A Multi-Objective Parametric Algorithm for Sensor-Based Navigation in Uncharted Terrains

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***Abstract*—Sensor-based motion planning is one the most challenging tasks in robotics where various approaches and algorithms have been proposed to achieve different planning goals. However, these approaches only focus on one single objective, i.e. path optimality, path safety, efficiency or trajectory smoothness. In this paper, a novel parametric algorithm is proposed that is able to handle different planning goals by means of a set of objective-controller parameters. These parameters are designed carefully to cover different requirements of the path planner. Readings of the sensors will be evaluated to determine the values of four decision variables and the next position of the robot will be selected accordingly. The performance of the proposed algorithm was tested through simulation studies in different types of environments to evaluate its ability to achieve different planning goals. Simulation studies have shown the algorithm to perform robust and effective in all environments.**

***Index Terms*—robotics, sensor-based, motion planning, parametric algorithm**

I. INTRODUCTION

Path planning for a mobile robot is a procedure to move the robot from an initial position to a goal configuration inside an environment filled by arbitrary shaped obstacles, while avoiding any collision with them. Canny [1], proved that the path planning problem is NP-Complete. In most of the path planning applications, there is no prior information about the environment, e.g. positions of the obstacles and surrounding boundaries. This class of path planning problems is called sensor-based or online path planning. In this class of path planning, the motion decisions are made as the robot moves and obtain new information from the environment. There are a variety of researches in this field resulting in different approaches, each with their specific characteristics, advantages and drawbacks [2]-[10].

These approaches share a common drawback which is the inability to consider more than one objective for the motion planning procedure. Some algorithms consider the optimality of the generated path as the primary objective [2]. These algorithms are more suitable when energy consumption is a critical issue. Another group of approaches take care of the safety of the robot while moving along the generated trajectories [5] which is a proper objective when the robot is too valuable or the obstacles are too destructive. Sometimes, a fast and acceptable trajectory generation is the main goal and therefore, low runtime of the motion planner is important [7]. Finally, in case of a non-holonomic system, the smoothness of the generated path is of a great importance and there are algorithms which have been designed specifically to deal with this kind of planning problems [9]. There are other possible objectives for a motion planning algorithm but the aforementioned goals are the most important ones [11]-[13].

The main objective of this research is to develop a sensor-based navigation algorithm which can be used to achieve different objectives. In other words, the characteristics of the final solution, i.e. path, can be changed based on the current objective by means of a set of objective-controller parameters. The proposed algorithm takes into account the readings of the robot's sensory system about the surrounding area and the position of the in-range obstacles. Based on these readings, the algorithm computes the values of four positional variables. An objective function will then be used to determine the suitability of the selected next position of the robot based on the objective parameters. This algorithm is designed for a mobile robot which possesses several range finder sensors on its perimeters which enables the planner to acquire the values of the decision variable including the distance to the goal position, the distance to the start position, the distance to the closest obstacle and the distance from the robot's previous position. The values of these variables will then be combined in the form of an objective function for further analysis and decision on the suitability of the selected position.

In the following sections, first, the motion planning system is specified and the details of the robot and the problem are presented. Next, the proposed algorithm is introduced and discussed in details. The results of the simulation studies are presented in the next section with

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relative analysis and discussions. Finally, the paper is concluded and the final discussion and conclusion is given.

II. System Speaifications

The problem of motion planning can be stated as follows. Inputting a start position $P_s = (x_s, y_s)$ and a goal position $P_g = (x_g, y_g)$, motion planning is to find a path which is a sequence of points that is feasible for a mobile robot to navigate from the start point to the goal position. The current position of the mobile robot is defined as $P_c = (x_c, y_c)$ under the global coordinate. The robot has two driving wheels in front and one Omni-directional wheel at the back and five ultrasonic sensors placed on its front side each with the detection range of R_s and the vision angle of θ as shown in Fig. 1.

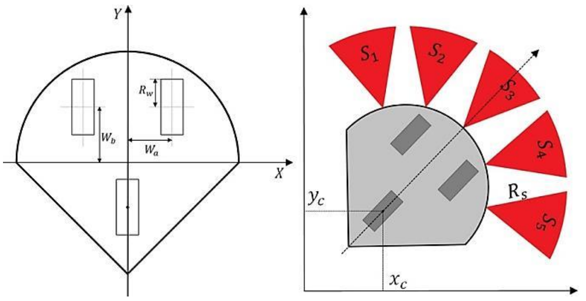

Figure 1. The considered mobile robot and its sensory system.

