A Hybrid Collision Avoidance Method for Mobile Robots

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Overview

- Introduction and Video
- Markov Localization
- Dynamic Window Approach
- Modeld-based Proximity Sensor
- Experimental Results and Conclusions

Requirements

- **Reactive:** fast detection of obstacles and selection of steering commands
- **Effective:** maximum progress towards the goal location
- **Reliable:** dynamics of the robot must be considered

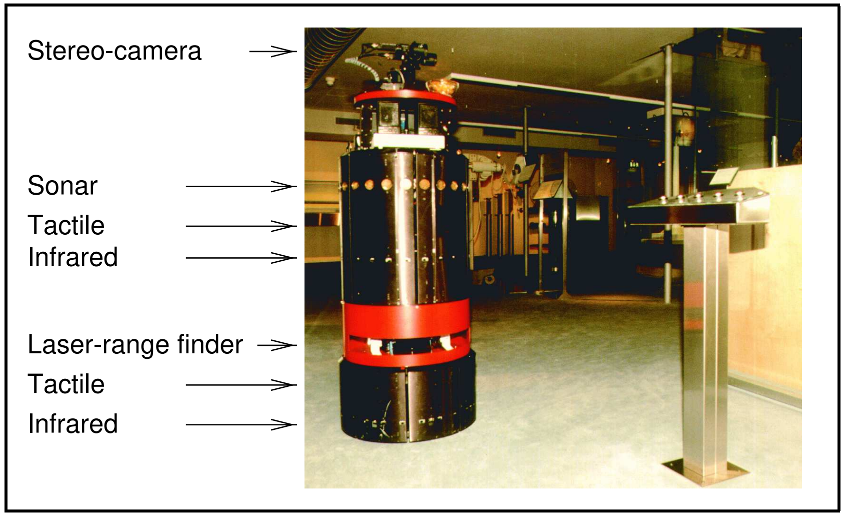
Most existing approaches[1] are purely sensor-based

Problem: Not all obstacles can be detected by the robot's sensors

[1] [Khatib '86, Borenstein and Koren '91, Khatib and Chatila '95, Simmons '96, Fox et al.'96]

Museum Tour-guide Project

Rhino as it gives a tour.



Sensors of the robot.

Hybrid Approach to Collision Avoidance

- **Goal:** Integrate map information into collision avoidance
- **Solution:** Introduce a **virtual** map sensor

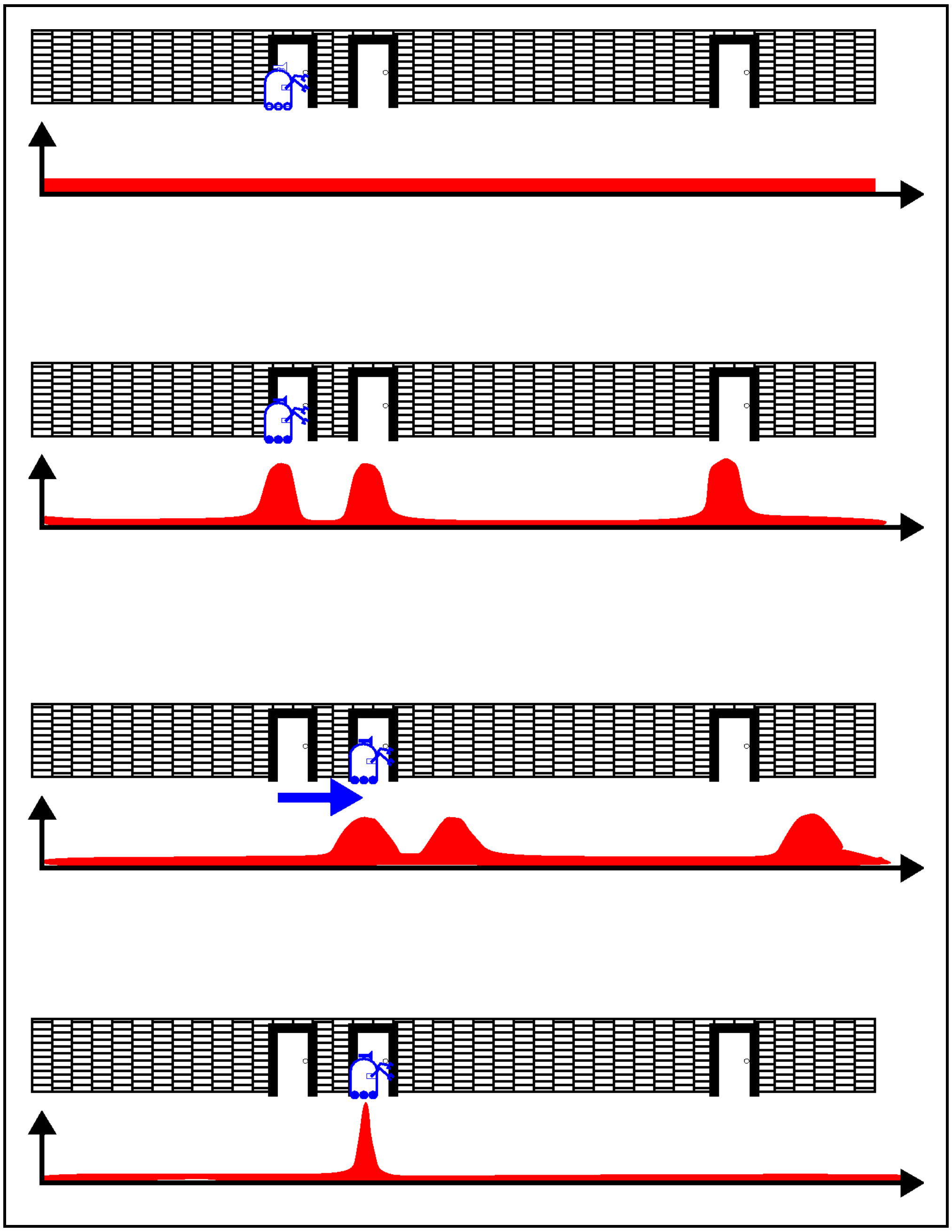
Problem: Position of the robot must be known

