information, using multiple decentralized robots with limited communication and no global position information.

Obstacle avoidance policy is discussed. Section IV discusses preliminary implementation results for the hybrid algorithm's performance in comparison to the basic levy flight method for multi-robot scenario. Section V consists of the conclusion for this extended abstract and future plan for the work that will be included in the full, final paper.

## II. BACKGROUND

In this section, Robotic applications of Levy flight movement and Particle swarm optimization are discussed. We developed this algorithm for multi-robot trajectory for a coordinated search to explore large unknown boundaryless area. A combination of LF and PSO is used to explore large areas avoiding paths already explored by other robots.

### A. Levy Flight(LF):

Searching for a target and foraging, which happens in nature is a form of exploration missions. The foraging behaviors of many creatures in nature resemble LF. Study in [2-3] is about the fight trajectories of albatrosses when foraging , the intermittent foraging fight trajectories of fruitflies [4], and the fight trajectories of pelagic seabirds [5]. All these species follow the Levy flight movement naturally. The Author in [1] compared different random walk methods, adapted to robots. It includes Brownian motion and Levy Flight, and proposed their modification for Levy flight for efficient area coverage.

A Levy Flight is a random walk where the step size is determined by a power-law distribution. The probability of larger step sizes is less, and smaller step sizes are chosen more often. In this way, smaller step sizes will do a local search and larger step sizes will help in exploring the unexplored area in the search space. By this varying step sizes chances of robot reaching all the corners of search space increase. The probability of choosing a step size is step_size raised to - λ as shown below.

$P(s) = s^{-\lambda}$ - (1)

where s is step size with $1 < \lambda \leq 3$. By using this probability of small step sizes are high and larger step sizes are less. This paper uses the mathematical formulation for levy flight proposed by Mantega [6] to calculate step size.

$S = \frac{u}{|v|^{\frac{1}{\beta}}}$ - (2)

where $\beta \in [0.3, 1.99]$; u and v are two normal stochastic variables with standard deviation $\sigma_u$ and $\sigma_v$ respectively.

$u \sim N(0, \sigma_u{}^2)$ - (3)

$v \sim N(0, \sigma_v{}^2)$ - (4)

$\sigma_u = \{\frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma[(1+\beta)/2]2^{(\beta-1)/2}\beta}\}^{1/\beta}$ - (5)

$\sigma_u = 1$ – (6)

where Γ(z) is the gamma function.

The simulated model of this levy flight is shown in figure 1.

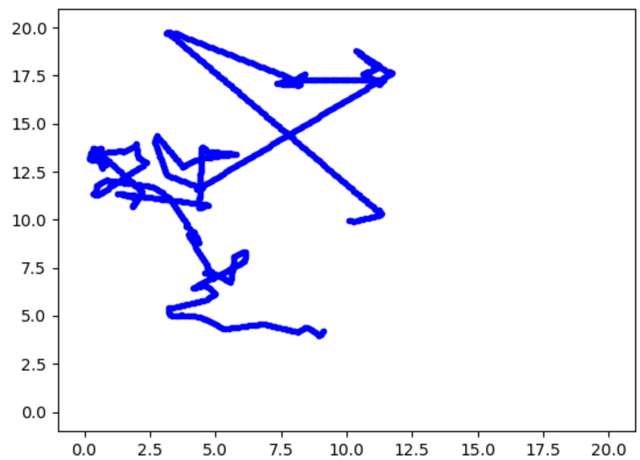


**Fig. 1: Path of single robot following LF in a 20m * 20m search space starting at (10, 10) for 600 timesteps**

In [1] the author uses modified LF for multi-robot coordination, which can be used in similar situations of limited communication range and GPS denied environment. The results of this hybrid algorithm will be compared to the method proposed in this Improved Random walk [1].

