Path Planning Optimization of a Mobile Robot based on Intelligence Algorithm

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Abstract. Motion planning is an important topic for researchers working in the field of autonomous robots, it finds an optimal feasible path from start to target point with avoiding the collision, this paper aims to improve motion planning of mobile robot by particle swarm optimization as a method for finding the collision-free optimal path. The objectives considered in this research for optimization are optimal static navigation path with taking into consideration the affect population size on performance for the algorithm to find the optimal path through various environments with population sizes 100, 80, 40, 20. The simulate and evaluate the proposed algorithm proved no strong affected to population size parameter on the optimal path length and its points, hence we can use a small population size for the minimum time in finding the optimal path between start point to goal point with colliding avoidance.

1. Introduction
Initially, the applications of automation of autonomous Ground mobile robot (GMR) have become an extremely fast-growing in many fields. This growth in applications of GMR is related to simple structure and fast motion in different environment, therefore autonomously navigation techniques of Ground mobile robot motion planning (GMRMP) has become most essential task in field of robotics, and include find optimal feasible path from start to target point with avoid collision by intelligent equipment equipped on GMR to convert high-level specification of tasks, that humans perform into low-level specification [1].

The autonomous navigation of GMR is achieved via path planning (by find optimal path and given it to the mobile robot as track or sequence of points to follow it as motion commands). So, according to the above, the planning problem of the navigation path is classified as an optimization problem. Therefore, technique choice of the navigational is an essential step in the motion planning of mobile robots at work in a simple and complex environment, in any task, there are multiple allowed paths for GMR to reach the target point, but the recognition the optimal path depends on adapted some optimization criteria such as path length, time and energy consumed. Therefore, several optimization algorithms have been used to solve the path planning problem [2]. These algorithms are divided into traditional algorithms such as (A-Star (A*), probabilistic roadmaps, potential fields, and many others) and intelligent algorithms (heuristic techniques) such as (genetic algorithm, swarm intelligence, fuzzy logic algorithm, neural networks). In general, traditional path planning techniques are needed high computational time and costly for solve path planning compares with heuristic techniques which easy in implementation with a great ability to handle the uncertainty present in the environment [3]. In this paper proposed particle swarm optimization (PSO) to find optimal navigation for a GMR. PSO is an optimization tool and based on swarm intelligent, easily in the implement, effective and fast when applied in many optimization problems. An optimization model is designed to find minimal path
length with taken into consideration path safety. Then, an improved PSO algorithm for solving the above model. The contributions of our study are as follows:

(1) The study of affect population size on performance for the PSO algorithm to find the optimal path through various environments with four sizes for population sizes to measure its effect on the efficiency of the PSO algorithm.

(2) We present the effective strategy of GMR movement path planning in an environment with a fixed position of obstacles and target points to reduce the total time for the path-finding.

(3) Prove the effectiveness of our method by conducting simulations with various scenarios.

2. Literature survey of Previous Research.
A lot of scientists and researchers have provided a huge methodology to solve the GMR path planning problem. In recent years notice that the traditional navigation approach such as cell decomposition and the road map not suitable to real-time mobile path planning due to high computation cost and failure to respond to the uncertainty percent in the environment, it’s less able to solve problems in complex environments [4,5]. While the intelligent algorithms have become extremely fast-growing to solve navigation problems for GMR, Chaymaa and et al [6], proposed improved genetic algorithms through crossover operators to solve the path planning problems in static navigation environment. Khaled Akka and Farid Khaber [7]. They compared a modified ant colony algorithm and the classic ant colony algorithm based on the performance for optimal static navigation path in grid maps. Patience I. and et al [8]. proposed used an improved form of PSO algorithm to find the optimal global path for a mobile robot in a known environment with different population numbers with a different environment. Yoney K. Evera [9]. presented simplified swarm optimization (SSO) as an effective solution for improving efficiency and high-quality mobile robots, suggested the processing based on developed particle swarm optimization (PSO) for finding optimal static navigation path.

3. The objectives
The objectives considered in this research for optimization are optimal static navigation path by finding the best and feasible next position for GMR with taking into consideration the affect population size on performance for the algorithm to find the optimal path through various environments with population sizes 100, 80, 40, 20. Before discussing our algorithm, there are some assumptions about the model we use in this paper.

3.1 The assumptions
1- The GMR in the 2D environment is represented as point by a set of Cartesian coordinate positions (x,y) in the square map (interesting area), contains a number of static obstacles.

2- Each surround area of obstacles should be increased by the amount of the GMR radius (GMR R) depending on the studied mobile GMR shape, in order to assure the safety of the robot while trying in the environment, as shown in Figure 1.

3- The GMR has no prior knowledge of environmental parameters such as locations, shapes, and sizes of the obstacles and it assumes equipping with sensor (camera) and Compass modules, the GMR can know its current position, moving directions and travelled distance.