Localization

- **Given:** Model of the environment
- **Task:** Estimate position of the robot based on sensor data

- Most existing approaches deal with the problem of **tracking** the robot's position: [Schiele et al.,94], [Weiß et al.,94], [Borenstein,94], [Gutmann,96]
- Markov localization estimates the position of the robot **globally**: [Nourbakhsh et al.,95], [Simmons et al.,95], [Kaelbling et al.,96], [Burgard et al.,96], [Thrun,97]

Markov Localization (1)



Markov Localization (2)

- L_t denotes the state of the world at time t.
- $Bel(L_t = l)$ is updated whenever ...

... **an action a is executed:**

$$\widehat{Bel}(L_t = l) \longleftarrow \sum_{l'} P(L_t = l \mid L_{t-1} = l', a)\ Bel(L_{t-1} = l')$$

... **new sensory input s is perceived:**

$$Bel(L_t = l) \longleftarrow \frac{p(s \mid l)\ \widehat{Bel}(L_t = l)}{P(s \mid L_t)}$$

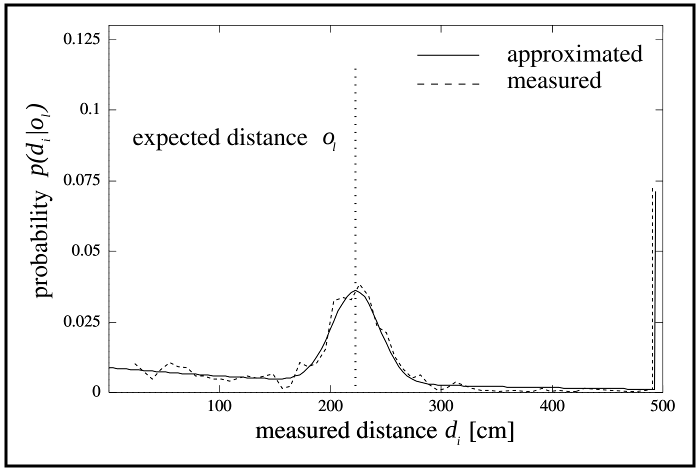
Position Probability Grids

- **fine-grained geometric** discretization (15 cm, 2°) of the state space
- sensors: **abstract** features and **raw** proximity data

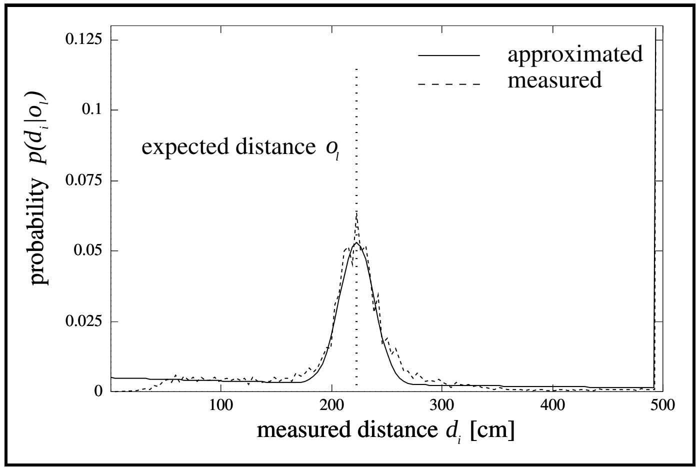
Combines both:

