Using Particle Swarm Optimization as Pathfinding Strategy in a Space with Obstacles

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**ARTICLE HISTORY**
Compiled June 24, 2022

**ABSTRACT**
Particle swarm optimization (PSO) is a search algorithm based on stochastic and population-based adaptive optimization. In this paper, a pathfinding strategy is proposed to improve the efficiency of path planning for a broad range of applications. This study aims to investigate the effect of PSO parameters (numbers of particle, weight constant, particle constant, and global constant) on algorithm performance to give solution paths. Increasing the PSO parameters makes the swarm move faster to the target point but takes a long time to converge because of too many random movements, and vice versa. From a variety of simulations with different parameters, the PSO algorithm is proven to be able to provide a solution path in a space with obstacles.

**KEYWORDS**
Particle swarm optimization, Swarm intelligence, Pathfinding

1. Introduction

Swarm intelligence (SI) is an artificial intelligence approach that aims to solve problems using algorithms based on the collective behavior of social animals. Swarm intelligence is different from evolutionary algorithms. This is because the evolutionary algorithm develops a new population for each generation/iteration, while the swarm intelligence algorithm improves the individual for each generation/iteration [Bansal 2019]. The most popular SI methods include Artificial Bee Colony Algorithm, Ant Colony Optimization, and Particle Swarm Optimization [Karkalos et al. 2019].

Particle Swarm Optimization (PSO) algorithm, which was invented by Kennedy and Eberhart [Kennedy et al. 1995], is an optimization method inspired by the social behavior of animal such as bird flocking and fish schooling. PSO is a population-based search algorithm, where each individual/particle changes its position each time to explore a multi-dimensional space. The PSO algorithm combines the local search with the global search method. Each particle has a position and velocity in the space of a certain dimension. Initialization of the PSO algorithm starts by setting the initial position of the particle, and then looking for the optimal value by updating its position randomly. For each iteration, particle updates its position following the two best values: the best solution that has been obtained by itself (local best) and the best solution in the population (global best). After the particle position is evaluated by the fitness
function, each particle "communicate" the information of best position to the other particles, so they can adjusts the position and velocity toward that best point.

Figure 1. Particle position update process (Chen et al., 2020)

One of the most important tasks in mobile robot navigation problems is to plan a collision-free route from the starting point to the target position. One of them uses an optimization process. However, traditional optimization techniques create local minima, and the robot may not reach its goal even if a solution exists (Falcó et al., 2020). Over the last few years, several heuristic algorithms have been introduced into path planning (Zhu et al., 2021), including PSO. The PSO algorithm is known to be very good for use in free space problems (Waluyo et al., 2010). This paper aims to investigate the ability of PSO algorithm to find solutions/pathfinding in a space with obstacles, so if it is successful, it can be used to find solutions for maze games and path planning in robot movement.

2. Algorithm

With the standard PSO algorithm, the path planning can be divided into the following steps, as shown in Figure 2.

First step is initialize a starting position, target position, obstacle coordinate in the search space. Then, for each particle \( i \), update the position of particle \( i \) according to equation (1).

\[
v_{i+1} = w \cdot v_i + c_1 \cdot \text{rand}_1 \left( x_{\text{best},i}^P - x_i \right) + c_2 \cdot \text{rand}_2 \left( x_{\text{best},i}^G - x_i \right)
\]

where \( v_i \) is the speed of the \( i \)-th iteration, \( x_i \) is the particle position of the \( i \)-th iteration, \( x_{\text{best},i}^P \) is the local best position of the \( i \)-th iteration, \( x_{\text{best},i}^G \) is the globally best position of the \( i \)-th iteration, \( w \) is the inertia weight of the current speed when updating the speed, \( c_1, c_2 \) are the follow factors, and \( \text{rand}_1, \text{rand}_2 \) are uniform random numbers from 0–1. After that, update the velocity of particle \( i \) according to equation (2).

\[
x_{i+1} = x_i + v_{i+1}
\]
Then evaluate its fitness value according to equation (3).

$$ f = (x_{\text{target}} - x)^2 $$

(3)

The fitness function is used to evaluate how close current position is to the targeted position. Next, update $x_{\text{best},i}^P$ and $x_{\text{best},i}^G$ if necessary according to equation (4 & 5).

$$ x_{\text{best},i+1}^P = \begin{cases} x_{\text{best},i}^P & \text{if } f(x_{\text{best},i}^P) \leq f(x_i) \\ x_i & \text{if } f(x_{\text{best},i}^P) > f(x_i) \end{cases} $$

(4)
\[ x_{best,i+1}^G = \min \{ f(y), \ f(x_{best,i}^G) \} \]

where, \( y \in \{ x_{best,0}^P, x_{best,1}^P, \ldots, x_{best,N}^P \} \)

(5)

If it has converged, the path is saved and the iteration is exited. Otherwise, it started again to continue the iteration.

### 3. Results

In this study, PSO algorithm is used to search the space of \( 100 \times 100 \) nodes to find the optimal path so the swarm can travel from its initial position to the target point. The investigation of the PSO parameters effect on algorithm performance is shown by the simulation result in Table 1.

**Table 1.** PSO Parameter and Algorithm Performance

| Initial Position | N Particles | \( w \) | \( c_1 \) | \( c_2 \) | Steps/Iterations |
|------------------|-------------|---------|---------|---------|-----------------|
| (-70, 80)        | 25          | 0.90    | 0.60    | 0.65    | 80-120          |
|                  | 50          | 0.80    | 0.65    | 0.90    | 48-58           |
| (-80, -10)       | 25          | 0.60    | 0.90    | 1.45    | 84-133          |
|                  | 50          | 0.45    | 1.20    | 1.70    | 40-56           |

The simulation shows that, the larger the population of particles, the fewer steps needed to reach convergence. Even so, the number of particles should be adjusted to the complexity of the obstacles. If the number of particles is too small, the swarm will have difficulty finding a solution due to minimal "communication" between particles during exploration. If the number of particles is too large, the time required to converge to the target will be longer due to too much random motion, but with the optimal number of particles and parameters, the algorithm can work efficiently.

The combination of the weight constant \( (w) \), particle constant \( (c_1) \) and global constant \( (c_2) \) is very important so that the search process becomes more optimal. If these constants are enlarged, the particles will spread easily so that the search process is faster but takes a long time to converge or to "summon" other particles to gather at the target. However, if the constant is too small, the particles will move closely so it will be difficult to find an alternative path if everything is stuck in the local minima. Examples of solution paths obtained from several simulation cases are shown in Figure 3.

Apart from the algorithm, simulation environment needs to be enhance because in some cases particles can penetrating the obstacles due to the velocity being too large. The algorithm above only refuses the particle position update if the particle is not in the free-moving area or is inside of the obstacles coordinates, but if the particle velocity is very fast, the particle displacement becomes larger and the program does not detect it, so particles possible to penetrates the obstacles wall. The solution to this problem is to increase the size of the obstacles wall or limit the particle velocity by setting the optimal constants.
4. Conclusion

This paper presented the algorithm of using the PSO approach to solve the path planning problem. This study also investigated the performance of the evolutionary process with the various parameter and number of particles. Based on the simulations,
the PSO algorithm can provide a solution path to different types of tasks in a space
with obstacles.

**Code availability**

The implementation code of this research is available for download at [github.com/dxid-dev/pathfinder](https://github.com/dxid-dev/pathfinder). This research has used [python](https://www.python.org) and [matplotlib](https://matplotlib.org) ([Hunter 2007](https://matplotlib.org)).

**Disclosure statement**

No potential conflict of interest was reported by the author.

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