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Path Planning through PSO Algorithm in Complex Environments

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ABSTRACT

The path planning through Particle Swarm Optimization (PSO) algorithm in complex environments is a novel approach for robotic path planning. The main challenges of robotics are its automation and detection capability and the preliminary step of achieving these is through optimized path establishment, formation, flocking, and rendezvous, synchronizing and covering. Robotic Path Planning is one of the main problems that deals with computation of a collision-free path for the given robot, along with the given map on which it operates. Path establishment is possible only when the environment is known and the targets location is estimated. This work focuses on Path planning problem. We have considered two cases, first one is coordinated target tracking and reaching in the unknown environment through obstacles avoidance when the location of the target is known. The second case is co-ordinated target searching in an unknown and unexplored environment through obstacle avoidance. These results are showing for both target tracking and target searching. We are also showing the comparative results for this algorithm with other state of the art techniques. Parameters that asses these algorithms are no of node visit (move), explored area (coverage), Manhattan distance (energy) and time elapsed (time).

***Keywords*:-** Bio-inspired Algorithm, Multi-Robot system, Path Planning, PSO, target searching, target tracking.

I. INTRODUCTION

Every automated and intelligent robotic system uses planning to decide the motion of root and a real world. Robotics is an extremely inter-disciplinary area that takes inputs from numerous disciples and fields with varying complexities. The autonomous robots make extensive use of sensors to guide them in and enable them to understand their environment. A mobile robot exploring an unknown environment has no absolute frame of reference for its position, other than features it detects through its sensors [1].

Soft Computing Tools and Techniques are finding increasing application in the field of robotics. Many of the robotic problems like planning, coordination, etc. are complex problems that are now-a-days solved using the most sophisticated soft computing tools. In many real-world applications, the workspace of robots often involves various entities that robots must evade, such as a fire in the rescue mission, objects in household applications, and instruments in automated factories [2].

Path planning in a robot is the problem of devising a path or strategy which would enable the robot to move from a pre-specified source to a pre-specified goal. This can be established through the map. The generated map needs to ensure that the robot does not collide with the obstacles. The path planning would depend upon the size of the robot and the obstacles. In many cases, the robot may be assumed to be point size. This happened when we are sure that the robot would be in most of the cases able to glide through obstacles, assuming the obstacle density is not high. Another important characteristic of the path planning algorithm is its optimality and completeness. The completeness refers to the property that the algorithm is able to find a solution to the problem and return the solution in finite time, provided a solution exists.

The paper is organized in as follows. In section II, we describe the background of the problem, Section III deals with the problem formulation, Section IV we show simulation result to test the effectiveness of proposed algorithm.

II. BACKGROUND

Path planning is one of the basic and interesting functions for a mobile robot [3]. Motion planning of the robot in respect of natural is a challenging task [4] due to the various constraints and issues related to it. The most vital issues in the navigation of mobile robot, which means to find out an optimized collision free path from the start state to the goal state according to some performance merits i.e. travel time, path-length etc. The optimization in terms of time and path length and limiting constraints, especially in large sized maps of high resolution, pose serious challenges for the researcher community [5]. The Robotic path planning in the presence of the obstacle is also a critical scenario [6].

Path planning can be classified into two categories global path planning in which all the information are available to the robot and local path planning in which partially information available of the environment [7]. The environment structure might be in static or dynamic in nature [8]. There have been many algorithms for global path planning, such as artificial potential field, visibility graph, and cell decomposition etc. The potential field has been used widely due to its simple structure and easy implementation, yet it still has some shortcoming [9-10].

Exploration and mapping also be a fundamental part of mobile robots navigation. In the past, any approaches have used occupancy grid maps to represent the environment structure during the map building process. Occupancy grids, however, are based on the assumption that each cell is either occupied or free [11].

Human beings are greatly inspired by nature [12]. Nature in itself is the best example to solve problems in an efficient and effective manner. During the past few decades, researchers are trying to create computational methods that can help human to solve complex problems. This may be achieved by transferring knowledge from natural systems to engineered systems. Nature inspired computing techniques such as swarm intelligence, genetic algorithm, artificial neural network, DNA computing, membrane computing and artificial immune system have helped in solving complex problems and provide an optimum solution. The parallel, dynamic, decentralized, asynchronous and self-organizing behavior of nature inspired algorithms is best suited for soft computing applications and optimized for solving the complex problems [13]

