

Obstacle Displacement Prediction for Robot Motion Planning and Velocity Changes

Soheila Dadelahi, Mohammad Reza Jahed Motlagh, and Ali Reza Mohammad Shahri

Abstract—This paper introduces a new path-motion planning method for autonomous mobile robot which should move safely in unknown Dynamic environment. The environment may have numbers of obstacles of arbitrary shape and obstacles are allowed to move. We describe our approach to solve the motion-planning problem, using neural networks-based technique. The neural network is used to model the obstacles motion and predict their movements. According to one step ahead prediction of obstacle's trajectory, a rule-based technique for avoiding obstacles by adjusting the robot's velocity is suggested. This sensor based online method gives a safe but near optimal path. Simulation examples of generated path with proposed techniques will be presented and show the efficiency of the method.

Index Terms—Mobile robot, dynamic environment, neural network, path planning, speed control.

I. INTRODUCTION

Path planning and obstacle avoidance are important and active regions in robotics. In human robots in interactive places, lots of intelligent methods have been developed. Most current path planning methods computed offline are unsuitable for application to a real-time problem with moving obstacles. Dynamic obstacle avoidance is a hot topic of mobile robots and unmanned vehicles. Many obstacle avoidance methods were based on potential field approach. There are many other approaches that use VFH, VO and DOV presented by KHATIB [1], SHILLER [2] and OWEN [3] respectively in a reactive algorithm, for obstacle avoidance problem in dynamic environment.

A sensor-based online method with a moving target and dynamic and static obstacles is presented in [4]. At each iteration, the set of all collision-free directions were calculated using velocity vectors of the robot relative to each obstacle and target, forming the Directive Circle (DC), a direction close to the shortest path to the target was selected from feasible directions in DC. The DC prevents the robot from being trapped in deadlocks or local minima.

In addition, some works introduce the factor of uncertainty in obstacles motion. A method was proposed in [5] to predict the motion of an obstacle and its uncertainty from the history of its movement. The short term and long term prediction was

used to know the one step ahead and final destination of the obstacle. The prediction was combined to a POMDP method to control robot movement. In another work a probabilistic model of uncertainty is used in [6]. The planning algorithm is based on an extension of the Rapidly-exploring Random Tree algorithm, where the obstacles trajectory and the probability of collision are explicitly taken into account. The algorithm is used in a partial motion planner, and the probability of collision is updated in real-time. The proposed method in [7] combines a dynamic occupancy grid with the Probabilistic Velocity Obstacle (PVO). The velocity space was considered and, under the hypothesis of linear constant velocity of the obstacles, the probability of collision was estimated for each possible linear velocity of the robot. The limits of the perception system, such as sensor range and occlusions, and the uncertainties on position and velocity estimation, contribute directly to the computation of the probability of collision.

In all of these works because of inclusion of robot and obstacles' velocity in the formulation, the complexity of solution increases. We choose not to include the speed of the robot, or include speed actions in the action set and in the formulation of the problem. We prefer to use robot or obstacle displacement instead, to make ease in computation. This choice would further decrease the complexity of solution.

Motion planning in unknown environment comprises of two principal behaviors 1) path planning 2) obstacle Avoidance. These two behaviors are combined in our study. We incorporated a reactive approach with abstract task planning to form a hybrid method to deal with unexpected situations. Ranges of possible tasks interactions are well modeled to be able to form safe motion. It is assumed that the location of static and dynamic obstacles while the displacement of dynamic obstacles are to be calculated and predicted online. This represents the direction and obstacle's movement velocity. The navigation algorithm must take into account that the environment changes dynamically and also time is limited to take decisions. Models and decisions must be continuously updated. The future state of the environment is uncertain. To make decisions the robot needs to know how the world changes in the future. So we use prediction to model the environment changes.

The rest of this paper is structured as follows: Section II represents some important delimitation. Section III describes how the robot perceives world around and the way it uses information extracted from sensing in path generation. In Section IV trajectory prediction is represented. Section V describes the obstacle avoidance method continuing the planning and navigation algorithm developed. Simulation

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results are presented in Section VI. Section VII ends the paper with conclusion and future work suggestions.

II. TERMINOLOGY OF IMPORTANT RANGES DELIMITATIONS

To understand this paper it's necessary to briefly introduce some ranges and delimitations used for the presented Dynamic obstacle avoidance algorithm first.

