Original Article

# Environment Specific Strategy for Mobile Robot Path Planning Problem

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## Abstract

Determining the optimal path for the mobile robot for a given environment to reach the destination from the starting location is implemented in numerous ways. To obtain the optimal solution Genetic Algorithm (GA) is predominantly used in this research domain. While applying GA, initial solution space is created by randomly generated paths. In this study, the solution space ascertained is environment specific which is directly influencing the computational cost. Three strategies are characterized to construct the initial path depending on the three classified environments. The experiments are conducted with different maps and the outcomes are analyzed quantitatively as well as qualitatively to defend the proposed methodology.

**Keywords:** Genetic Algorithm, Mobile Robot Path Planning Problem, quantitative analysis, qualitative analysis, optimal path, computational cost.

## Introduction

The Mobile Robot Path Planning Problem (MRPPP), a crucial area of research influencing anything from domestic appliances[1] to industrial automation[2], is solved using several approaches with different variations. The goal of mobile robot path planning is to find the best, obstacle-free navigational path from the given starting point to the destination. The physical design of the robot as well as the environment it explores has an impact on the MRPP solution. The scope of the navigational zone is predictable in a static environment, making it simpler to simulate the scenario and derive the solution path.

The initial population is a significant attribute to applying GA, even if the performance of the algorithm is highly subjective to other criteria also[3]. If there are many potential solution paths in the solution space, it may take longer to find the best one when applying the GA principle. In the context of a working environment, the solution space may be perceptibly narrowed to arrive at a better solution in less time and with a higher level of precision. The robot path planning solution space consists of paths that may be created by interpolating the cells to travel from one cell to another while satisfying all constraints[4].

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| Quick Response Code: | Website: www.pnrjournal.com |
| | DOI: 10.47750/pnr.2022.13.04.007 |

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Received date: 11 August 2022 Accepted: 14 September, 2022
Published: 10 October, 2022



**For reprints contact:** pnrjournal@gmail.com

How to cite this article: Suresh S K , Venkatesan R, Venugopal S, Environment Specific Strategy for Mobile Robot Path Planning Problem, J Pharm Negative Results 2022;13(4):64-69.

The size of the population is influencing the quality of the path as well as computational cost. From [5], it is observed that the minimum cost of the path is only moderately correlated to the population. Hence the convergence to the minimum cost does not depend on the size of the solution space. GA consists of important three phases considered as operators to apply to the initial population called selection, crossover, and mutation for each generation. The fitness value is evaluated for each generation by applying the fitness function. The fitness value is estimated from the objective values computed from the objective function for each objective. Therefore the implementation phases of GA for each generation cause a high computational burden for employing GA. It starts with an initial population which directly depends on the computational cost. By reducing the size of the initial population, the computational cost may be reduced. But the quality of the resultant optimal path is not guaranteed.

## Related works

MRPP is an NP-hard problem to choose the optimal path from the starting point to the destination while avoiding collisions with the obstacles for mobile robots. Numerous studies have been conducted in the area of mobile robot path planning in both static[6] and dynamic[7] working environments. Deterministic[8] and non-deterministic[9] methods have been devised to solve the path planning problem in several conventional ways. The best path, if it exists, is guaranteed by deterministic techniques. However, as the complexity of the working environment rises, the temporal complexity of the approaches becomes extremely high. Instead, non-deterministic methods are created to create the best paths under the limitations.

Non-deterministic methods are recommended to achieve the best outcomes because MRPP is regarded as an NP-hard category. The MRPP problem is solved using a variety of strategies divided into several approaches. Heuristic approaches[10] replaced classical approaches as the dominant paradigm in the late 1980s. The methods are tested and used either singly[11]–[13] or properly combining the phases of various methodologies[14] to capitalize on their individual advantages and increase the system's overall efficacy. The temporal complexity grows as a result of the computational complexity of the traditional methodologies[15]. Particularly, population-based evolutionary algorithms[16] do better than other methods to find the best solution in complicated contexts with a large solution space. Evolutionary algorithms are utilized to get optimal solutions against the traditional approaches with lesser computational cost.

The widely used approach for choosing the best path for robot navigation is the Genetic Algorithm (GA). Principally, the path planning problems are considering the length as the primary objective, but in addition to that if more objectives are accounted for, then the Multi-Objective Genetic Algorithm (MOGA) is so popular to find the optimal path.