**B. PSO for Multi-robot systems**

PSO is an optimization technique developed by James Kennedy and Russell Eberhart [7-8] that uses particles in space, searching for the best solution. It is inspired by the movement of a flock of birds and their interaction with their neighboring birds. In PSO particles are initialized randomly in search space. Each particle can calculate fitness value for its position and velocity for its next step. In every iteration, velocity gets updated based on its local best position of the particle and global best position of all the particles combined. Velocity for the particle in that iteration is calculated by the following equation:

$v_{i,j}(t + 1) = \omega.\ v_{i,j}(t) + p_{\omega}.\ rand(Plb_{i,j}(t) - x_{i,j}(t)) + n_{\omega}.\ rand(Pgb_{i}(t) - x_{i,j}(t))$ – (7)

$x_{i,j}(t + 1) = v_{i,j}(t + 1) + x_{i,j}(t)$ – (8)

Equation 7 contains three parts: momentum, cognitive component, and social component. $\omega$ in momentum part is inertia coefficient which tries to get away from current velocity path by decreasing its intensity. $p_{\omega}$ is the weight given to the attraction to local best position of particle and $n_{\omega}$ is the weight given to the attraction to the global best position, which is best local position of all the particles in the neighborhood. rand() is a sampling of number in range (0,1).

In this version of PSO, the following main assumptions are made to suit the real-world scenarios:

- Robot calculates PSO for every timestep. Each timestep is considered as one second and updates its velocity, with certain cap on maximum velocity, for the next time step.
- Robots are assumed to go with in straight line within the timestep and it is assumed to have no collision in between timesteps, as detection range is higher than the distance covered in each timestep with maximum capped velocity, Vmax.
- The range of communication is limited and it can communicate with other robots when they are in a certain range and at any point of time in the search process robot can detect other robots when they are within this communication range and can calculate relative distance between them
- Robot does not have information about its own start location and location of other robots in the search environment.

- Robot does not have any information about the size and shape of search space and it can only follow collision avoidance behavior when encountered with the wall of search space.

The method used in this paper does not require a fitness function as it is modeled differently to conventional PSO. We also assumed robot dispersion from each other when accompanied with levy flight movement creates maximum area coverage, which is replaced with fitness function. Modified PSO used here accommodates for robot - robot collision term. An obstacle avoidance policy is currently being designed and fine-tuned, which reflects the robot away from the wall and obstacles by certain rules based on sensor information on the front, left, and right side of the robot. Robots are assumed to have a certain kind of sensor to detect the targets, like victims in urban search and rescue scenario, when they are in a certain range from the target. The robot does not have any information about the targets position prior to the exploration.

## III. METHODOLOGY

We present a hybrid LF-PSO method for exploration tasks in an unknown environment. In most practical scenarios robot does not have information about the position of target in the search space, it has to follow the exploration task until it gets near the target. Once it gets very near a target, a simple camera sensor or IR sensor can detect the target. In this hybrid algorithm, local best and global best factors are modified to suit the exploration task where continuous feed from target is not required. All equations in this paper are for a two-dimensional search space, but these can be extended to three dimensional space for UAV search applications.

### A. Proposed Hybrid Algorithm

Levy flight movement is suited for larger space explorations with sparse targets because of its nature of the movement. Inter-robot repulsion is considered for dispersing robots away from each other to minimize paths crossed by robots. PSO algorithm is a type of movement which takes into account different kind of behaviors. The developed hybrid algorithm combines the LF movement and the Repulsion factor using PSO. PSO provides a weighted average of these two movements for effective area exploration. The local best position of the individual robot is the position with the best fitness value in the path covered by the robot. This term is modified to suit the exploration task as the position robot wants to be in the direction and step size obtained from the levy flight method. If the robot follows only the local best position obtained from LF, it might be exploring the area which is being explored by another robot or which is already explored by another robot during the search. To avoid this, the global best position is defined as the repulsive force which is inversely proportional to distance from other robots and direction is away from other robot.

#### 1) Local best Position, LF:

LF is best method for foraging and other exploration tasks adapted by various species and it is proven practically viable. It is assumed if a single robot is deployed in a search space LF is proved to be better exploration strategy compared to other random walk methods [1]. Sutantyo [10] proposed the combination of LF and an artificial potential field for multirobot explorations. If step size from the LF is s and the direction of movement is L_theta. Then local best position is determined by following equation.

$$Plbx_j - x_j = s_j * \cos(L\_theta_j) \text{ and } Plby_j - y_j = s_j * \sin(L\_theta_j) \quad (9)$$

In equation 9, where Plbx and Plby are Local best position in x and y direction. (x,y) is current position of robot in cognitive component. After the robot covered distance of this stepsize, new local best is updated by new step size and new heading direction for local best term.

