1 Problem Description

A pivotal problem in robotics is to generate collision free paths through environment that allow a robot to move from an initial configuration to a goal configuration without colliding with any obstacle. In many cases, these environments will have dynamic obstacles that do not stay in the same position. Using machine learning algorithms, it is possible to predict the future positions of the obstacles by observing the obstacles' past positions. The machine learning algorithms provide a probability distribution of where obstacles are going to be within a certain amount of time into the future. The amount of time within the future is provided as an argument to the machine learning algorithm. More formally, the machine learning algorithm,

$$P : \mathcal{O} \times \mathbb{R} \to (\mathbb{R}^2 \to [0, 1])$$

Where $\mathcal{O}$ is a set of all the obstacles and their past positions. What is returned from P is a function that given an x, y position it will return a probability of a obstacle being at x, y within a certain amount of time in the future. Using the function that is returned, we hypothesize that it is possible to generate safe paths through cluttered dynamic environments where there is a measurable uncertainty of an obstacle moving off its current path.

2 Proposed Approach

The current state of the art for planning around moving obstacles where the trajectories are known consists of planning in space-time and by waiting until the current path is clear, and afterwards moving towards the goal. The first approach lacks the ability to deal elegantly with uncertainty in the trajectories of the moving obstacles. The second approach generates suboptimal paths in terms of the amount of time it takes to move from the initial configuration to the goal configuration. Our approach will elegantly deal with the uncertainty in the obstacles' trajectories whilst generating paths that will lead the robot to the goal without waiting unless absolutely necessary. We plan to do this using a Probabilistic Roadmap that will sample points in space and time (x, y, t). An edge will be added between a point (x_0, y_0, t_0) and (x_1, y_1, t_1) as long as it is feasible for the robot to move between (x_0, y_0) and (x_1, y_1) in $t_1 - t_0$ seconds. The control model for the robot will determine the feasibility of moving between two points. A PRM with a suitable number of sample points will capture the space-time connectivity of the environment.

Using this roadmap, we will be able to assign weights to nodes based on the probability of an obstacle being in the same location as the node. The edges will be weighted using a combination of the probability of a robot colliding with an obstacle if travelling along said edge and the length of the edge. Using a shortest path algorithm such as A*, we will be able to generate paths in space-time that minimize the length of the path and the probability of colliding with an obstacle. The path that is generated will be the initial path used by the robot to plan its motions. Since obstacles may move off their initial trajectories, the PRM can be used for replanning. Once it is noticed that an obstacle has changed its trajectory, the roadmap can be re-weighted, and a new shortest path can be generated from the current configuration of the robot to the goal configuration.