- **Velocity delimitations:** Robot velocity is represented by displacement robot takes at each time step. Three limits in displacement are considered, minimum, normal and maximum. These represent low normal and fast velocity respectively. The robot can choose many different speeds upper than minimum velocity and lower than maximum velocity to avoid the obstacles and reach the goal faster.

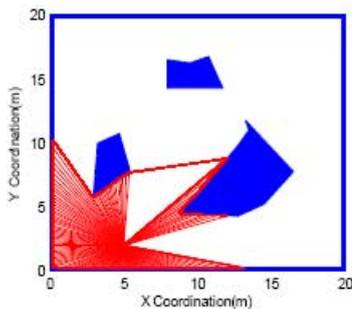
- **Safety distance:** Is minimum distance between obstacle and robot to have a safe move.

- **Minimum corridor(MC):**

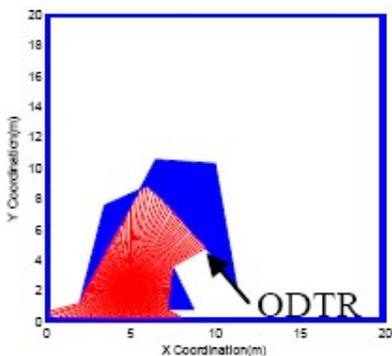
Minimum distance between two obstacles to form a safe passage for robot (Fig. 1-d).

$MC = \text{Robot width} + 2 \times \text{Safety distance}$

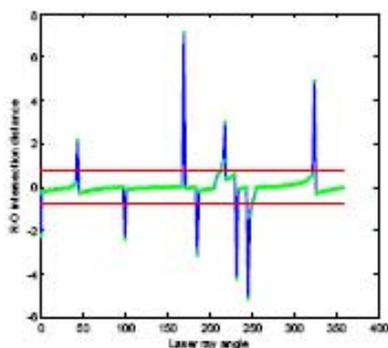
- **Safety Territory:** A circle around robot. is used to determine risk of collision between robot and obstacles in next step to adjust Robot speed or displacement.



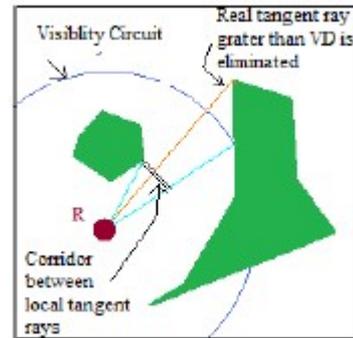
(a)



(b)



(c)



(d)

Fig. 1. Illustration of different situations and environment perception; a) Determining corridor or gaps between obstacles by applying VD b) No Corridor around robot. Too close obstacles, detecting ODTR. c) represents obstacle distinction vertices with peaks in diagram. d) Determining safe corridor between two obstacle local boundaries.

III. ENVIRONMENT PERCEPTION AND PATH GENERATION

Environment perception has two stages. 1) Environment Sensing 2) Environment prediction.

For environment sensing the robot can use laser scanner which measure distances to obstacles at constant angular intervals. Finding the intersections of ray and viewable surface of objects, results are stored in environment Detection Matrix .this matrix is processed to determine tangent rays[4]. Two types of tangent rays are used. First local tangent rays (LTR), second obstacle distinction tangent ray (ODTR). A visibility distance (VD) is considered for the robot. All intersection ray segment magnitude less than visibility distance are eliminated to determine LTRs . robots decision is only based on objects in its VD .In this way robot detects free spaces between obstacles borders in its visibility as in Fig. 1-a. These spaces are passages for robot to move. The passage between two obstacles should be greater than minimum corridor. If not two obstacles will be combined. In this way the objects that are too close to each other are considered as a single object. This combination is very important when the environment is cluttered. In experiments it was found that Sometimes, at some directions, the SICK scanner cannot get correct range data (very big values) due to laser reflection, which causes “holes” in the perception. This combination effectively eliminates these holes [8].The ray in the middle of safe corridors will be Tracked by robot for next move. In this way the distance between robot and obstacles will be maximized as in VORONOI diagrams.

