Optimal Traversability Analysis for the Safety of Robots Displacements

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Context & Motivations

In a context of autonomous mobile robots, we want to

1. Evolve in the environment without taking too much 'risk'
2. Prove that the robot takes a 'risk' below a certain threshold
3. Define mathematically the notion of risk

Occupancy Grids

- LIght Detection And Ranging (lidar) are often used to estimate the traversability of the environment [1].
- Using lasers, they measure the distance to the closest obstacle for several orientations.

Figure 1: Lidar LMS-1xx

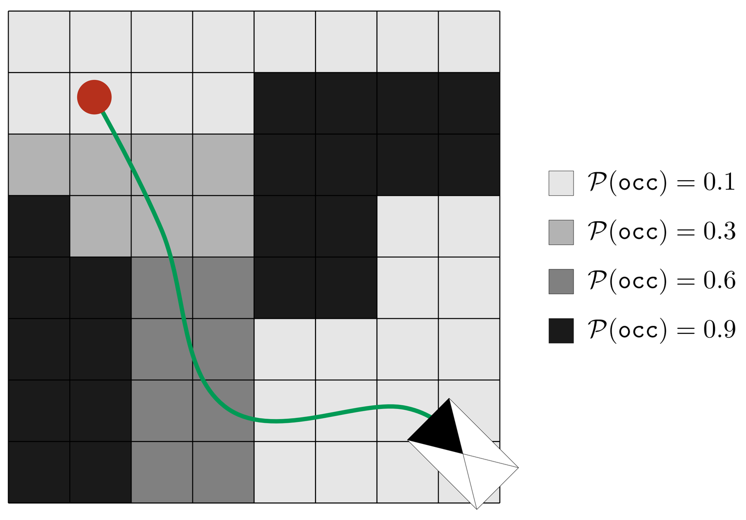

Figure 2: Example of occupancy grid

- The traversability is represented by cells of fixed size containing the probability of occupancy.
- The robot wants to go to the goal (red dot) while minimizing the probability of collision.

Lambda-Field: A Continuous Counterpart for Risk Assessment

- Occupancy grids are however not fitted to assess the probability of collision.
- The probability of collision indeed depends on the size of the cells, which is counterintuitive.

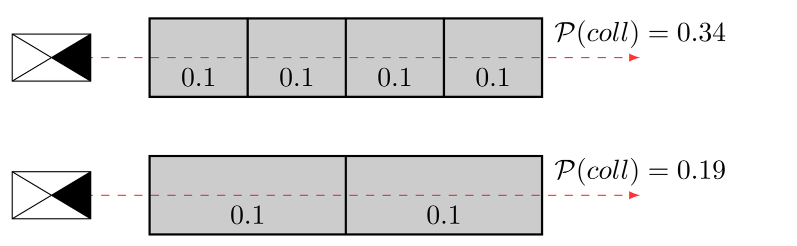

Figure 3: The robot wants to cross the same field with different discretisation sizes.

We introduce the concept of Lambda-Field, which allows the computation of path integrals over a field.

For a positive real-valued field $\lambda(s)$, $s \in \mathbb{R}^2$, the probability to encounter at least one obstacle in a path $\mathcal{P} \subset \mathbb{R}^2$ is

$$\mathbb{P}(\texttt{coll}|\mathcal{P}) = 1 - \exp\left(-\int_{\mathcal{P}} \lambda(s)ds\right) \approx 1 - \exp\left(-\mathcal{A}\sum_{c_i \in \mathcal{C}} \lambda_i\right) \quad (1)$$

where the approximation is valid for a discretization of the field into cells of area $\mathcal{A}$ and the path $\mathcal{P}$ crosses the cells $c_i \in \mathcal{C}$.

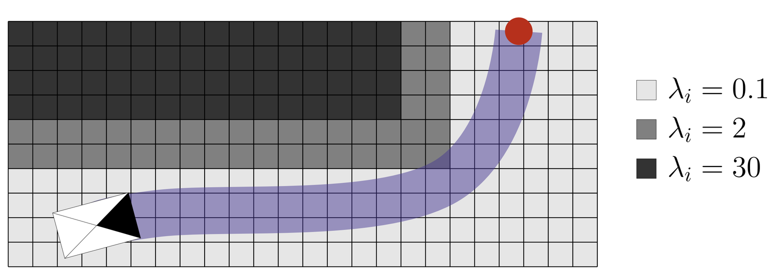

Figure 4: Example of lambda-field. The robot want to cross the path in blue, where each cell has an area of 0.04m^2.