Figure 1. Extend obstacle size corresponding to GMR.
4. Particle Swarm Optimization (PSO)

PSO is a research method that has roots in the main two components of methodologies is the artificial life in general life and swarm theory in the group of bird flocking or fish schooling. PSO is the simulation was based simplified social system when searching for food in the defined search-space. In theory, the PSO has individuals (particles) moving within a natural swarm, PSO was proposed by Kennedy and Eberhart in 1995 [10], its included that each particle in swarm is representing potential solution, moving iteratively through the problem space in search of the best-fitted solution, at initialized, the system started with a population of random solution, also, each individual (particle) in the swarm has random position and velocity that guide the particle through its navigation space. Then, each particle tries to modify its position using Equation 1 and Equation 1, through iterations toward two ’’best’’ values are the best fitness (P_Best) has achieved for each particle and another ’’best’’ value (G_Best) is the best fitness achieved over the whole swarm. This process repeats until the maximum number of iterations is attained or until the whole swarm converges to the same point.

\[
\begin{align*}
    v_{id}^{t+1} &= w v_{id}^{t} + c_1 r_1 (p_{Best,i} - x_{id}^{t}) + c_2 r_2 (G_{best} - x_{id}^{t}) \\
    x_{id}^{t+1} &= x_{id}^{t} + v_{id}^{t+1}
\end{align*}
\]

Where,

- \( w \): Represent the inertia weight-factor that determines the contribution rate of a particle’s previous velocity to its velocity at the current time step \( t \).
- \( v_{id}^{t} \): Represent the speed of particle \( i \) in dimension \( d \) at time step \( t \).
- \( x_{id}^{t} \): Represent position of particle \( i \) in dimension \( d \) at time step \( t \).
- \( c_1 \) and \( c_2 \) are balance factors between the individual knowledge and the collective knowledge when particle flying towards the target.
- \( r_1 \) and \( r_2 \) are random numbers between 0.0 and 1.0.

4.1. Modified Particle Swarm Optimization

In the current research, we used linear decreasing inertia weight (LDIW) as a mechanism to enable control of the exploration and exploitation of the swarm. The small value of \( w \) helps the algorithm in local search, while the high value of \( w \) help individual of the swarm to explore the problem space more easily and improve global search, for balance between global and local search exploration, used linearly decreasing weight factor approach [11]. Equation 3, shows how the \( w \) value is updated.

\[
    w = (w_{max} - w_{min}) \frac{\text{iter}}{\text{iter}_{max}} + w_{max}
\]

Where

- \( w_{max} \): the max value of the inertia weight.
- \( w_{min} \): the min value of the inertia weight.
- \( \text{iter}_{max} \): the max number of iterations.
- \( \text{iter} \): current iteration.

each particle in swarm randomly initialized for velocity and position within a uniform range from \([x_{min}, x_{max}]\) and \([v_{min}, v_{max}]\) respectively.

\[
\begin{align*}
    x_{i}^{t} &= x_{min} + \rho_1 (x_{max} - x_{min}) \\
    v_{i}^{t} &= v_{min} + \rho_2 (v_{max} - v_{min})
\end{align*}
\]

Where \( \rho_1 \) and \( \rho_2 \) represent random-numbers from 0 to 1.
5. Evaluation Function

The Evaluation Function in this research based on two estimation function, first function ($F_1$) is the criteria to find minimal path length (minimum optimization), it is defined as Euclidean distance between the current position and the goal position in each iteration. The performance evaluation considered in this research is positions that are given the minimum value of objective function must be selected for the next move of a ground mobile robot, hence for tracking. The minimal path length from the start point at $(x_0, y_0)$ to target point at $(x_f, y_f)$ via intermediate points in the 2D environment can be given by the following formula.

\[ F_1(i) = \sum_{i=0}^{n} \sqrt{(R_{x_i} - G_X)^2 + (R_{y_i} - G_Y)^2} \]  

(6)

Where:
- $F_1(i)$: distance function between GMR and goal.
- $i$: current iteration
- $(R_{x_i}, R_{y_i})$: coordinates of the GMR at the current position.

While second function ($F_2$) is taken into consideration collision avoiding, during path planning the GMR should have the safety distance from the obstacles and it should be larger than the radius of GMR ($R_{GMR}$). Therefore, we used penalty value, if maximum distance between GMR and obstacle is equal or less than safety distance ($\varepsilon$), the penalty value will be added to the main function ($F_1$) and path become infeasible because the optimization problem is minimization, otherwise penalty value is equal to zero, the distance between GMR and obstacle can be given by the following formula.

\[ Dis(i) = \sqrt{(R_{x_i} - O_{x_n})^2 + (R_{y_i} - O_{y_n})^2} \]  

(7)

Where:
- $Dis(i)$: Distance function between GMR and obstacle.
- $(O_{x_n}, O_{y_n})$: Coordinates of the obstacle, $n$ is the number of an obstacle.
- $F_2(i) = \begin{cases} 1, & \text{if } Dis \leq \varepsilon \\ 0, & \text{otherwise} \end{cases}$

Hence, the total fitness function is

\[ Z_i = F_1(i) \times (1 + \delta_i) \]  

(8)

Where $\varepsilon$ is a minimum distance between intermediate path points and obstacle, $\delta_i$: penalty value and its 100 unit
Based on Equation 8, the P\text{Best} (local best position) and G\text{Best} (global best position), and the new position for GMR is determined. This process repeats for interpolating positions (intermediate points) until the GMR is reaching the target point.