#### 2) Global best position, Inter-robot Repulsion:

This repulsive term is inspired by the method followed by the author in [11] where modified PSO is used for exploration. This repulsive term will be zero if there is no other robot in its communication range. A new concept of robot clusters are used for effective dispersion of robots from away from each other to cover wide area of exploration.

When more than two robots are in communication range then robot clusters are defined. Cluster is defined such that each robot can communicate with at least one robot in the cluster, if d is the communication range of robot.

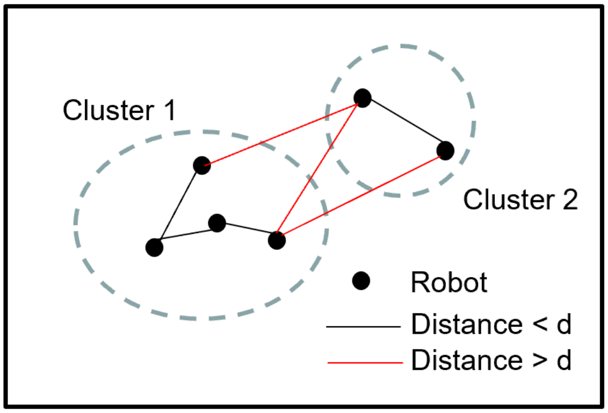


**Fig. 2: virtual clusters formed by robot for inter-robot repulsion force**

Each robot exerts a repulsive force on other robots with in a cluster in the direction away from each robot as shown in figure 3. By this dispersion it is expected that robot cover wide range of search space. Global best position will be in direction away from all the robots combined and it will be at a distance which is average of inverse of distance between robots in the cluster.

Dj = 1/d1 + 1/d2 –(10)

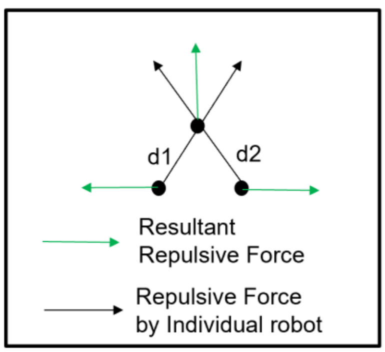


**Fig. 3: Repulsive force direction due to neighboring robots**

Pgbxj - xj= Dj * cos(R_thetaj) and Pgbyj - yj = Dj * sin(R_thetaj) – (11)

In equation 10, d1 and d2 are distances of robot from robot 1 and 2. In equation 11, Pgbx and Pgby are global best position in x and y direction. (x,y) is current position of robot in social component.

Modified equation for PSO is shown below:

Vi,j (t + 1) = ω. Vi,j (t) + pω. rand. (Plbj(t) - xi,j (t)) + nω. rand. (Pgbj (t) -xi,j (t)) – (12)

xi,j (t +1) = vi,j (t + 1) + xi,j (t) – (13)

Every robot updates its velocity in every timestep based on equation 12. Local best is updated after robot completes its current LF step_size distance and global repulsive will be updated, when robot comes near other robots. Individual robot moves with velocity taking all three components into consideration. In full paper, we are planning on tuning parameters for increasing search efficiency.

### B. Obstacle Avoidance:

A separate policy is added for obstacle avoidance unlike the Robotic PSO [20], which includes an extra term in PSO for obstacle avoidance (robots and obstacles). In our hybrid algorithm, the social component is already taking the effect of the neighboring robots, so an extra Inter-robot collision avoidance term would be redundant for Hybrid PSO. We use a simple policy for obstacle avoidance when near any obstacle, other than robots. Obstacle avoidance as currently followed in this paper is modified from the method followed by [12]. As the robot goes through the search space following the hybrid algorithm, a conditional statement checks the obstacle collision avoidance based on the information from the sensors. The obstacle avoidance algorithm is activated if at least one sensor is activated and it will remain in this state until it gets away from the obstacle. During this obstacle avoidance phase, the robot does not follow the hybrid algorithm rules. Every robot is assumed to have three sensors on the front, left, and right of the robot for detecting obstacles when at a certain distance. When the robot detects other robots or any obstacle, It follows movement based on following rules to avoid the collision. In future, we are planning on refining this obstacle avoidance policy using fuzzy logic.