- **Ability of global (re-)localization**
- **Efficiency of tracking methods**

Model of Proximity Sensors

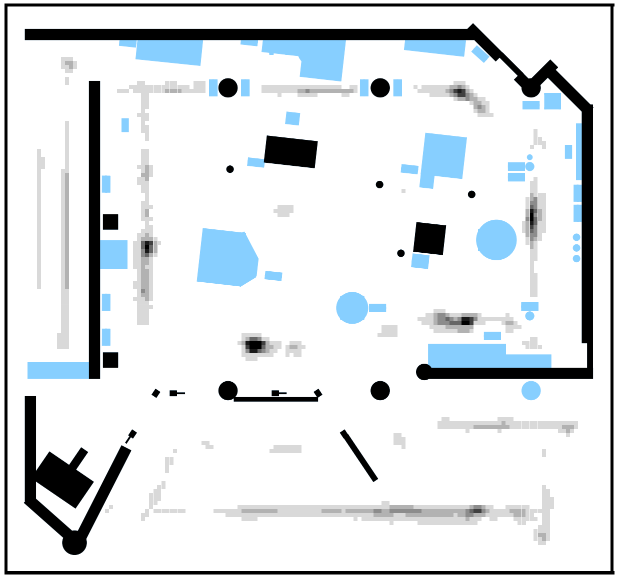


Probabilities for ultrasound.

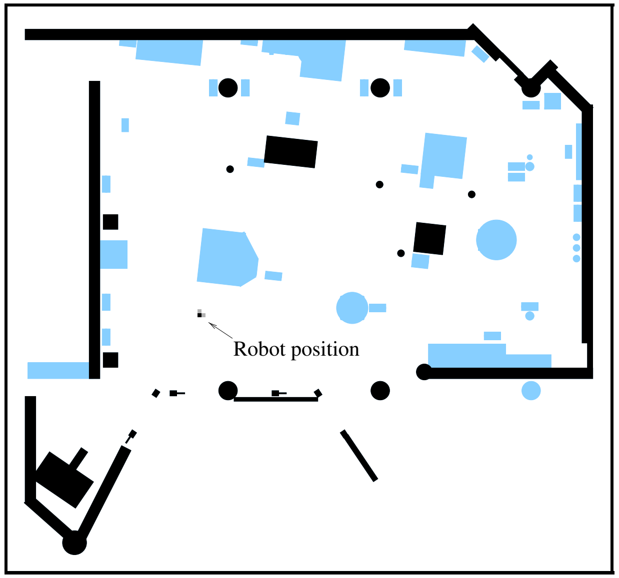


Probabilities for laser range-finder.

Markov Localization in the “Deutsches Museum Bonn, Germany”



Belief during global localization



Typical belief during operation

Dynamic Window Approach

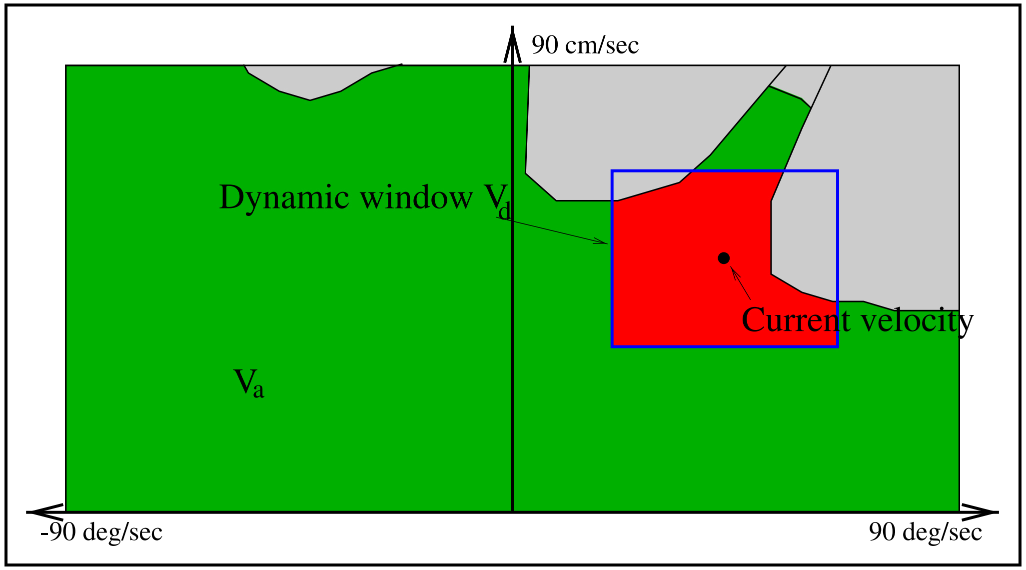
- Consider combinations (v, ω) of translational and rotational velocities
- Two-dimensional search space of circular arcs