In the case that no gap or safe corridors are detected, robot moves tracking obstacle ODTR. consider two adjacent rays distance samples s_i and s_{i+1} , their length magnitude will be nearly same if they are from same obstacle, but if they are from different obstacles, in front of or behind each other, there will be a significant difference in these two distances as shown in Fig 1-b.such rays are split positions and called obstacle distinction tangent rays (ODTR) and are used for tracking and path generation in situations that there are no safe corridor between obstacles around robot. In figure1-c the ray segment magnitude difference is provided. The differences that exceed the red line threshold are considered

as ODTR.

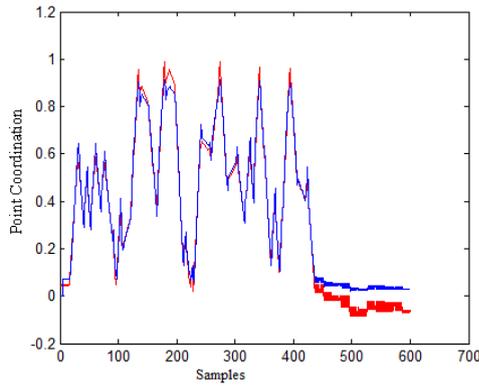


Fig. 2. Results obtained from neural network for evaluation data set

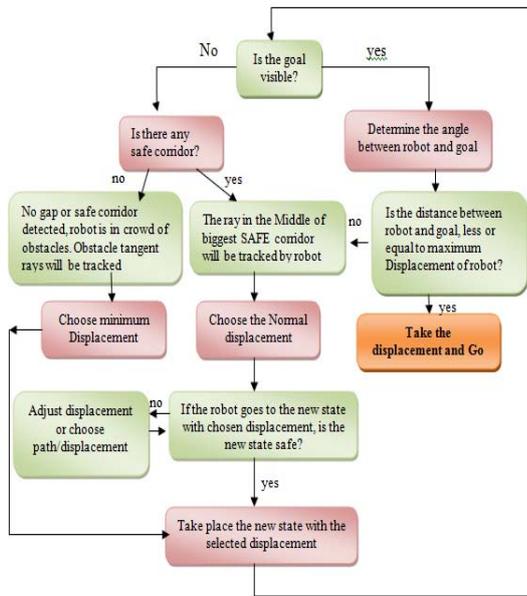


Fig. 3. Obstacle avoidance algorithm chart

IV. OBSTACLE TRAJECTORY AND DISPLACEMENT PREDICTION

The one step ahead prediction of obstacle displacement is obtained by a back propagation Neural Network. The NN can model the motion of obstacles. Obstacles have different constant linear speed and move in arbitrary different directions.

The input to the network, x_1, x_2, x_3 and x_4 are the moving obstacle's position at times $t, t-1, t-2$ and $t-3$. The positions of the moving obstacle are given to the network as a state. The output of the network is the predicted position of obstacle at time $t + 1$.

The used training set was composed of 1500 samples. It was obtained by arbitrary movement in the environment. A data set of 600 samples that network has not trained for, is used for evaluation of the network. The result is shown in Fig. 2 and the computed network error shows that the obtained network can predict unforeseen situations.

$$\begin{aligned} \text{Mean Square Error} &= \sum_{i=1:N} (Y_{\text{output}} - Y_{\text{desired}})^2 / N & (1) \\ \text{MSE} &= (\text{sum}((x_{\text{hist}} - y)^2)) / 601 = 0.0023 & (2) \\ \text{Root MSE} &= \sqrt{\text{MSE}} & (3) \\ \text{SQRT}(\text{MSE}) &= 0.0481 & (4) \end{aligned}$$

V. OBSTACLE AVOIDANCE

In this work Robot generated Path is based on: 1) goal visibility 2) gaps between obstacles and Local Tangent rays 3) obstacle distinction tangent ray.

In Fig. 3 the algorithm is presented, as you see, If goal is visible and no obstacle is located between robot and goal. Robot can choose maximum displacement or any displacement less than that to reach the goal if Euclidian distance between robot and goal is less than maximum displacement.

In section IV we described application of two types of tangent rays in different situations. These situations were shown in Fig. 1-a and Fig. 1-b the robot takes different displacements in two situations. In situation a biggest safe corridor is determined. The ray in the Middle Of safe corridor will be tracked by robot to keep maximum distance from obstacles. Robot chooses normal displacement for next state but before going to next state the safety checking procedure will be done for the chosen upcoming position.