## Need for the Proposed Methodology

Accuracy and computational cost are the main parameters to be assessed to identify the quality and performance out of various measurement elements. Numerous solutions may be viable for given restrictions in non-linear situations. Therefore, it is difficult to find the optimal solution for both parameters out of all possible ones. As a result, the only way to identify the best solution is to optimize the parameters and find a trade-off between accuracy and computational cost.

## Phases of Environment Specific Strategy for MRPPP (ESS for MRPPP)

The methodology is proposed to overcome the increase in computational cost due to an increase in initial population size. According to the model, three strategies are formulated and prescribed to choose the strategy based on the characteristics of the environment which will be optimal to reduce the computational cost with less probability to sacrifice the quality of the path. The environment is classified into three categories to the availability of the navigation space available or in terms of blocked cells due to obstacles. To apply the Genetic algorithm, the initial population is generated for creating solution space with randomly generated paths from the occupancy matrix representing the environment.

describes the phases of ESS for the MRPPP algorithm.

In the environment, the obstacles occupied cells are considered unavailable for navigation which is a key criterion to measure the density of the obstacles named Obstacle Density Indicator (ODI).

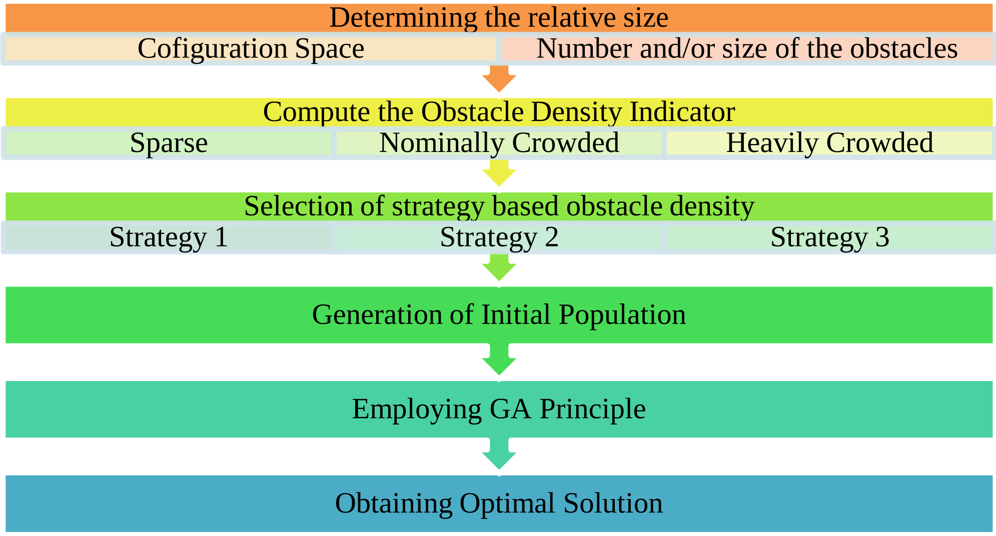


**Figure 1**:Phases of the Proposed ESS for MRPPP algorithm

## Estimation of ODI

Obstacle Density Indicator (ODI) = $\frac{\text{Blocked Cells}}{\text{Size of the Occupancy Matrix}}$

The ODI indicates the free space available for the navigation of the robot. If the indicator value is high, the obstacles occupied by the Environment are high.

Length of the configuration space = L units

Breath of the configuration space = B units

Area = A = L x B units2

Number of rows = R

Number of columns = C

Total number of cells = T = R x C

If the size of the obstacles is equal in size and shape, then the calculation for Equi-sized obstacles is used. Otherwise, the non-equi-sized computations are used while computing the total number of cells blocked in the environment.

For Equi-Sized Environment

Size of unit cell = U = $\frac{\text{size of configuration space}}{\text{number of cells}} = \frac{A}{T}$

Size of equi-sized obstacles = O units

Size of individual obstacles I = $\frac{\text{Size of obstacle}}{\text{Size of unit cell}} = \frac{O}{U}$ in terms of a unit cell

Number of obstacles = N

Total number of cells occupied by obstacles = Number of obstacles x Obstacle size in cell units

Total number of blocked cells = B = N x I cells

For Non-Equi-Sized Environment

Total number of cells occupied = B = $\sum_1^N \textit{blocked cells}$

ODI = $\frac{\text{Number of Blocked cells}}{\text{Total number of cells}}$ =

## Categorization of environment space

If ODI < 15 - Sparse environment(SE)

ODI > 45 - Heavily crowded environment (HE)

15 > ODI < 45 - Nominally crowded environment (NE)

Depends on the category of environment three different strategies are employed.