- **Hard constraints** restrict search space to guarantee safe navigation
- **Soft constraints** express preferences among velocities

Hard Constraints

Only consider velocities which

- yield **safe** navigation (V_a) and
- obey the **dynamics** of the robot (V_d).



Space of velocity combinations (v, ω).

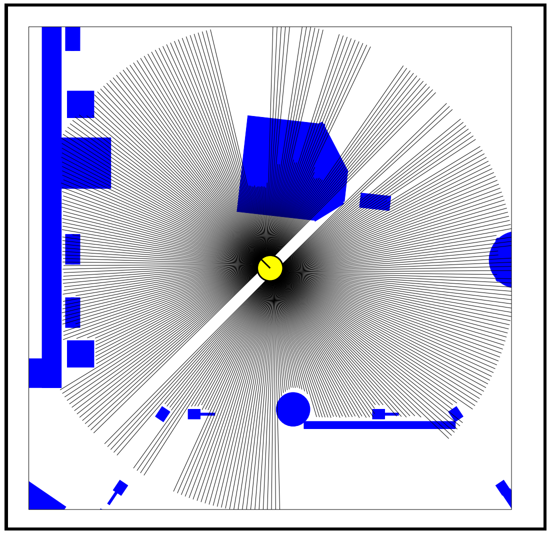
Soft Constraints (1)

Maximze **objective function** $G(v, \omega)$

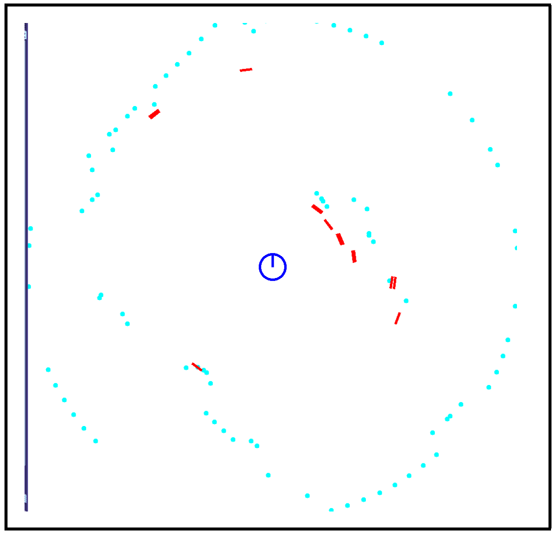
$$G(v, \omega) \;=\; \sigma(\alpha \cdot \text{heading}(v, \omega) + \beta \cdot \text{dist}(v, \omega) + \gamma \cdot \text{vel}(v, \omega))$$

- **Target heading:** Alignment with the goal direction
- **Clearance:** Distance to the closest obstacle on the trajectory
- **Velocity:** Forward velocity of the robot

Representing Sensor Data

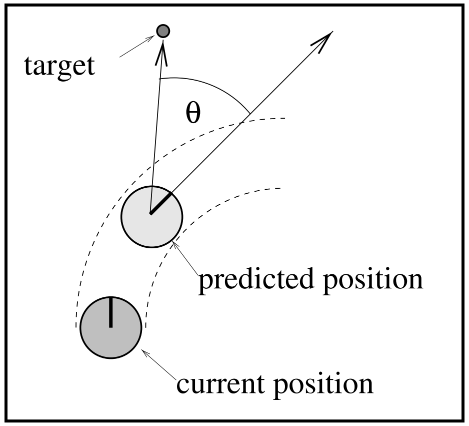


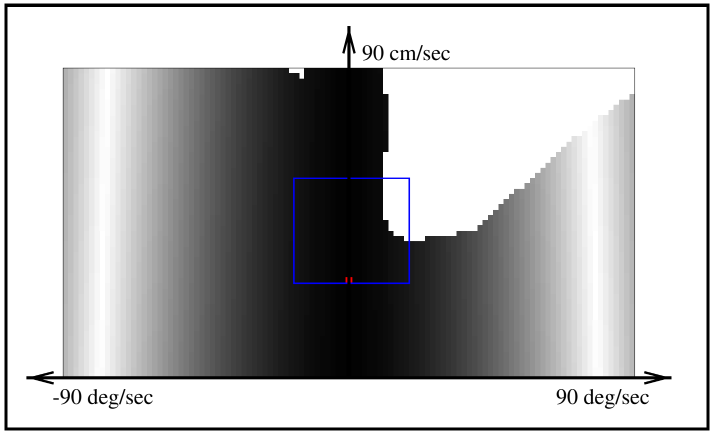
Scan of the laser sensors.