A. Safety Checking and Collision Avoidance

Safety Territory is used for safety checking to determine possibilities of collision between robot and obstacles in next step to change chosen displacement or path in next step if needed. Before taking place in new position, robot checks if the new position will be occupied by any obstacle in next step or not. For this robot imagines itself in the new position. If any visible obstacle or their prediction shadow will be in intersection with safety territory circle around robot, the chosen situation will be in risk of collision. It shows that while robot reaches to chosen position, an obstacle also will reach to that position and the collision may occur. So robot should increase speed and choose a larger displacement less than maximum to pass obstacle, if still the new position is risky the robot changes its path. This path can be a backward path also, if there is no other nearer path to optimum chosen path.

In the case there is no gap or safe corridor detected, choosing low speed or minimum displacement, robot moves tracking ODTR with largest difference in magnitude from adjacent ray, in the peak of Fig. 1-c, until it finds a safe corridor and switches to situation Fig. 1-a.

VI. SIMULATION RESULTS

This section presents simulations of algorithm's performance. To present the motion planner's capabilities, three types of problems are simulated. it is assumed that each moving obstacle move with arbitrary constant velocity. The robot can choose many different speeds upper than minimum velocity and lower than maximum velocity to avoid the obstacle. Maximum speed of robot must be equal or upper than any obstacle's speed. The total number of states of the robot was 1 hundred for 20*20 environment dimension.

The robot minimum, normal and maximum displacements are respectively set to 0.5,1 and 2.5. The robot's position at each time step is shown with a circle. Blue patches show current state of obstacles and Green patches show prediction of Next state.

In first example, shown in Fig. 4-a the robot generates a

path in each step to reach the goal position with normal displacements. The robot starts moving in the optimal direction to reach the goal position but as shown in Fig. 4-b The robot has the prediction of an obstacle's movement that is going to block its trajectory from right side. As shown in Fig. 4-c , the robot moves with fast velocity or maximum

displacement to bypass the obstacle. After the robot has passed the area that was predicted to be occupied by the obstacle as shown in Fig. 4-c , it returns to the normal velocity to continue its movement to the goal position. With this behavior, the robot has no need to make a detour to avoid the obstacle.

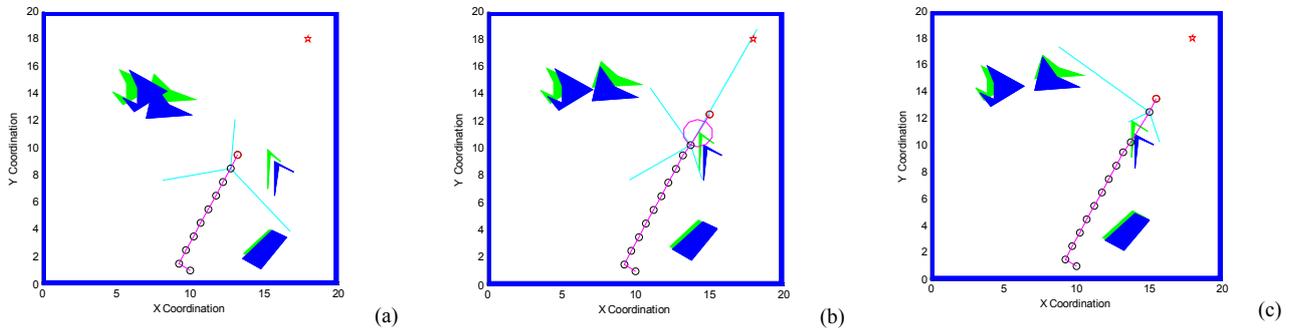


Fig. 4. By making change in displacement in the same path, robot avoids unnecessary detour in path and passes the obstacle.