| Moving Action | Left Sensor | Front Sensor | Right Sensor |
|---|---|---|---|
| Turn Pi/2 Left/Right | FALSE | TRUE | FALSE |
| Turn Pi/2 Left | FALSE | TRUE | TRUE |
| Turn Pi/2 Right | TRUE | TRUE | FALSE |
| Turn Pi | TRUE | TRUE | TRUE |
| Turn Pi/2 Right | TRUE | FALSE | FALSE |
| Turn Pi/2 Left | FALSE | FALSE | TRUE |

**Table 1: Obstacle Avoidance Policy**

## IV. Preliminary results.

To test the performance of the proposed algorithm, the Hybrid algorithm is simulated in a 2D environment in python. The search area for simulation is a 20 m * 20 m with no obstacles. Robots are assumed to have a communication range of 2 m and the maximum speed of the robot is 0.2 m/s. Beta term for LF is taken as 1 and other parameters in PSO w, pw and nw are taken as 0.6, 2, 2 respectively. In this simulation each iteration is considered as a timestep of one second. The size of the robot is considered as 0.6 * 0.6m and the area covered by the robot by its size is considered as explored. As a starting scenario, the search space does not have any targets in search space to find and the performance measure is simply the amount of area covered in the total search space volume. For comparison, we choose improved random walk method proposed in [1], as this algorithm can work in search scenario we have chosen. We conducted 20 trial simulations with 10 robots in the environment. Results below are average of 20 simulations for each test scenario.

When robots are started at random locations in the search space, hybrid algorithm covers 76% of the exploration area in 600 timesteps when averaged over 20 simulations, in comparison to about 61% coverage by the improved random walk algorithm proposed by Author in [1]. Figure 4 shows example of the simulation results by the proposed algorithm for 10 robots starting at random locations. Percentage of area covered for this example simulation using Hybrid method is 76.49%. Figure 5 shows example of one simulation results of the improved random walk method for 10 robots starting at same random start locations, the percentage of area covered for this example simulation is 61.13%.

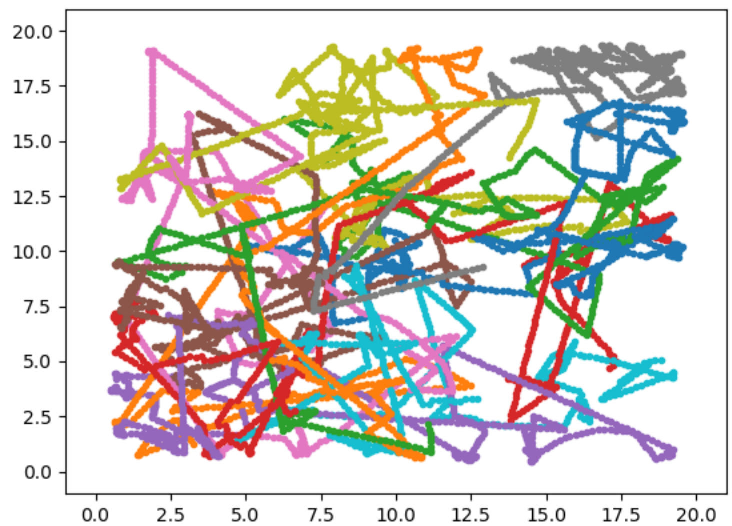


**Fig. 4: Robot path simulation of 10 robots starting at random position in a 20m * 20m search environment for 600 time steps with proposed hybrid algorithm.**