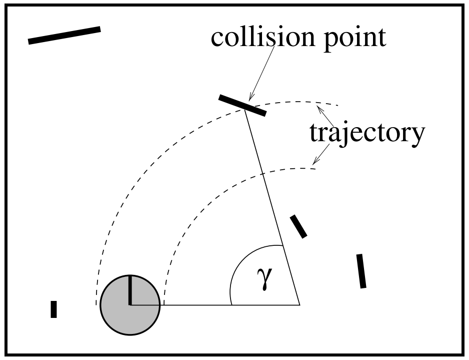
Obstacle line field.

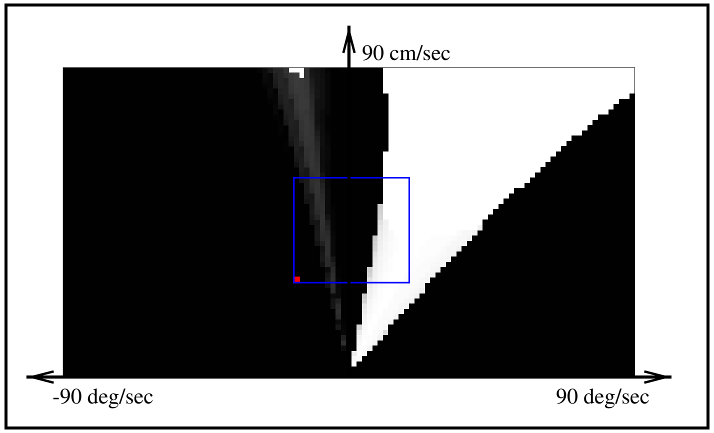
Soft Constraints (2)





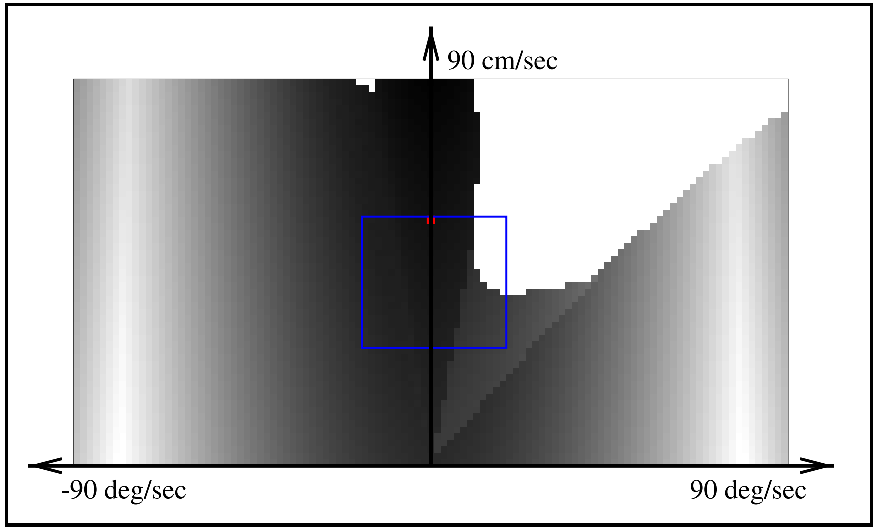
Target heading.



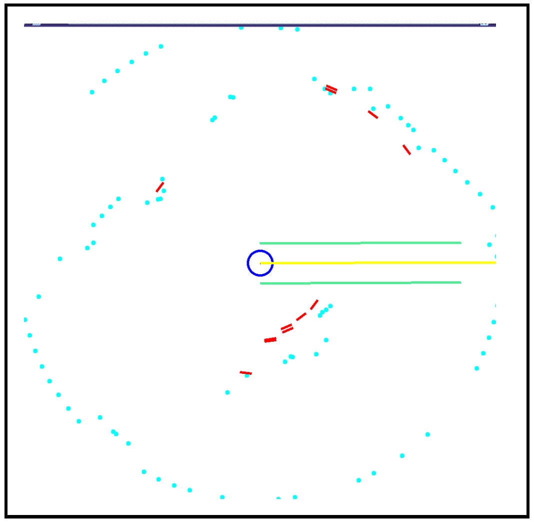


Clearance.

