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Dynamic Path Planning Around Moving Obstacles by Collaborating Robots for Space Exploration

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We investigate dynamic control of collaborating robots by integrating methodologies from path planning and dynamic prediction of moving obstacles. Predicting for a finite horizon, instead of one step ahead, provides far better results. Efficient distributed algorithms are implemented and demonstrated via simulations. A combination of optimization and logic is needed for best performance and efficiency.

I. Introduction

NASA's Adaptive Sensor Fleet (ASF) system is a control software package developed for application to a wide array of sensor-equipped autonomous vehicles. The software is designed so that a user can adapt the system to the dynamics of various types of vehicles and their operating environment. The two specific platforms of interest are the Ocean-Atmosphere Sensor Integration System (OASIS) boats and Personal Exploration Rovers (PERs). Our research considers a situation in which there are multiple agents functioning in a dynamic environment. This environment could include non-communicating autonomous robots, communicating autonomous robots, and communicating non-autonomous robots. In the simplest situation a single agent is given a starting position and a target position, and told to traverse the distance optimally while avoiding static obstacles. In the most advanced situation, a group of agents is given a starting distribution and a target distribution, and are told to traverse the distance while maintaining a formation and avoiding unknown dynamic obstacles including other autonomous agents. An example would be a construction site on Mars where teams of autonomous agents and remotely human-controlled agents are working in close proximity. The autonomous agents have no information about the future movements of the human-controlled agents, but simply have past and present position data as well as motion constraint data. Our goal is to allow the autonomous agents to perform their mission as efficiently as possible by modeling the future probabilistic location of the human-controlled agents and creating a near optimal path to avoid them.

The current system deals only with static obstacles and uses a map of known obstacles to create an optimal planned path via dynamic programming methods. A more interesting, and until now an unexplored, situation involves unknown static and dynamic obstacles that the agents must also avoid i.e. other boats, other robots, shallow water, buoys, cliffs etc. We want to model the dynamics of these unknown obstacles given a small number of noisy observations (rfid, gps, sonar, laser range finder, radar, visual). The probabilistic location of these dynamic obstacles at times in the future can be compared to the planned path of the agent. The objects will be avoided by treating the probabilistic distribution of their location at the time of intersection with the agent's planned optimal path, itself as a static obstacle. At this point a new near optimal path will be calculated using the originally uploaded map as well as an overlay of the previously unknown obstacles.

II. Practical Implementation

The analytical and simulation results of this research will be practically applied to a group of mobile robots on a Mars terrain yard called MERS (Multipurpose Exoterrain for Robotic Studies) in the courtyard of building 23 at Goddard Space Flight Center. MERS is shown in Figure 1 below.

Figure 1. The MERS facility and its robots.

For the experiments and tests we have access to five PERs. Each PER is equipped with an Ultra-wideband RFID locator which provides accurate position data. As an experiment, certain rovers will be designated “dumb” rovers being given only a preplanned path to follow or be remotely controlled. The intelligent rovers will then be told to progress between a series of objective waypoints while avoiding the “dumb” rovers which may intersect their path at any time. The intelligent rovers will do this given only obstacle position data and motion constraints in a near optimal manner. The possible future location of any obstacle is determined by modeling the obstacle’s speed and angle of travel as a random walk with a Gaussian distribution. The variance of the speed and angle distribution is learned by the agent as it observes the movement of the obstacle. There are multiple constraints on the obstacles’ movement including maximum linear and angular speed which help to narrow the location distribution. Once the possible future location distribution is determined a new agent path is created using dynamic programming on a small windowed region of the entire operating environment.