- Using Equation 1, the probability of collision for the blue path is

$$1 - \exp(-0.04(58 \cdot 0.1 + 1 \cdot 2)) \approx 0.27$$

Construction of the Lambda-Field

- Under the assumption that the error region e of the lidar is small, the λ_i that maximizes the expectation is

$$\lambda_i = \frac{1}{e}\ln\left(1 + \frac{h_i}{m_i}\right) \quad (2)$$

where h_i (resp. m_i) is the number of times the cell has been counted as 'hit' (resp 'miss').

- We also define confidence intervals over the lambda field, such that

$$\mathbb{P}(\lambda_L \leq \lambda_i \leq \lambda_U) \geq 95\% \quad (3)$$

Risk Assessment in Lambda-Field

- The strength of the Lambda-Field is its ability to compute path-integrals. Under the assumption of small cells, we are able to compute the expectation of a risk $r(X)$ over a path crossing the cells $\{c_i\}_{0:N}$, where X is a random variable which stands for the position of the collision:

$$\mathbb{E}[r(X)] = \sum_{i=0}^{N} r(\mathcal{A}i)\exp\left(-\mathcal{A}\sum_{j=0}^{i-1}\lambda_j\right)(1 - \exp(-\mathcal{A}\lambda_i)) \quad (4)$$

- The risk function $r(X)$ can take several shapes:
  - $r(X) = 1$ leads to the probability of collision for a given path.
  - $r(X) = m_R \cdot v(X)$, where m_R is the mass of the robot and $v(X)$ its velocity at X, leads to the expected force of collision the robot will encounter in the path for static obstacles (walls, ...).

Simulations: Robot-Follower Scenario

- The robot (black & white box) has to follow the pedestrian (green dot) knowing only its position (not the environment nor its future path).
- The robot samples trajectories every second, and chooses one such that it is sure at 95% that the expected collision is below $1\,\text{kg}\,\text{m}\,\text{s}^{-1}$ and stays as close as possible to the pedestrian.