Soft Constraints (3)



Combination of soft constraints.

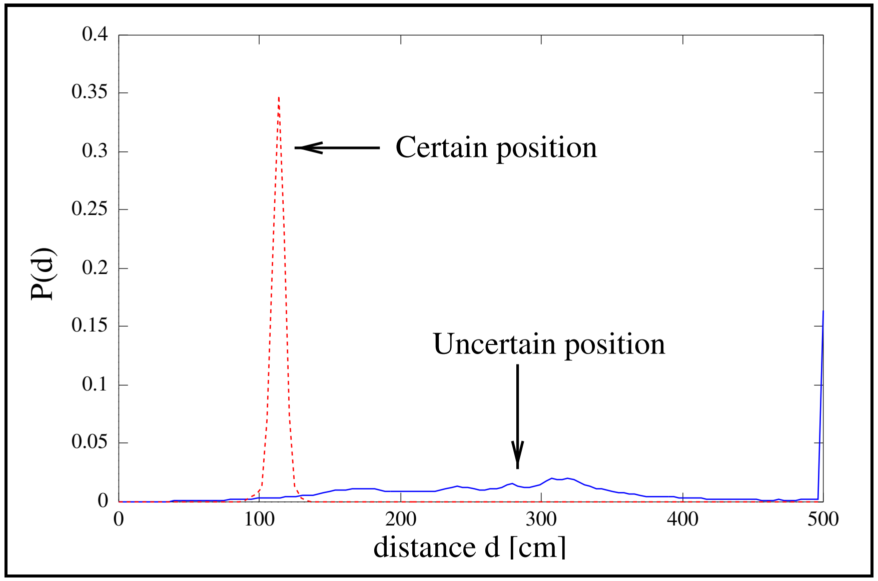


Resulting trajectory.

Probabilistic Representation

- $o(l, \alpha)$: Distance to the next obstacle in the map given position l
- $P(X_\alpha = d \mid l)$: Gaussian with mean at $o(l, \alpha)$

$$P(X_\alpha = d) \quad = \quad \sum_l P(X_\alpha = d \mid l)\; P(l)$$



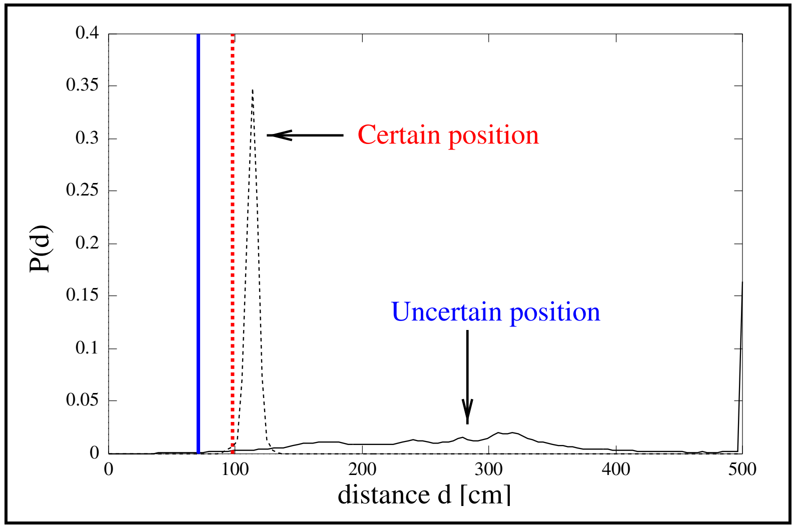
Typical probability distributions of a virtual sensor.