III. Problem Formulation

In our research so far the problem has been slightly simplified. Identifying obstacles and determining their location from a simple sensor such as a camera is a whole other field of image processing research. One focus of our research is on the prediction of future obstacle motion once each obstacle is identified and its current position is determined. The other focus is on methods for determining efficient paths around the probable location of the obstacles at future times. For this reason we have assumed perfect past and present location information. The problem is now simplified to the following:

> *To plan the motion of a mobile robot(s) from an initial to final location while avoiding known static obstacles and known moving obstacles with unknown future paths, subject to the motion constraints of the robots and obstacles.*

Thus our approach to the problem is based on two interacting components: (dynamic) path prediction and (dynamic) obstacle avoidance (i.e. dynamic path planning).

One of the intended usages of the ASF software system is for controlling a team of exploration robots or construction robots. Prior to our research the system had no method for avoiding unknown or dynamic obstacles. Our goal is to apply obstacle prediction and avoidance methods to an existing robot system in a simulated Mars terrain. Each of the robots involved, some of which in our tests would be considered moving obstacles, have a locator system. Therefore, we simplified initially the problem to the avoidance of obstacles with known current locations but unknown trajectories. We modeled the obstacle motion as a Gaussian random walk. The variance of this Gaussian random variable is composed of a learned variance component and a maximum variance component, and is adapted as the obstacle is observed. Specifically, more weight is given to a learned variance and less is given to the maximum variance the longer the obstacle is observed. Another important aspect of motion prediction is a motion model. Motion dynamics are constrained by the physical capabilities of the obstacle, and in our simulation we took guidance from the dynamics of the robots being used in ASF. The basic motion model consisted of constrained rates of change of the linear and angular velocities. Once an obstacle path is predicted a path must be planned around the future location of the obstacle. The path planning methods we used include dynamic programming (DP) and artificial potential fields (APFs).

IV. Approach and Methodologies

A key portion of our work involves the integration of obstacle path prediction and robot path planning simulations. The simulations work independently but joining the two has proven to be challenging. The path planning simulation works independently of the moving obstacles. This simulation uses the principle of dynamic programming to navigate across a grid of hexagonal cells while avoiding cells designated as containing obstacles. We have developed efficient numerical schemes for computing the prediction zone of each robot, and for determining whether a specific hexagon intersects it or not. We have also investigated the size of the tracking ring and prediction ring surrounding each mobile robot. Each robot has the ability to track a moving obstacle. The longer it can track the moving obstacle, the more accurately it can narrow its variance and allow the path planning to be more optimal. We investigated the coupling between the size of these rings and their dependence on other scenario parameters.

The proper integration of the motion prediction and planning required a combination of methods from optimization and logic. This is indeed a novel approach to such problems. The integrated method, including the logic part, involves time varying constructs, as obstacles and robots are moving and thus the constraints are changing with time progression. We have also investigated the learning aspect of our obstacle motion prediction algorithm. We have investigated several analytical methods using the Gaussian random walk motion model, and in particular the adaptation of the variance in the model, and the computation of both the fixed and adjustable (learned) part of the overall variance.

In addition to this ‘quasi-dynamic’ approach, whereby obstacle positions are predicted in the future for some time interval using the motion model, and then path planning is executed around these predicted positions with some tolerance (or slack), we have formulated and analyzed a more ‘dynamic’ obstacle avoidance approach. In the latter we make path planning decisions at each time step based on the probability of a collision upon choosing each of the possible paths.

A. Integrating Prediction and Planning Simulations

The integration of the prediction and planning simulations presented several challenges. The simulations work independently but joining the two is still giving me problems. We specifically defined situations and special scenarios where our method gives demonstrably better results. We have also identified scenarios where our method breaks down and additional logic must be added. An example of the latter would be in the OASIS boat project. In this situation an autonomous boat is tasked to move from one location to another. While doing this it encounters a moving obstacle and begins tracking its motion. Once the future location of the obstacle is plotted we find that the possible locations block a narrow isthmus that the boat was originally planning on traveling through. If the path planner would simply recalculate the new optimal path, it would tell the boat to travel a long distance around the entire landmass. Instead, a better solution is to insert some logic that works with a time variable. We also performed, in this example, cost analysis to see if it might be worth simply telling the boat to wait and allow the obstacle to progress. Once this has occurred the boat can continue through the isthmus unobstructed.

