

Toward a Generalized Risk Assessment Method on Occupancy Grids

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Abstract—To navigate safely and efficiently, a robot must be aware of its surroundings. Although Bayesian occupancy grids are an efficient way to map the environment, they are not well-suited to assess risks of a specific path. In this paper, we extend the work of Laconte *et al.* [1] to generate meaningful risks in 3D environments. Here, we define the risk as the deformation energy of the robot’s wheels due to collisions.

I. INTRODUCTION

Several recent works implemented a notion of risk in occupancy grids (e.g., [2]). In particular, Laconte *et al.* [1] introduced the Lambda-Field theory in 2D environments where each cell c_i of a map stores the intensity λ_i of a given event (the higher the intensity, the more likely the event is to happen), and then use this field to compute a generic risk over a path. They defined the event as a harmful collision with an obstacle. In this work, we extend the theory of the Lambda-Field, using a 3D LIDAR sensor and a novel map measurement function that allows the robot to be aware of 3D obstacles (e.g., sidewalks or speed bumps). Thus, the robot is able to make more nuanced decisions such as climbing a road curb at low speed.

II. THEORY

We extend the definition of a harmful event defined as a collision with the environment in Laconte *et al.* [3]. In our work, the event is defined as the deformation of the wheel due to a collision. Note that this generalizes the aforementioned definition of the collision, as every collision induces a wheel deformation. To assess whether a cell is too risky to cross, we build a Digital Elevation Map (DEM). We assume that the robot can safely climb 5 cm structures. We also adapt the harmful probability p_i defined in [3] which corresponds to the probability that the event will be harmful to the robot. We compute the intensities $\lambda_i \in \mathbb{R}_{\geq 0}$ of the map as

$$\lambda_i = p_i \cdot \frac{1}{e} \ln \left(1 + \frac{u_i}{s_i} \right) \quad \text{with } p_i = \min \left(\frac{|H_i|}{R}, 1 \right), \quad (1)$$

where $H_i \in \mathbb{R}$ is the maximum elevation difference between the cell c_i and its neighbors, and $R \in \mathbb{R}_{>0}$ is the radius of the robot’s wheels. The variables s_i and u_i are respectively the number of times that the cell c_i has been measured as safe (i.e., below 5 cm) and unsafe (i.e., above 5 cm and will trigger a harmful event).

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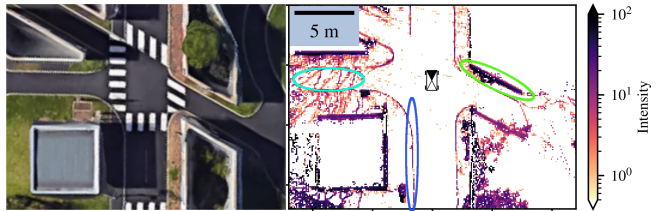


Fig. 1. *Left*: Aerial view from our urban-like test site with sidewalks that may be hazardous. *Right*: Lambda-field computed from the DEM. The higher the intensity, the more likely the event will happen if the robot crosses the cell. The robot is depicted by the rectangle (front represented by the black triangle).

III. EXPERIMENTATIONS

First, a DEM was created by accumulating several point clouds generated by a 3D LIDAR sensor. Then, by using Equation 1, we constructed a Lambda-Field as shown in Figure 1 with a wheel radius of $R = 25$ cm. Road curbs and walls have a high intensity, indicating that if the robot goes through, the event of collision will be very likely to occur. We can also see that the lambda values for a curb (blue ellipse) is lower than for a wall (green ellipse), meaning that a harmful collision is more likely to happen if we hit the wall. The cyan ellipse shows an area where not enough 3D points were accumulated to get a good intensity assessment. Using this Lambda-Field, we can now compute the risk for a given event defined as the elastic energy stored in the wheel due to the collision. The risk function can take into account numerous factors such as the incidence angle or the vehicle’s speed. Thus, the robot could decide to drive onto a sidewalk only at low speed as the stored energy would be lower.

IV. CONCLUSION

In this early work, we extended the Lambda-Field by using it in association with a DEM, which resulted in risk assessments of going over hazardous structures like curbs or walls. As done in [2], we intend to fuse several maps into the Lambda-Field for more generic risk assessments and provide it to a path planning algorithm.

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