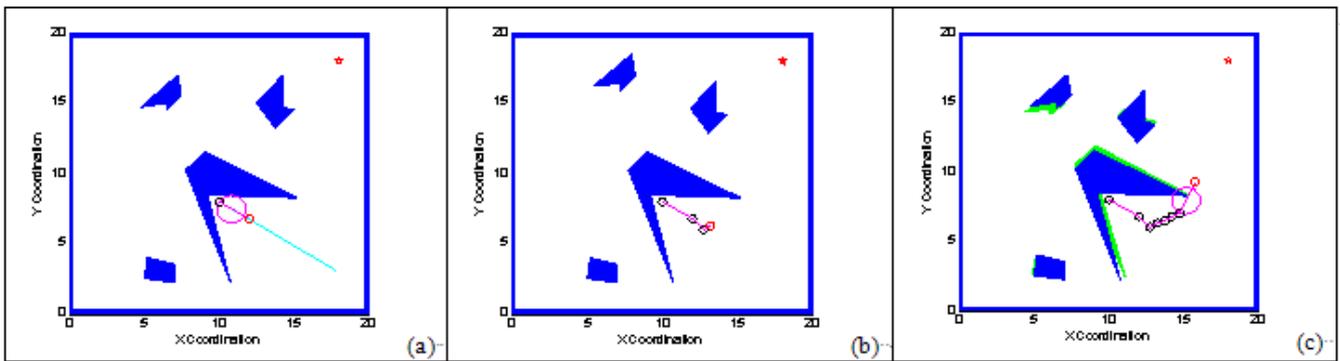


Fig. 5. Moving away from the concave obstacle by applying the algorithm to the robot

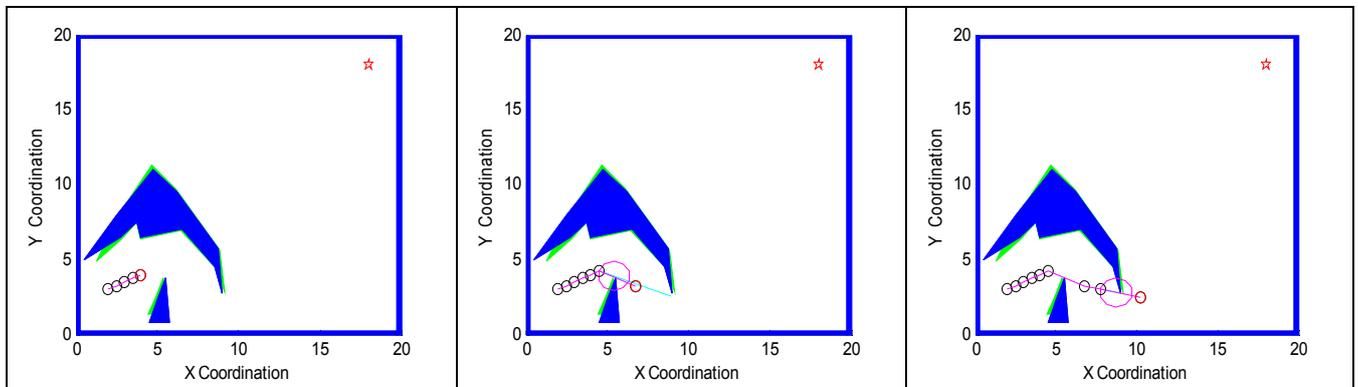


Fig. 6. Moving away from the crowd of obstacles by choosing minimum displacement and tracking ODTR

In second example, Fig. 5 demonstrates an example that the motion planning is in the presence of two static and two dynamic obstacles. At starting moment the robot is inside a concave obstacle. By applying the obstacle avoidance technique, the robot moves away from the concave obstacle and goes toward the goal.

In third example, shown in Fig.6 there is no gap or free space around robot because obstacles are too close. Robot chooses minimum velocity and continues movement on obstacle ODTR. By applying the obstacle avoidance technique, the robot moves away from the crowd of obstacles and goes toward the target. After it reaches to vertex Of obstacle, it finds a corridor, changes its displacement to maximum to come out of obstacles crowd.

These simulations demonstrate the efficiency of the method and its responsive performance. As shown in figures, the robot's trajectory is collision-free, safe, and near optimal. It can be implemented in dynamic real world environments.

VII. CONCLUSIONS

In this paper we proposed to use obstacle's one-step-ahead movement modeling with neural network within a rule based frame work for autonomous robot navigation. We used the result of prediction technique to detect risk of collision and decide either increase or decrease robot velocity with choosing specific displacements, following desired path to avoid Dynamic obstacles and reach fast access to goal more

effectively. The paper presents our simulation results which show that designed strategy is acceptable for solution of this problem for point robot and disk robot. Applying this technique with simple control rules, robot can avoid unnecessary detours that usually increase the robot movements steps and tracked trajectory to goal position in dynamic environments, and robot can reach to goal in fast manner.

Future work involves applying new Learning strategies. The prediction of obstacles can be improved by using different prediction techniques for more complicated obstacle movements. This method can be extended to multi robot and multi target problems. An interesting extension to the algorithm can be the problem of moving target.

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