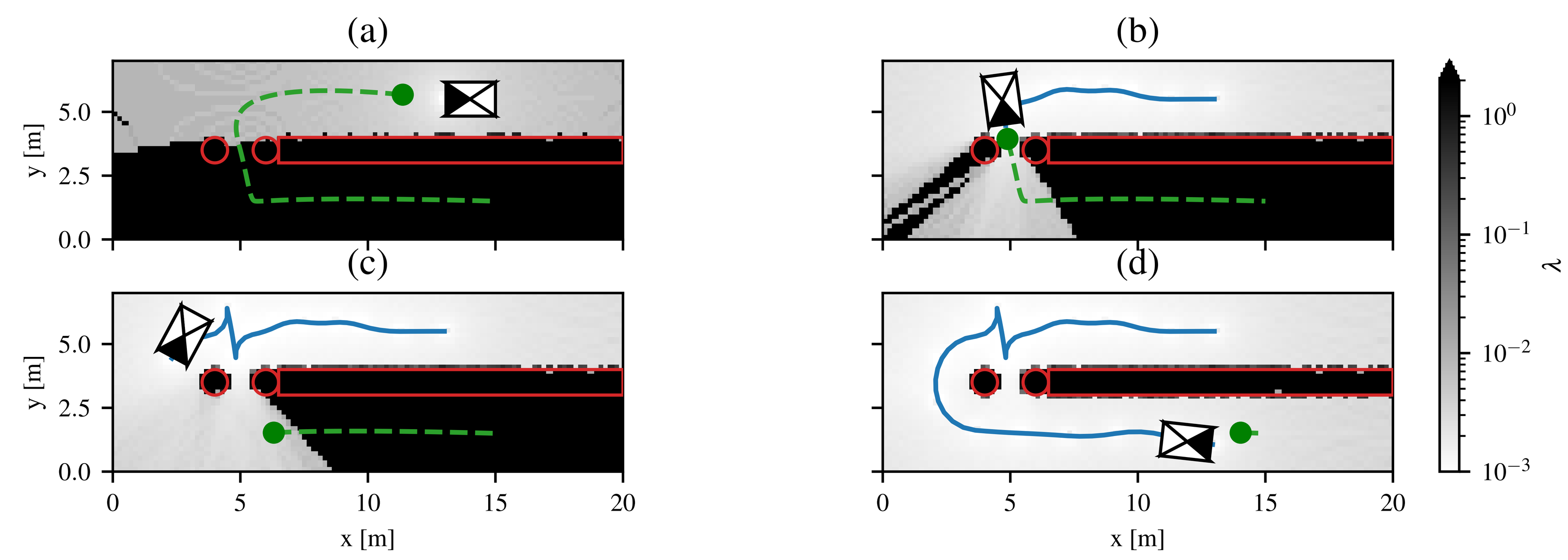

Figure 5: Simulation of a robot-follower scenario

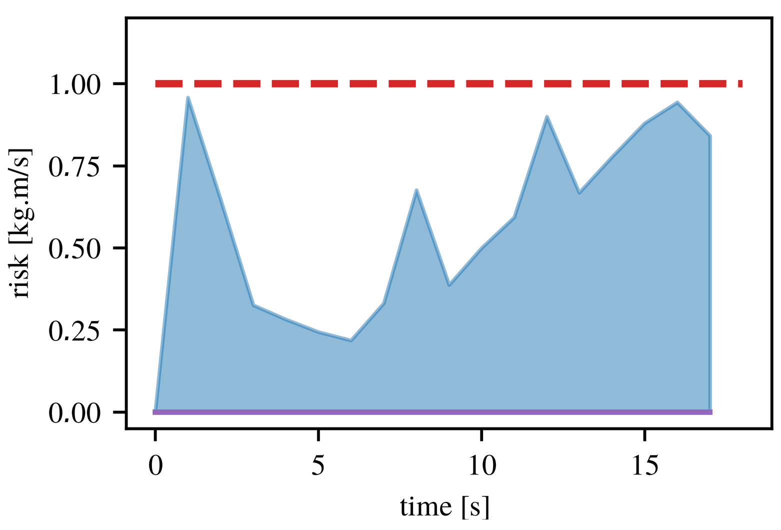

Figure 6: Expected risk (purple) taken by the robot, with its upper bound at 95% in blue. The risk is always below the maximum allowed (dashed-red).

- At $t = 6\,\text{s}$ (Figure 5b), the pedestrian goes through a passage too narrow for the robot. The risk being too high, the robot choose to go around the obstacle.
- The robot rejoins the pedestrian after the narrow passage. The upper limit risk is higher for $t > 6\,\text{s}$ because the robot has to raise its speed to quickly reach the pedestrian.

Experimentations & Future Works

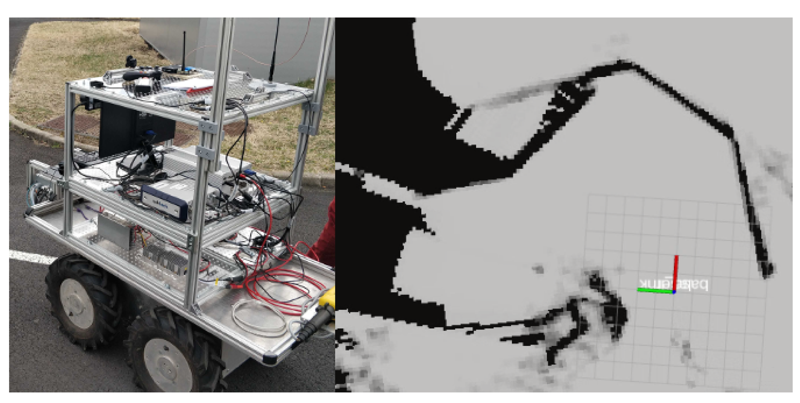

Figure 7: Left: Robot used in experimentations. Right: Lambda-Map created while the robot navigates in the environment

- We implemented our method onto a real robot, leading to promising results [2].
- Future works will add dynamic obstacles, as well as a better risk function. It is indeed far more dangerous to hit a pedestrian than tall grass!

Acknowledgments

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References

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[2] Johann Lacontе, Christophe Debain, Roland Chapuis, François Pomerleau, and Romuald Aufrère. Lambda-Field: A Continuous Counterpart of the Bayesian Occupancy Grid for Risk Assessment. *Submitted to IROS 2019.*