Selecting a Virtual Measurement

$$P(X_\alpha > d) \quad = \quad \sum_{d_i > d} P(X_\alpha = d_i)$$

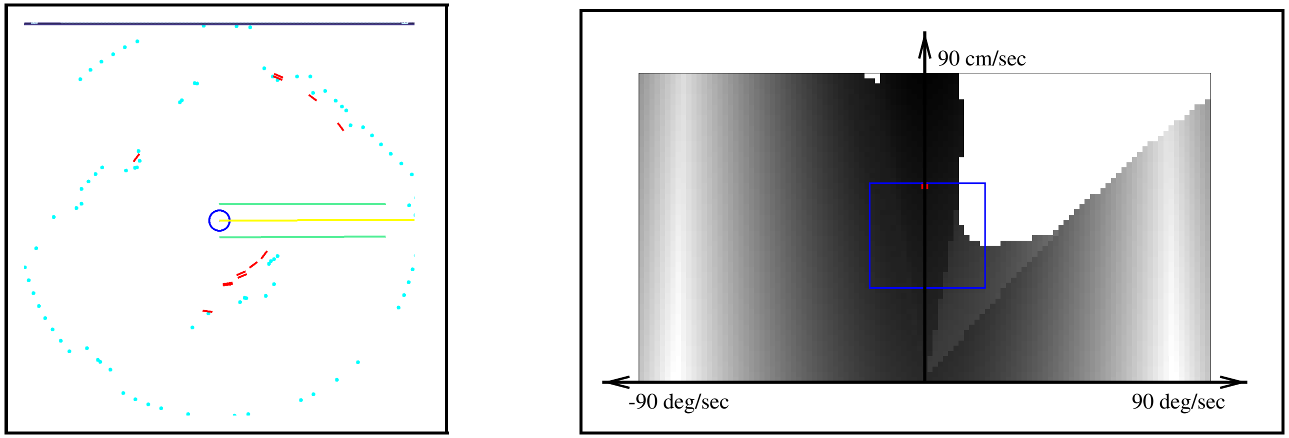
- Pick the largest distance d^* which with high probability is **shorter** than X_α.

$$d^* \quad = \quad \max\{d \mid P(X_\alpha > d) \geq .99\}$$

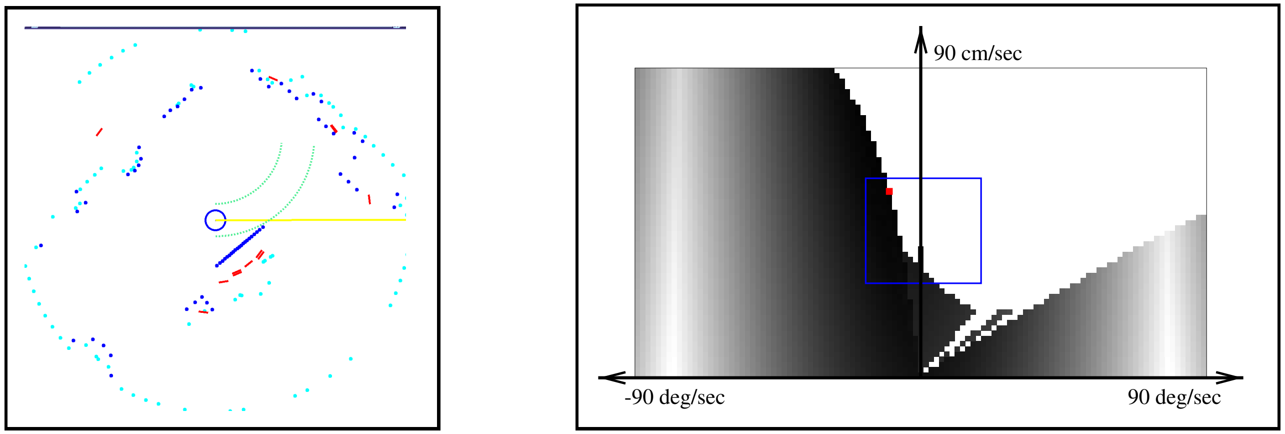


Selected measurements.

Inluence of the Virtual Sensor



Trajectory chosen without virtual sensor.



Trajectory chosen when inclduding virtual measurements.

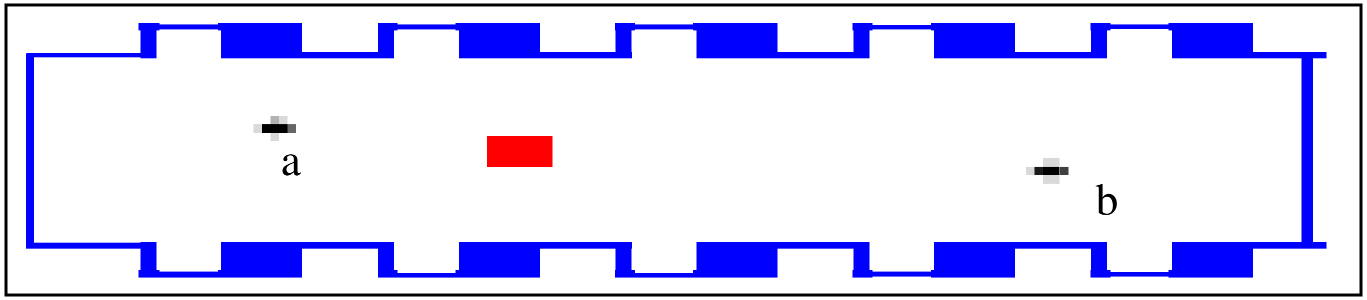
Museum Tour-guide Project

Hours of operation	47
Number of visitors	$>$ 2000
Kilometers traveled	18.6
Maximal speed of travel	$>$ 80 cm/sec
Average speed during motion	36.6 cm/sec
Number of collisions	6
Number of requests	2400
Percentage of completed requests	99.75