Strategy 1:

To generate the initial population, Strategy 1(S1) is suggested for SE where the ODI is less than 15%. According to S1, a robot is navigating diagonally adjacent cells without obstacles toward the destination. There is a lot of navigational space, so high probability to reach the destination through diagonal movement.

Strategy 2:

S2 is an upgraded version of S1. In this scheme, the robot path follows the S1 until it encounters an obstacle over the path. If it encounters then it prefers the non-diagonal adjacent cell ie vertical and horizontal adjacent cells positively towards the goal. It ensures that it will generate a path with an even lesser length compared to S1.

Strategy 3:

S3 exploits all possibilities to move in all directions, not skipping the possibility of achieving the optimal solution. It may generate the minimum length but at the cost of astronomically increasing population size which is directly proportional to the computational cost.

## Implementation of ESS for MRPPP

To analyze the proposed model, 9 different sized sample maps[17] are taken and tested with a different number of obstacles. The environments are occupied by 15, 30, and 45 percent of $\frac{B}{T}$ obstacles to the experimental method. The sizes of the occupancy matrix taken for the experiment are in different ranges according to the requirement of the map. The size of the occupancy matrices is from 5 X 5 to 30 X 30. For each environment, all the 3 strategies are employed.

To justify the model, the observed results are analyzed in 2 ways

a) Quantitative analysis and

b) Qualitative analysis

The quantitative analysis is to compare the number of paths generated by the three different strategies in the three categorized environments. This is to prove how the population size directly influences the computational cost.

In qualitative analysis, the length of the path is considered a feature to be compared to decide the quality of the path. The minimum length of the generated population is used to measure the quality of the path which is used to justify the proposed method.

## Quantitative analysis

The range of the population is inordinate for different environments. Since the differences in the number of paths produced by the three strategies are vast, for ease of comparison the Inferences from Figure 2 are,

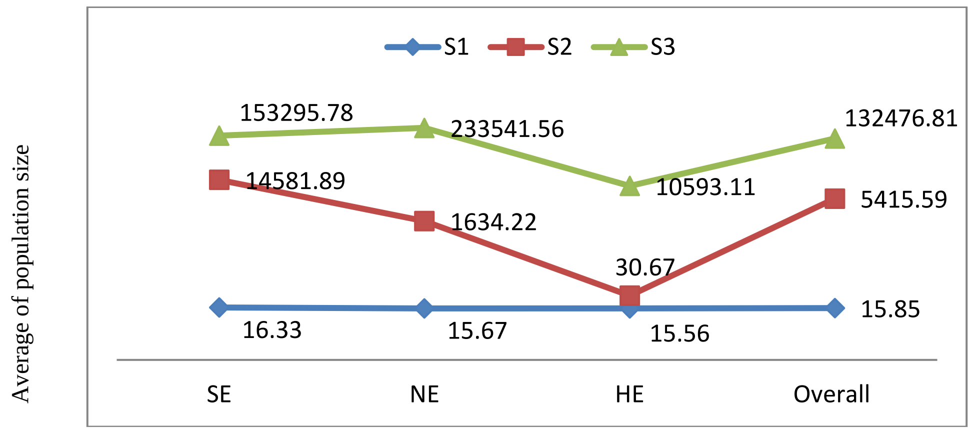


**Figure 2** Comparison of average population size

- From the graph, it is observed that the difference in the average population size generated by employing S1 is only around one percentage only for all obstacle densities.
- By comparing S1 with other strategies S2 and S3, there is a substantial difference in average population size for all types of environments.
- At the same time, the average population size reduces if there is an increase in obstacle density. This is due to the less availability of space for navigation in the environment.
- In the overall observation, S1 generates less population size and relatively S2 and S3 generate a massive population.