Path planning algorithm of robots also is inspired by a social behavior of birds and fish. This types of algorithm known as Nature Inspired Algorithm (NIA). NIA Algorithms are flexible and work in changing the environment to organize and grow accordingly**.** These algorithm qualities perform in highly complex problems and can even show very good results when a problem is not properly defined. This tends to find the best available solution in every changed environment and very good decision maker. Nature inspired systems do not adapt to real world system fully in terms of scalability and performance. Systems can work well in some domain but not in other. As systems are nature inspired, then not having proper knowledge of nature can affect the design of algorithm. So for effective results no ambiguity in data is required. This needs Cluster of data. Clustering is the process of organizing data into meaningful groups, and these groups are called clusters [14]. Many specialized models of soft computing also face these problems of large data processing. This technique is restricting the amount of data that the system can serve. This achieved by clustering the data. These algorithms have the ability to self-learn, self-train, self-organize, and self-grow. They can find best optimal solutions to complex problems using simple conditions and rules of nature.

Particle Swarm Optimization (PSO) is a Natural-inspired algorithm. PSO was used as optimization method because it has interesting results in situations with local minima. It is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best-known position but, is also guided toward the best known positions in the search space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. It is used many field i.e. social modeling, computer graphics, simulation, and animation of natural swarms or flocks with artificial neural networks and evolutionary computation due to simplicity and efficiency [15-16].

Coordination among interacting agents with a common group behavior is not only a recent engineering problem, but it is something that happens every day in nature. The interest in multi-agents systems has grown in the last decade, mostly because a group of collaborating agents can often deal with tasks that are difficult, or even impossible, to be accomplished by an individual agent. A team of agents typically provides flexibility, redundancy, and efficiency beyond what is possible with single agents. Having several agents deployed often means that they can be flexibly organized into groups performing tasks at different locations. Robustness is ensured by the numerous of the group if an agent fails the other can continue the task. Having many agents rather than one can allow performing tasks in a faster and more precise way. The multi-robot system is used for many applications due to robustness, potential to finish a task faster, varied and creative solution [17-18].

In this paper, we deal with the behavior of PSO algorithm, the next location of robots movement, target searching and path planning problem for multi-robot.

III. PROBLEM FORMULATION

For problem formulation, we have considered two kinds of problems, namely the known target and the unknown target. Known target is one kind of target tracking problem which involves reaching the target in an efficient way and with an optimized expenditure of the resources. Target tracking involves mainly avoidance of obstacles in an intelligent and explorative way so that new options get revived and recognized. Mainly the direction or the location coordinates of the target is known, whereas in the unknown target, the target needs to be search and tracking is difficult as the position is not known. So the challenge lies in searching for the various nooks of the environment and search for the target. There are some complex environments like the indoor environment where due to complex structure of walls, doors, and windows even the known target problems are tackled like unknown target problems. Gradually the various results are discussed for the various environments under both known and unknown target schemes and the performance is evaluated and compared.

A. *Assumptions*

The simulation work was performed as a multi-agent system where the agents represented the robots, with all its inherent behavior and characteristics. Assumptions made in simulations are: Agents are homogeneous that is uniform in capacity, strength, size (the capacity of the unit cells) uniformity in the environment and the agents also make the fitness calculation simple and easy to compare between agents.

1. No failure of robots during path planning and exploration.
2. Speed is non-uniform but bounded and the maximum is same for all the agents.
3. There are instant breakings and no stretching happens following that.
4. Sensor range is Omni-directional and there is coordination fusion between all the sensors energy.
5. The position of the obstacle is known with reference to the co-ordinate system.
6. The obstacles can be of any shape inside a circular region as shown in Figure 1.
7. The obstacles can be adjacent but not overlapping.
8. The path planning algorithm runs until the goal has been reached.

Figure 1: Obstacles having different shapes

B. *PSO for Robot*

A big concern to find global best and the inertia best and, more importantly, they do not exist as the solution is not completed and it is very difficult to determine any temporary fitness regarding it. But we can actually or up to a certain extent determine the fitness function approximately using the distance for each agent left to reach the target when the target is known. So less the distance left better is the particle, but in the realistically constrained environment, it is half true and there are much more than it is anticipated. However in a case of target searching, the determination of the area coverage made by an agent and more the area covered more is its fitness. In this way, the positional vector is mapped into the fitness vector of the PSO particle.

The particle position and velocity are updated using equations (1) and (2).

$$P_j^i(t+1) = P_j^i(t) + V_j^i(t) \quad (1)$$

$$V_j^i(t+1) = V_j^i(t) + c_1 r[pb_j^i(t) - p_j^i(t)] + c_2 r[pg_j(t) - p_j^i(t)] \quad (2)$$

Where $P_j(t)$ as position vector, $V_i(t)$ as velocity vector, $Pb_i(t)$ as best position, $Pg_i(t)$ as globally best position at iteration t of any particle j, r is any random number in the range of 0 to 1 and c_1, c_2 are constants.