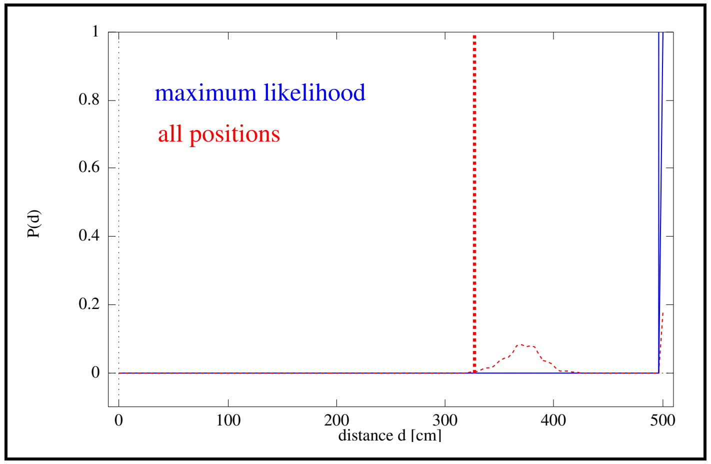
Key figures

Path of the robot (1.6 km)

Role of Probabilistic Integration

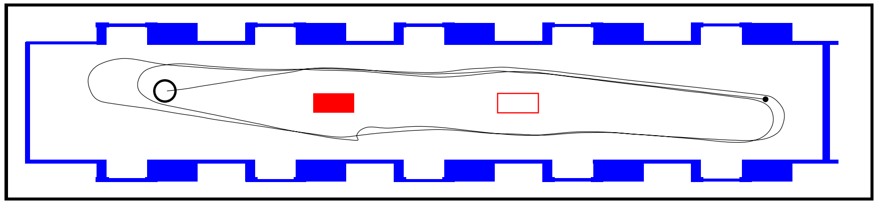


Ambiguous position estimation.

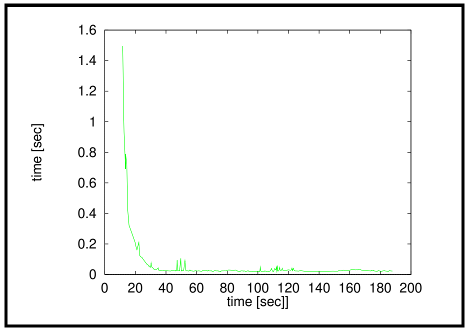


Virtual sensor for maximium likelihood position and when considering all positions.

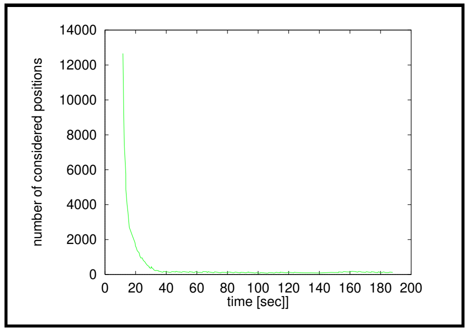
Role of Probabilistic Integration



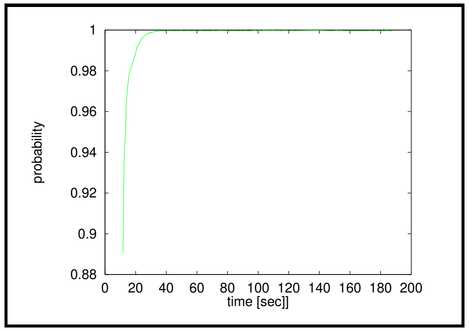
Path of the robot.



Computation time.



Number of considered locations.



Probability of considered locations.

Conclusions

- Paradigm of purely sensor-based collision avoidance is **not sufficient** to guarantee safe navigation.
- μ**DWA** integrates sensor data and **model-based information** into collision avoidance.
- μDWA yields safe navigation even
  - in the presence of **invisible obstacles** and
  - under **position uncertainty**.
- Additional application: restrict the work space of service robots.