As the robot moves, the sensory system is able to detect the surrounding area and determine the values of four positional variables including the distance to the goal position, the distance to the start position, the distance from previous position and the distance to the closest obstacles. These values will be used later in the proposed algorithm.

III. The Proposed Algorithm

The proposed algorithm performs discretely as the robot moves. At each iteration of the algorithm, the robot scans the surrounding areas and selects a random position of the vision circle which is $(R_s + R_g)$ distance far from the center of the robot where R_r is the radius of the robot and R_s is the reading range of the ultrasonic sensors. After this random position was selected, the controller utilizes the readings of the sensors and calculates the values of four decision variables based on the positional values. These variables are defined as follows.

$$\varphi_s = D(P_n, P_s) - D(P_c, P_s) \quad (1)$$

$$\varphi_g = D(P_n, P_g) - D(P_c, P_g) \quad (2)$$

$$\varphi_p = D(P_n, P_p) - D(P_c, P_p) \quad (3)$$

$$\varphi_o = D(P_n, P_o) \quad (4)$$

where, P_n, P_c, P_p, P_s, P_g *and* P_o are the coordinates of the random position, current position of the robot, previous position of the robot, start position, goal position and the closest point on the closest obstacle respectively. These positions are shown in Fig. 2.

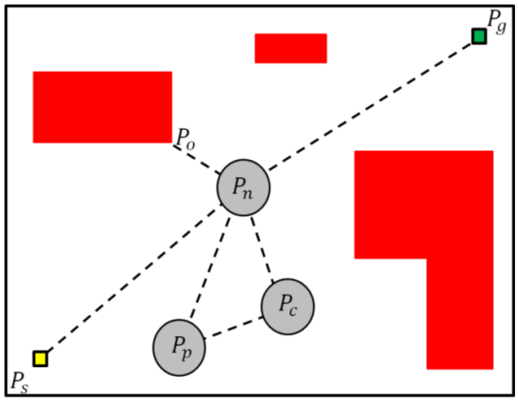

Figure 2. Measuring the positional and decision variables.

These variables are designed carefully to cover different objectives. φ_s is used to force the robot to get farther from the start position, φ_g keeps the robot moving closer to the goal, φ_p keeps the robot away from its previous position and finally φ_o controls the robot's distance to the closest obstacle.

After calculating the values of these variables, the algorithm computes an objective or cost function which is defined as follows.

$$C(n) = \alpha_1\varphi_s + \alpha_2\varphi_s + \alpha_3\varphi_s + \alpha_4\varphi_s \quad (5)$$

$$\alpha_1 \in [0,1], ? = 1, \ldots, 4 \quad (6)$$

where $\alpha_1, \alpha_2, \alpha_3$, and α_4 are objective controller coefficients and changing their values will change the features of the final solution. For instance, high values for α_1 and α_2 with low values for α_3 and α_4 provides short paths which achieves the optimality objective. In the simulation studies section, it will be discussed how to arrange these coefficients in order to achieve different objectives. Based on the simulation results, the following graphs show the effect of each coefficient on different objectives. The value of the objective function will be compared against a maximum cost constant $(C_{\max})$. If the result of the cost function is less than the maximum allowed cost, then the robot will move to the selected position. Deciding about the value of $C_{\max}$ is an important task in planning. This value is normally selected based on the dimension of the environment. The effect of each decision variable on different planning objectives is shown in Fig. 3.

The proposed algorithm receives the reading of the sensors when the robot is placed at its current position (P_c) and then it selects a random position on the vision circle of the robot. Next, the algorithm computes the values of four decision variables and the value of the objective/cost function accordingly. Based on the result of this function, it will be decided to select the random point as the next destination of the robot or select another random point. Then, the algorithm checks if the goal position is reachable and if it is, the robot moves to the goal position and the algorithm terminates. Otherwise, the whole process will be repeated. The flowchart of the proposed algorithm is presented in Fig. 4.