The obstacle motion prediction is accomplished by restricting the dynamics of the obstacles and then modeling their motion as a Gaussian random walk. Specifically their linear and angular accelerations are restricted to some maximum and minimum values which are known to the mobile robots *a priori*. The mean for the Gaussian random variable is simply the value of the process at the previous time step. The variance is calculated using a weighted combination of the maximum speed increase of the obstacle during a set time period and the observed average change in the speed during each time step over some time period.

The path planning simulation works independently of the moving obstacles. This simulation uses the principles of dynamic programming to navigate across a grid of hexagonal cells while avoiding cells designated as containing obstacles.

A specific problem arises when combining these two aspects, specifically designating a hexagon as possibly containing an obstacle. The idea is to consider a hexagon occupied when some portion of the prediction zone is contained in the hexagon. Unfortunately, both the hexagons and the prediction zone are drawn by the simulator using line segments. Therefore there is really no concept of a hexagon or a prediction zone as a unit. Therefore we encountered difficulties in determining the intersection of these two regions. Our original method involved individually checking each line segment in the prediction zone against all of the hexagon line segments. This was computationally very intensive. We developed a more efficient method of determining whether a hexagon was occupied. This latter method involves drawing radial line segments from the obstacle's center to the center of the hexagons found at the minimum and maximum angles of the prediction zone. The intersection of these radial lines with the prediction zone forms a series of points. These points can then be compared to the lines forming the hexagon as a less computationally intensive search.

Another problem we considered was the size of the tracking ring and of the prediction ring surrounding each mobile robot. Each robot has the ability to track a moving obstacle. The longer it can track the moving obstacle, the more accurately it can narrow its variance and allow the path planning to be more optimal. This is more of a practical consideration due to the fact that the only thing needed for longer and more accurate tracking is larger memory and processing power. Determining the size of the prediction ring however is more of a geometric problem. It is clear that the size of the ring will depend on the speed of the obstacle and the speed of the mobile agent as well as how far into the future we are trying to predict. We have investigated analytic method for determining how far into the future to predict the obstacle motion. The optimal prediction range depends on a multitude of factors including the size and number of stationary and other mobile obstacles and the size of the entire operation field. We have not determined all these relationships. In the current implementation we simply choose a prediction range *a priori* so that we can use this (range) information to determine the appropriate prediction ring size.

B. Learning

We have also investigated the learning aspect of our obstacle motion prediction algorithm. Again, the motion is predicted by modeling it as a Gaussian random walk. The mean for the Gaussian random variable is simply the value of the process at the previous time step. The variance is calculated using a weighted combination of the maximum speed increase of the obstacle during a set time period and the observed average change in the speed during each time step over some time period. Initially the weighting of each of these variance terms had been simply chosen a priori and could be tuned after observing multiple tests of the system's performance. We are currently investigating a more adaptive approach which models the first term (sample variance) as an AR, MA or ARMA process. This follows from the assumption that the longer we can observe the moving obstacle, the more accurately we can define its variance. As we do this, we can give more and more weight to the first variance term $(1/(N-1))\Sigma e^2(t)$ where $e(t)= \text{speed}(t) - \text{speed}(t-1)$ and less on the second term, which is the maximum speed term.

C. Algorithm Implementation and Simulation Experiments

The obstacle motion prediction and mobile robot path planning were simulated in a Matlab environment with consideration given to applying the control techniques to the mobile robots of NASA's ASF project. We simulated multiple adaptations of the motion prediction method and combined this with various iterations of the path planning methods. This allowed us to compare the success of various configurations in dealing with a range of dynamic environments.