Algorithm 1: Algorithm for Robot Movement:

1. Initialize the agents and required data structure

2. Start the particle from sources
3. If condition <= Threshold Value
    Move the agent using PSO
   Else
    Move using directional movement
   End of if
4. Determine fitness of the particles
5. Update the global and iteration best
6. Continue the loop until stop condition is true.

The PSO algorithm for mobility of Robots is described in the Algorithm-1. The condition is nothing but a threshold value for finding the next movement of an agent through PSO or directional movement. Directional Movement is Clustering Based Distribution Factor (CBDF) which can be used in scattering the robot agents randomly towards the various portion of the search space for efficient an opportunistic search and exploration of the target.

C. Steps for directional Movement for known and unknown target

(a) Detect the present position P_{old}

(b) If (target known)

   a. Detect the known target position P_T

   b. Calculate unit vector for each direction as

$$\delta = \frac{(P_D - P_{old})}{\|P_D - P_{old}\|} \quad (3)$$

(c) If (target unknown)

   a. Select P_D from cluster direction

   b. Calculate unit vector for each dimension is

$$\delta = \frac{(P_D - P_{old})}{\|P_D - P_{old}\|} \quad (4)$$

4. Calculate new variation for each dimension as

$$V_K = \delta_k * D \quad (5)$$

Where $\delta_k \in \delta$ and $D \in S$ (Detection range)

$$P_{new} = P_{old} * V_k \quad (6)$$

Where $V \in (V_1, V_2, \dots, V_k)$ and V is the variation.

IV. SIMULATION STUDIES

Parameters	**Values**
Map Size	500x500 pixel
Number of maps	1
Map Type	Chess
Sensor Range	1 to 15 pixel
Target	Known & Unknown
Number of Robots	3, 6, 9, 12 & 15
Start & Ending point	Any point set within map
Algorithms	PSO
Features	Move, Time, Coverage, Energy

Table I: Experimental Parameters

The problem of path planning deals with the determination of a path which navigates the robot in such a way that no collision occurs. In order to solve the problem, it is assumed that the input is already available in the form of a map. The region is traversable and may be used for the purpose of travelling. The black regions here signify the presence of obstacles. The size of the map is restricted according to the computational capability and time constraints in all the real life specific problems under consideration. Otherwise, it would become computationally impossible for the algorithm to find a result. The algorithm would generate output path that can be used by the robot for the navigation purposes. The path may be traversed using any robotic controller. This is for the execution of the steps given by the planning algorithm.

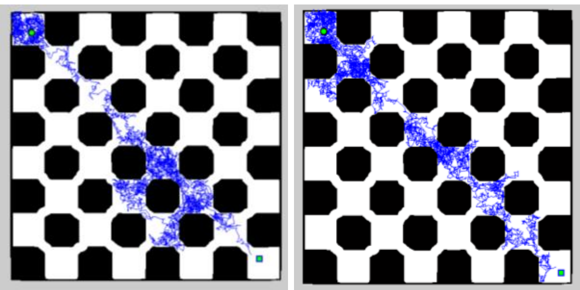
The summaries of experimental parameters are showing in below Table I. The proposed Algorithm-1examine through the no of node visit (Move), Manhattan distance (Energy calculation), Coverage area adjacent to node (Coverage) and simulation time (Time) which various when the number of agents is varied. The exact time calculation will be approximately the average timing factor that is the noted time calculation divided by the number of agents.

A. Simulation Result Analysis for PSO Algorithm

PSO Algorithm is useful for planning a path in dynamic, complex state space environment. Figure 2a and 2b are shows the results for complex environment i.e. chess-box. We have following observation based on Figure 2a and 2b.

i. The reaching up to target in a known environment is must fast as compared to the unknown target.
ii. For the indoor environment, we have to use target tracking due to the limitation of a structure of the environment.
iii. When robots search to target for unknown target the covered area is more because robots move without knowing the direction of a target.

iv. Searching of targets also depends on the environment structures.