6. Simulation Result and Analysis

6.1. Setting and Environment

In simulation, the proposed method in this study is coded in MatLab R2014b and tested on Intel(R) core i7, 2.2 GHz CPU, 8.00 GB RAM system for getting simulation results for the performance of developed PSO model with taking into consideration the affect population size on performance for the algorithm to find the optimal path through three environments with taking different of population sizes, The PSO parameters used in the test for each environment as shown in Table 2.

| parameters          | value   |
|---------------------|---------|
| population sizes    | 100, 80, 40, 20 |
| c\text{1}, c\text{2} | 1.5     |
| w\text{min}        | 0.3     |
| w\text{max}        | 0.9     |
| No of iterations    | 100     |

During simulation setting, we create three maps with dimension (10x10) units, each map is tested in the different scenario for GMR has circular shape and red colour and its move from the start point at (0,0) to the goal point at (10,10) in Presence the different number of obstacle for each map, and location for each obstacle shown given in Table 3.

| Environment | No of obstacles | Obstacle options (in pixels) (x,y, radius) |
|-------------|-----------------|------------------------------------------|
| Map 1       | 1               | (5,5)                                    |
| Map 2       | 3               | (2,4,0.3), (5,5,2), (4,2,0.4)            |
| Map3        | 5               | (2,4,1), (5,5,1), (4,2,0.5), (6,8,0.5), (8,6,0.5) |

6.2. Simulation Results

This section compares the performance analysis of our developed PSO model in a simulation environment, each map and its fitness function are modelled base on the GMR sensory information, first environment is map1 with one obstacle, second environment is map2 with three obstacles, third environment is map3 with five obstacles, result of simulation proved that proposed algorithm is effective in finding the optimal path in all of three maps as shown in Figures 2, 4 and 6. The results analysis through compare the path length and the algorithm execution time in each map with different population size as summarized in Table 4, after effect analysis the population size on performance for the PSO algorithm in each map, results indicated that the population size effect on results for the travelled path length and the travelled path time through effect on a central processing unit (CPU) by consumed time to algorithm run as shown in Figures 3, 5 and 7.
Figure 2. Optimal path in map 1.

Figure 3. The execution time of the PSO An algorithm in map 1.

Figure 4. Optimal path in map 2.

Figure 5. The execution time of the PSO An algorithm in map 2.

Figure 6. Optimal path in map 3.

Figure 7. The execution time of the PSO
Table 4. Comparison of the Travelled Path length and the time of execution of the PSO algorithm in three maps

| Environment | Population size | Optimal path length (in pixels) | PSO execution time (in seconds) |
|-------------|----------------|---------------------------------|---------------------------------|
| Map 1       | 100            | 14.3679                         | 1.6943                          |
|             | 80             | 14.3679                         | 1.4605                          |
|             | 40             | 14.3682                         | 1.0595                          |
|             | 20             | 14.433                          | 0.883                           |
| Map 2       | 100            | 14.3743                         | 1.7259                          |
|             | 80             | 14.3748                         | 1.5289                          |
|             | 40             | 14.3752                         | 1.1071                          |
|             | 20             | 14.3755                         | 0.890                           |
| Map 3       | 100            | 14.3754                         | 1.7726                          |
|             | 80             | 14.3749                         | 1.5708                          |
|             | 40             | 14.3807                         | 1.1244                          |
|             | 20             | 14.6255                         | 0.867                           |

7. Discussion and Conclusion
The path planning of GMR based on modified PSO was conducted in this paper, we present a strategy of GMR navigation in an environment with a fixed position for obstacles and target points to reduce the total time for the path finding. the compared results of the performance analysis of our developed PSO show that it can successfully track the optimal path with avoiding the collision. Additionally, the analysis of the results showed affect population size parameter on performance for the PSO algorithm to find the optimal path through various environments, results notable indicate that the population size effect on the CPU by consumed time to algorithm run, where increase population size gives better result but with increaser consumed time by CPU to algorithm run, while the small population size represents decrease time for algorithm execution but result maybe not optimal. Therefore, we should select a suitable population size for each map, for reducing the time of the algorithm run and good results.

In future works, we would like to study our work with another objective criterion such as a smooth path that could be added to the algorithm.

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