The need for metrics in order to compare our different methods led to some major restructuring of our simulations. However, the result was a much better version of dynamic obstacle prediction and obstacle avoidance methods. One change that was made involved the prediction of the motion of the dynamic obstacles. Originally we were simply predicting their position at a single future time which is governed by a simulated restriction in the observation range of the agent's sensors. Our most recent method predicts a dynamic obstacle's position at multiple times in the future, and also requires that these prediction zones overlap. The prediction zones are compared to the agent's planned path at the corresponding time instants, any common cells indicate the chance of a collision. This method allows the predicted obstacle locations that are avoided to be smaller, therefore increasing the optimality of the path planning.

In Fig. 2 the beginning snapshot of such simulations is shown. The associated animations demonstrate the performance of our dynamic obstacle motion prediction and path planning. In the figure the red and green circles represent the agent and the obstacle respectively. The agent is trying to go from its initial position to the final position located at the blue dot. Black areas correspond to static obstacles. In the current version the green dynamic obstacle doesn't avoid the static obstacles but can go right over them. A giant blue circle appears when the dynamic obstacle has come within the prediction range of the agent. (Note: *predict_range* = *max_velocity*time_step*max_steps* where *time_step* is the time unit for the simulation and *max_step* is the maximum number of *time_steps* into the future). At this point the agent predicts the dynamic obstacle's path at 2, 5,and 10 steps (time steps) into the future (these zones overlap and are shown in yellow in the animations). These zones are compared to the planned path of the agent and a zone that intersects the planned path at the respective number of steps into the future turns black, essentially representing a static obstacle. At this point the agent's path is replanned around this new threat and eventually reaches its destination.

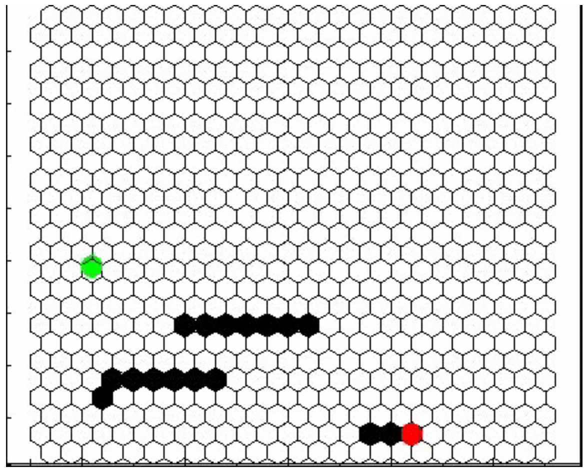

Figure 2. Initiation state of a dynamic simulation

V. NASA Missions

Our research results will greatly improve the autonomy of robots functioning in many NASA environments. An obvious area of interest is construction of space facilities on the Moon or Mars. It will be very important for multiple robots from many different projects, and possibly many different countries to be able to operate collision free and in an efficient manner while in close proximity to each other. The autonomous sea-sensor project involving the OASIS boats is another mission critical application of this obstacle avoidance technology. The OASIS boats must operate autonomously in dynamic environments while avoiding sea obstacles such as other boats, buoys, and unknown shallow water.

VI. Future Directions

Our future research plans involve removing some of the simplifications stated above. We would like to implement on-line identification of obstacle location without relying on a centralized positioning system. Depending on which sensors we chose for this task this could involve some exploration into areas such as image processing, particle filtering, and Kalman filtering. Another interesting scenario involves intelligent robots traveling between objective waypoints while maintaining a required distribution. An example would be two construction agents working together to carry a large beam. This task would require some form of communication between the agents therefore revealing interesting research problems in the field of communications and control interaction and integration.

We are also currently developing algorithms based on the Artificial Potential Fields (APF) method. We have this operational, but quantitative elements are under development. A challenge in the resulting simulations is to regulate the speed of the agent so that it corresponds to the speed of the agent in the path planning method. A solution is provided by increasing the quantization of the grid mesh to correspond to the hexagonal grid that is used in the path planning method.

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