(a) known target (b) Unknown target

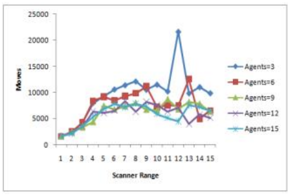
Fig. 2: Explored Area to reach known and unknown target using PSO Algorithm

B. Comparisons of individual Algorithms for Target searching and Tracking with varying Agents

The detection capability of the robot agents plays an important role for detection and local search movement while taking decision for the next course of movement. There is no doubt that the visibility of the robot is directly proportional to the step-size of movement and will help in movement and simultaneously in exploration denoted by the parameter coverage. However it must be mentioned that the directional capability of the robot agent in an environment depends on the distance between the obstacle and must not be too large or too small with respect to the average distance between the obstacle else it can be a wastage of the resources as the detection capability requires for hardware detection and analysis capability and the consumption of energy increases with increase in detection capability. Hence, the optimal detection capability must be justified for the robot system and must be optimized. In the simulation, we have used a range of detection ranges and have shown how the convergence rate applies for the situations. Another thing that needs to be mentioned is that the result is biased and optimized for the agents with least movements and the other three parameters like time, coverage and energy are the corresponding of that agent. Hence always the other three parameters like time, coverage and energy may not be optimized but in most of the cases, they are, however, it has been seen that agents with better timing are found in the iteration but it does not have the best moves count.

1) Known Target

The following graphs are shown between sensor range and move, time, coverage, energy parameters in different known environments with varying number of agents. The PSO algorithm is used for reaching the goal.



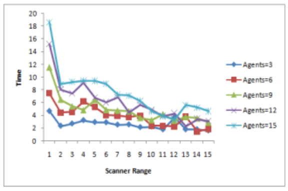
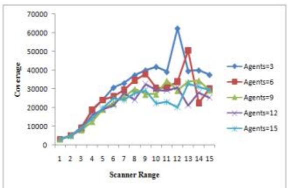


Fig: Move parameters Fig: Time parameters



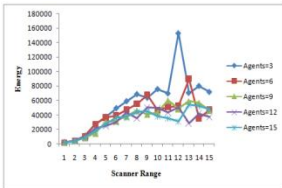
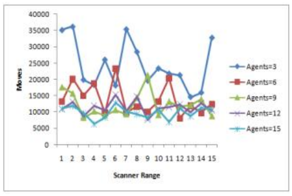


Fig: Coverage parameters Fig: Energy parameters

Fig. 3: Move, Time, Coverage and Energy parameters comparison for PSO algorithm in known target

2) Unknown Target

The above graphs are shown between sensor range and move, time, coverage, energy parameters in different unknown environments with varying number of agents. The PSO algorithm is used for reaching the goal.



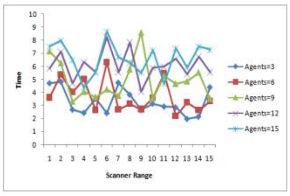
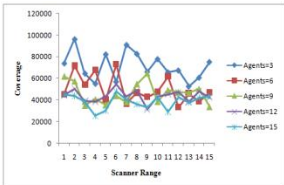


Fig: Move parameters Fig: Time parameters



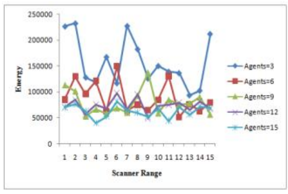


Fig: Coverage parameters Fig: Energy parameters

Fig. 4: Move, Time, Coverage and Energy parameters comparison for PSO algorithm in known target

3) Observation

Following are observed are derived from the gradual development of simulation setup and the environment.

i. More diversified results when the social effect of the co-agents is determined from a randomly selected co-agent.

ii. For a particular environment, there is some optimal sensor range which will be sufficient.

iii. Effectively more proportion of bio-inspired computation in target tracking produces more combination of paths.

iv. Best Ratio of exploration and exploitation depends on the environment and the associated topology.

v. Quality of solution depends on the ratio of exploration and exploitation.

vi. If exploration depends on randomization and each event have equal probability of occurrence, then it may happen that after certain number of steps, the robot may end-up at the same place as it was before.

vii. Effectively more proportion of CBDF in target searching procures more combination of paths.

C. Parameter to be compared between known and Unknown Environments with varying Agents

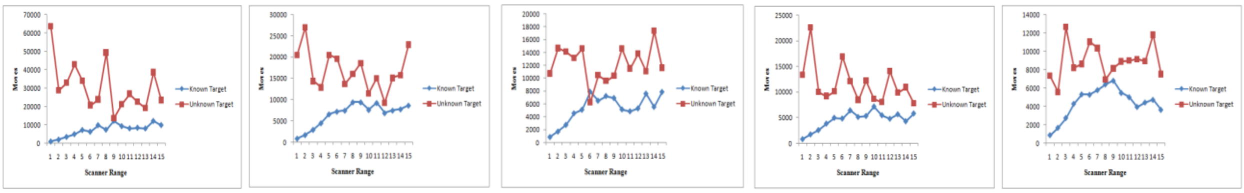
The graph shown the comparisons result between known and unknown environment. Here, we have used PSO algorithms for move, time, coverage and energy parameters when agents are fixed.