**Table 1** Strategy-wise comparison of the difference in population size

| Strategies / Envt Category | S1 vs S2 | S2 vs S3 | S1 vs S3 |
|---|---|---|---|
| SE | 8.92E+04 | 9.51E+02 | 9.38E+05 |
| NE | 1.03E+04 | 1.42E+04 | 1.49E+06 |
| HE | 9.71E+01 | 3.44E+04 | 6.80E+04 |
| Overall | 3.32E+04 | 1.65E+04 | 8.32E+05 |

To substantiate the results to understand the huge difference in the population size for S1, S2, and S3, the percentage difference in population size generated by the different strategies for three categorized environments are tabled in Table 1.

As observed from

Table 1, for SE compared to S1, a huge

difference in population size is in the order of ten to the power of 4 and 5 concerning S2 and S3, due to the sparse environment. S3 has a high population size for NE compared to S1 and S2 due to less probability for diagonal movement. For HE, only less space is available for the movement of the robot. Therefore comparing s1 with s3, a high percentage of difference is exhibited. The S2 with S3, the difference is very less. Considering the overall average, the vast difference is in the size of the population by applying S3. The overall difference shows that the high volume of the population is generated by S3 compared to other strategies.

Hence employing S1 less number of paths is generated, while S2 and S3 produce more number of paths as an initial population to apply GA.

## Qualitative analysis

However by applying the strategies, the number of paths for the initial population is getting increased astronomically from S1, S2, and S3 correspondingly, to test whether these approaches ensure the quality of the path, the qualitative analysis is being employed. Though the quality of the path can be attributed to different characteristic features, it is modestly justified in terms of minimum length for different strategies across different environments.

While analyzing the average minimum length, even if we attain the minimum length in S3, same as the case of S1 and S2, the computational cost increases rapidly due to the huge population size. As the minimum length and population size are in different ranges, a normalized weighted code is estimated to compare the three strategies with three different environments using the quality score.

Quality Score (QS) = 0.9 X Lmin + 0.1 X Pavg

where Lmin = Minimum of Path Length

Pavg = Normalized Average Population size

The QS is defined as 90% weightage given to minimum length which decides the quality and 10% to population size.

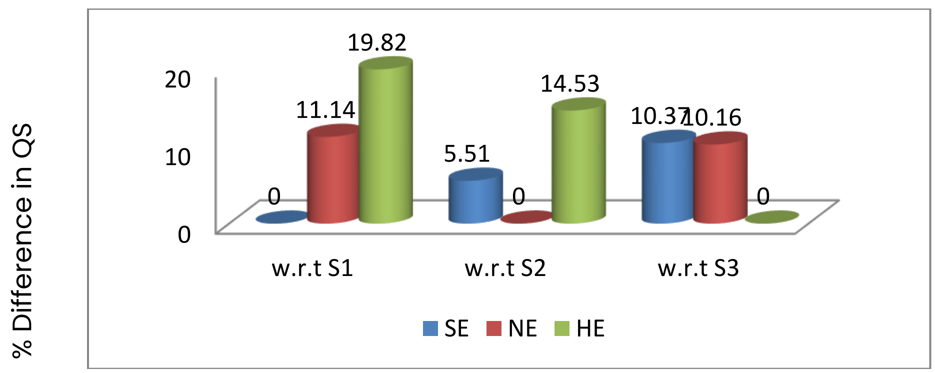


**Figure 3** Quality Score with respect to Strategies

Evaluating the QS with respect to S1, S2, and S3, the observations and suggestion of strategy are enumerated as follows.

S1 is prescribed for a sparse environment because the quality scores of the HE and NE are 11.14% and 19.82% high against SE. Whereas S3 is advisable for HE since it is obvious that the QS for the other two environments is more than a 10% disparity. The S2 is claimed as a better approach for NE, as the 6% and 16% difference with SE and HE.

## Conclusion

In the proposed model, the environment is categorized into three according to the obstacles in the environment, which are blocked cells for the navigation of the robot. The value of the ODI is determining the category of the configuration space, computed with the percentage of obstacles that exist in the environment named SE, NE, and HE. The method set down three types of navigation strategies to generate the initial population defined as S1, S2, and S3. As the population size increases tremendously, the computational cost will increase. To justify the computational cost, the quantitative analysis and qualitative analysis are done on the population generated by the strategies for the different environments. It is proved that the above strategies confirm the environment-specific decision-making depends on the QS. As S1 is for SE, S2 is for NE, and S3 with HE, by

comparing the percentage difference of QS between the strategies for various environments.

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