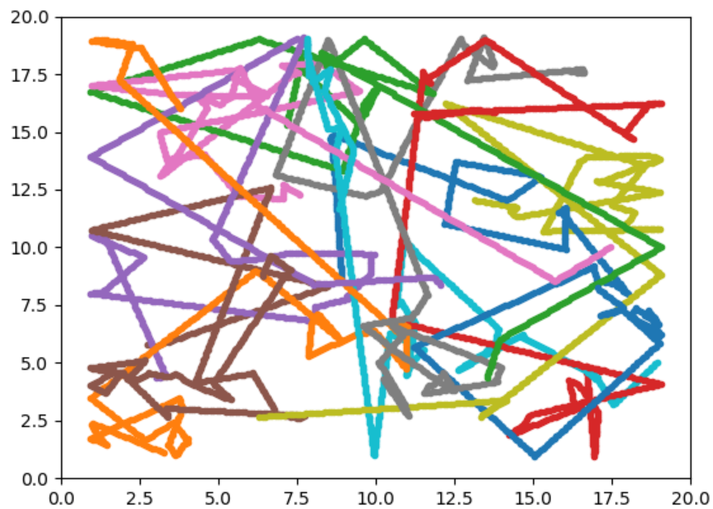


**Fig. 5: Robot path simulation of 10 robots starting at random position in a 20m * 20m search environment for 600 time steps using proposed Improved Random Walk method.**

When all the 10 robots starts at one corner of the room, area coverage by our hybrid algorithm is on average 72% over 600 timesteps (as inter-robot repulsion is helping for robot dispersion in the entire area), whereas for the method in [1] it decreased to around 52% when averaged over 20 simulation runs. Figure 6 shows example of the simulation results by the proposed algorithm for 10 robots starting at corner of the search space (10,2). Percentage of area covered for this example simulation using the hybrid method is 73.15%. Figure 7 shows an example of one simulation result run of the improved random walk method for 10 robots starting at corner of the room; the percentage of area covered for this example simulation is 53.30%. Figure 8 shows increase of area coverage for all these 4 cases over 600 timesteps.

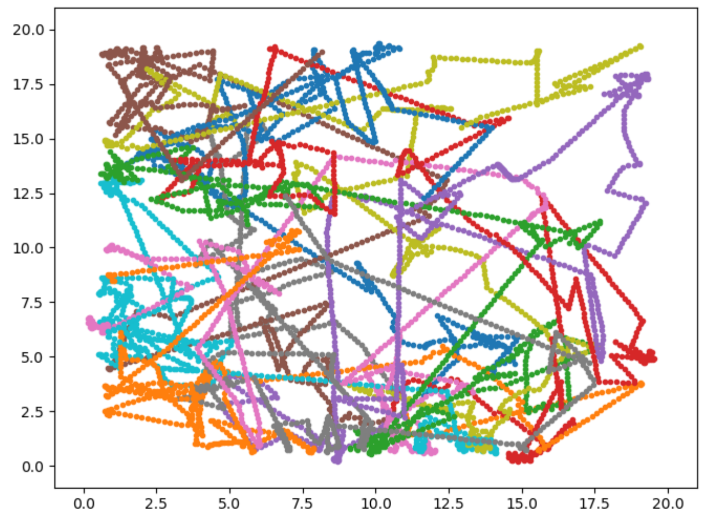


**Fig. 6: Robot path simulation of 10 robots starting at (10, 2) in a 20m * 20m search environment for 600 time steps using proposed hybrid algorithm.**

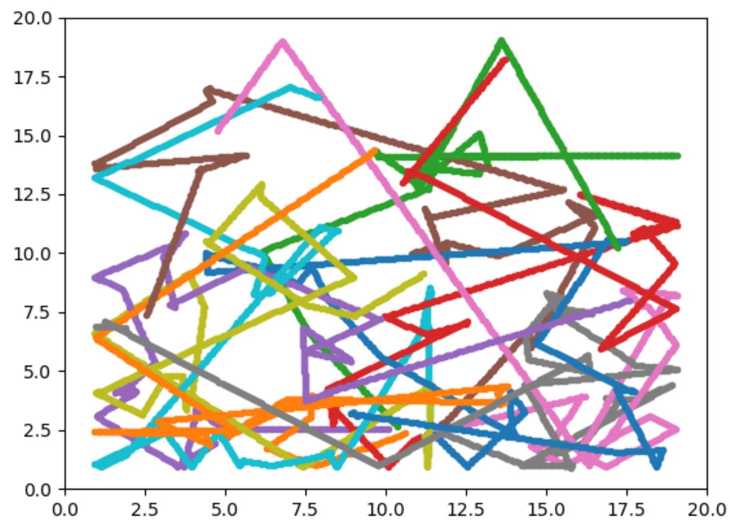


**Fig. 7: Robot path simulation of 10 robots starting at (10, 2) in a 20m * 20m search environment for 600 time steps using Improved Random Walk method.**