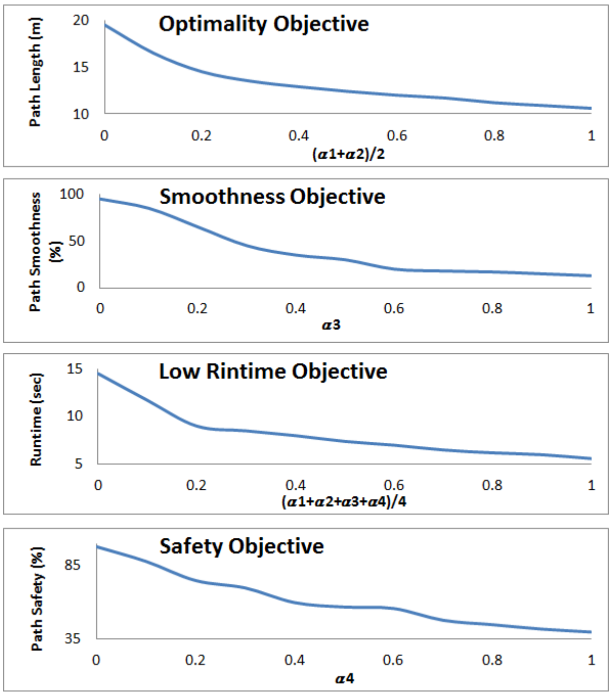

Figure 3. The effect of each coefficient on different objectives.

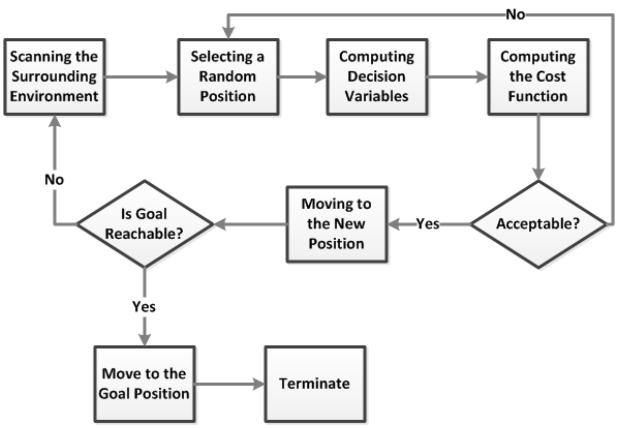

Figure 4. The flowchart of the proposed algorithm.

IV. SIMULATION STUDIES

The proposed algorithm was simulated in MatLab in different types of planning environments. Four instances of the results are shown in Fig. 5. The proposed algorithm is able to efficiently guide the robot through the environments filled with different types of obstacles. Different types of planning environments have been chosen in order to have a more general understanding about the capabilities of the proposed algorithm. Besides simple convex obstacles, the environments also include more challenging types of obstacles such as concave obstacles with one or more local minima, narrow passages, and simple mazes in order to test the ability of the algorithm in more difficult situations.

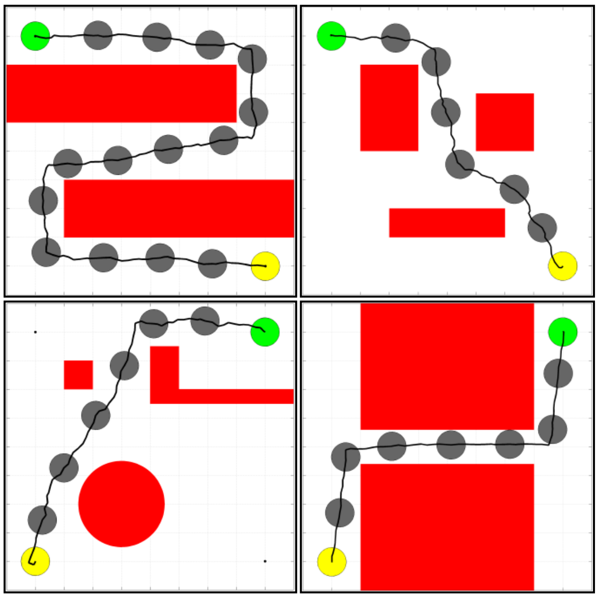

Figure 5. Simulation results of the proposed algorithm in four different environments. Only certain positions of the robot have been presented while the trajectory line is available. Start and goal configurations are shown by yellow and green circles respectively.

The algorithm generates safe and smooth paths while avoiding collision with obstacles and environments' boundaries. Especially in narrow passage where classical path planning has shown poor performances, the proposed planner successfully guides the robot to pass the narrow corridors. Furthermore, in maze environment where the existing motion planners generate long paths, the resulted solutions are relatively short and close to the normal paths. However, in some cases the optimality of the generated path is relatively low due to the shape of the obstacles.