The Figure 5-8 showed the comparison results between known and unknown environments of simulation setup. The results are shown the more value of move, coverage, energy and less time taking in the unknown environment than known environment when agents are fixed and PSO algorithm is used. The searching of new node is always higher in unknown target as compared to known target as shown in Figure 5. The coverage depends on the sensor range for known target. Whereas, random values for coverage in the unknown target as shown in Figure 7.

V. CONCLUSIONS

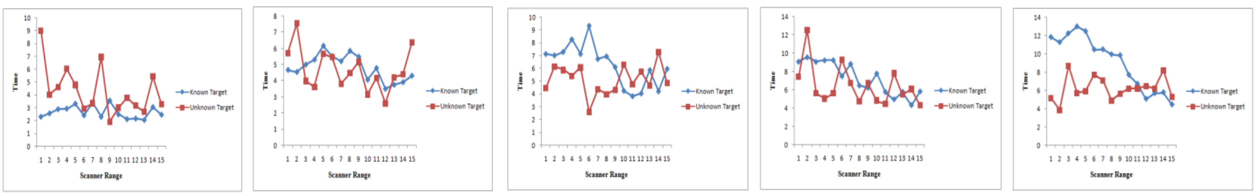
In this work, we are particularly interested in the use of Nature inspired algorithm in multi-robot path planning and area exploration. We discussed PSO based path planning technique. Mathematical details were discussed and simulation results are shown for path planning in two different cases, known and unknown target position. The approaches presented in this work have been tested in various simulated environment with different complexity and different team size. The results positively show the optimality of proposed algorithm as compared to other state of the art techniques.

Since the work presented here is independent of robot model, it can be easily extended to different robot models as compared to point mass model considered. It can be easily applied to consensus of robots performing task in different but interconnected environment.



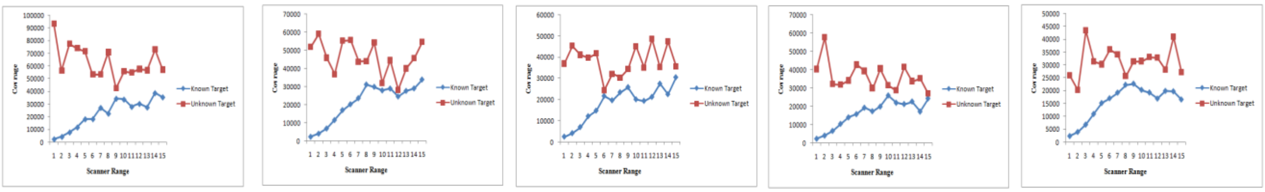
(a) Agents = 3 (b) Agents = 6 (c) Agents = 9 (d) Agents = 12 (e) Agents = 15

Fig 5: Move parameters comparison for PSO algorithm between known and unknown target



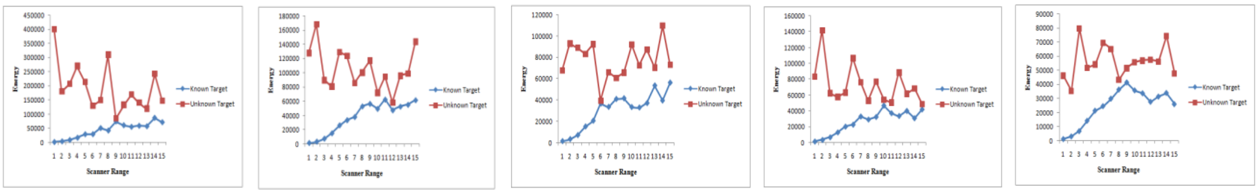
(a) Agents = 3 (b) Agents = 6 (c) Agents = 9 (d) Agents = 12 (e) Agents = 15

Fig 6: Time parameters comparison for PSO algorithm between known and unknown target



(a) Agents = 3 (b) Agents = 6 (c) Agents = 9 (d) Agents = 12 (e) Agents = 15

Fig 7: Coverage parameters comparison for PSO algorithm between known and unknown target



(a) Agents = 3 (b) Agents = 6 (c) Agents = 9 (d) Agents = 12 (e) Agents = 15

Fig 8: Energy parameters comparison for PSO algorithm between known and unknown target

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