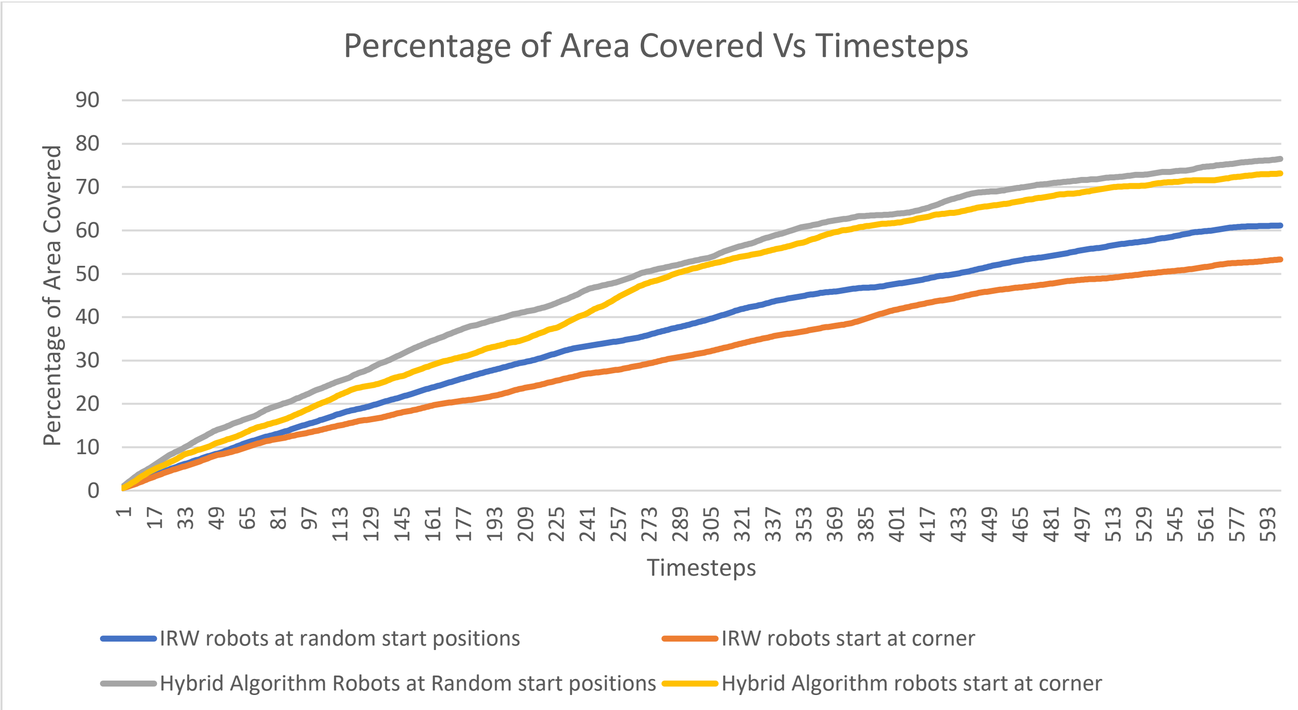


**Fig. 8: Percentage of Area Covered versus Timesteps for scenarios in fig. 4,5,6,7**

## V. Conclusion and Future Work

We propose an algorithm, which is a hybrid of LF and PSO, for searching tasks using multiple decentralized robots with limited communication and sensing capabilities. This algorithm works in an environment where the area of search space is not known and where the environment has no global positioning system. Simulation tests are conducted for the algorithm. The developed hybrid algorithm is tested in 2-dimensional space using python. The preliminary results show that the area covered by the robot team using coordinated movement is impressive when compared with the existing method[1]. Particularly this algorithm covers a wide area even when robots started at one corner of the room.

Further, we would like to introduce obstacles in the environment (such as walls and rubble) and check how the algorithm behaves; we then plan to introduce the targets to be found and test the policies and algorithms in this case next. Simulations for different environments and different team sizes will also be conducted. More comparison studies will also be done with standard frontier exploration strategies [13] used in current exploration missions by multi-robot systems. We are planning to do more refined dynamic tuning of PSO parameters for the inertia, cognitive, and social factor to increase the search efficiency by studying how efficiency is varying with time, as well.

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