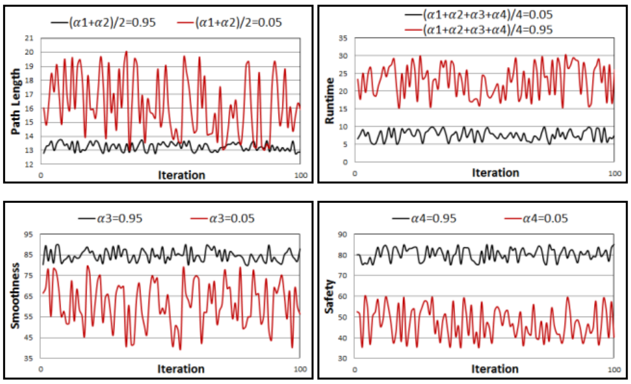

Figure 6. Best and worst achieved values for objectives using different values for corresponding coefficients. (a) path length (Optimality), (b) runtime, (c) smoothness, and (d) safety.

Fig. 6 shows the best and worst achieved values for different objectives during the simulation results. Note that since the proposed algorithm selects the next position of the robot, i.e. P_n randomly, the path length runtime smoothness and safety values are different in different executions. Therefore, the average values over 100 iterations are being used for discussing the performance of the algorithm. As mentioned before, four different planning objectives are considered in this research including short path, low runtime, high smoothness and high safety.

According to the graphs in Fig. 6, the path lengths are very high when the average of the first two coefficients is close to zero but as this value increases, the path lengths decrease. For running time of the planner, the best case happens when all variables are close to zero meaning that the chance of acceptance of a point is high. For smoothness and safety, the corresponding coefficients, i.e., α_3 and α_4 respectively, are the only active coefficients and high values for them improve the related objectives achievement.

Table I presents the simulation results in all test environments. Each of these objectives is defined differently. Path length (PL) is total travelled distance by the robot from the start configuration to the goal. Runtime (RT) is the processing time required by the planner to compute the trajectory. Smoothness (ST) is defined as the ratio of the angles between different segments of the final path to the length of the path. Finally, safety (SF) is calculated as the ration of the average distance of the robot from the closest obstacles to the dimension of the environment.

TABLE I. AVERAGED RESULTS IN ALL TEST ENVIRONMENTS

Decision Variable	Value	PL	RT	ST	SF
$\sum_{i=1}^{2} \alpha_i/2$	0.0	17.23	14.56	72.45	63.19
	0.5	15.17	14.56	72.45	63.19
	1.0	13.46	14.56	72.45	63.19
$\sum_{i=1}^{4} \alpha_i/4$	0.0	15.17	7.85	72.45	63.19
	0.5	15.17	14.56	72.45	63.19
	1.0	15.17	23.50	72.45	63.19
α_3	0.0	15.17	14.56	60.07	63.19
	0.5	15.17	14.56	72.45	63.19
	1.0	15.17	14.56	85.16	63.19
α_4	0.0	15.17	14.56	72.45	48.77
	0.5	15.17	14.56	72.45	63.19
	1.0	15.17	14.56	72.45	81.95

The range of the decision coefficients for achieving each objective can be summarized as follows.

- Short path: $\sum_{i=1}^{2} \frac{\alpha_i}{2} \to 1$

In order to have a short path, the robot needs to incrementally get closer to the goal position and get farther from the start position.

- Low runtime: $\sum_{i=1}^{4} \frac{\alpha_i}{4} \to 0$

In order to reduce the running time of the planner, the sensitivity of the cost function needs to be as low as possible so as soon as a random point was generated, it can pass the cost function criterion.

- Smoothness: $\alpha_3 \to 1$

In order to have a smooth trajectory, the robot needs to keep its distance from its previous position and therefore the coefficient of φ_p need to be maximal.

- Safety: $\alpha_4 \to 1$

Finally, the safety will increase if the robot keeps its distance from the surrounding obstacles. This can be done by increasing the coefficient associated with φ_o.

V. CONCLUSION

A common disadvantage of motion planning approaches has been studied in this research which is the inability to handle more than one objective. For most of the available algorithms, there is only one primary objective, i.e. generating short paths, low runtime requirement, path smoothness and path safety. To overcome this drawback, a new motion planning approach was proposed in this paper which enables the planner to consider different objectives. The proposed algorithm utilizes the readings of the robot's sensory system and calculates the value of four decision variables. In the next phase, an objective or cost function is evoked to measure the cost/suitability of the candidate position based on the decision variables. This function possesses four decision coefficients and by changing the values of them, the planner is able to provide solutions for different objectives. The performance of the proposed algorithm has been tested through computer simulation in several test environments. The simulation results indicate the efficient and robust performance of the algorithm. Moreover, in difficult planning tasks like mazes or narrow passages, the algorithm provides suitable solutions with high efficiency.

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