Hochschule
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University of Applied Sciences

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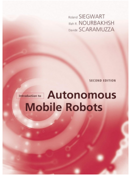
Institute for AI and Autonomous Systems

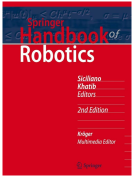
Path Planning

How a Robot Finds Its Way Around

Dr. Alex Mitrevski
Master of Autonomous Systems

Structure

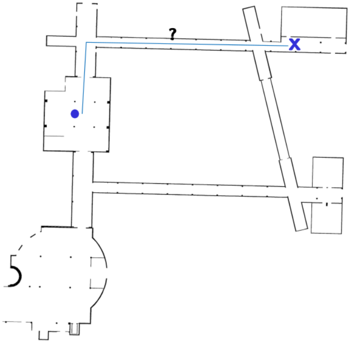




- Path planning preliminaries
- Path planning algorithms
- Local obstacle avoidance

Path Planning Preliminaries

What is Path Planning?



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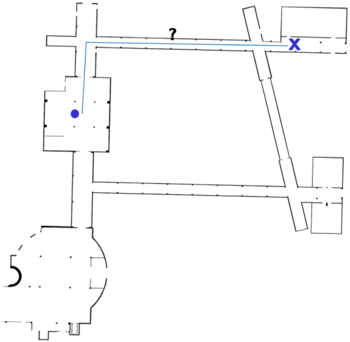

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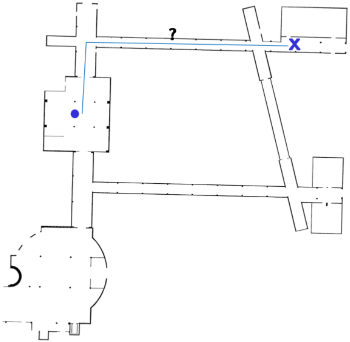

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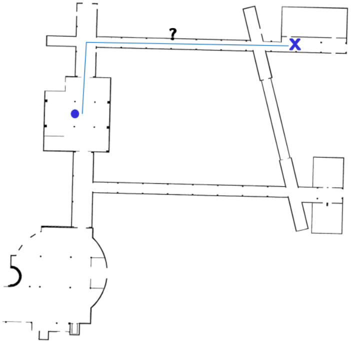

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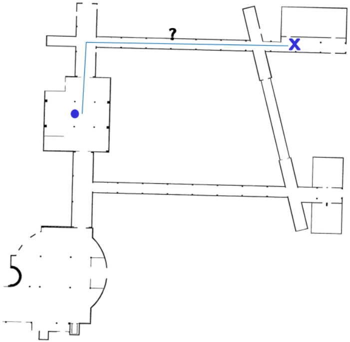

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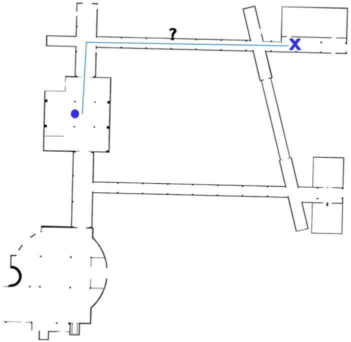

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- Note that path planning **requires an environment map to be performed** — obstacles need to be known so that collisions with them can be avoided

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The property of a path planning algorithm to produce valid paths that start at P_s and end at P_g

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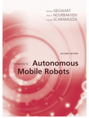
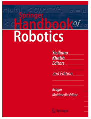
- A desirable property of path planning algorithms that **cannot always be guaranteed** — due to the complexity of a planning configuration, **it may be impossible to find a path within a given time or memory budget**

Configuration Space





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  - Achieved by planning not in the robot's physical space, but **in configuration space**, where each configuration is a point

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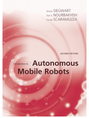

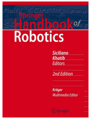

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  - For a planar navigating robot, the configuration space can be defined by planar poses $\boldsymbol{q} = (x, y, \theta)$

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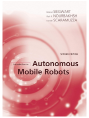

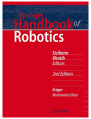

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- If $\mathcal{O} \subset \mathcal{W}$ is a workspace region occupied by an obstacle and $\mathcal{A}(\boldsymbol{q}) \subset \mathcal{W}$ is the set of workspace points occupied by a robot in $\boldsymbol{q}$, the **occupied region** in C-space is

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- **Obstacles are typically enlarged in the C-space**, and a valid path is one that **passes only through the free space** $C_{free} = C \setminus C_{obs}$

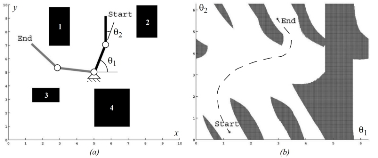
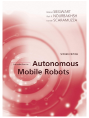
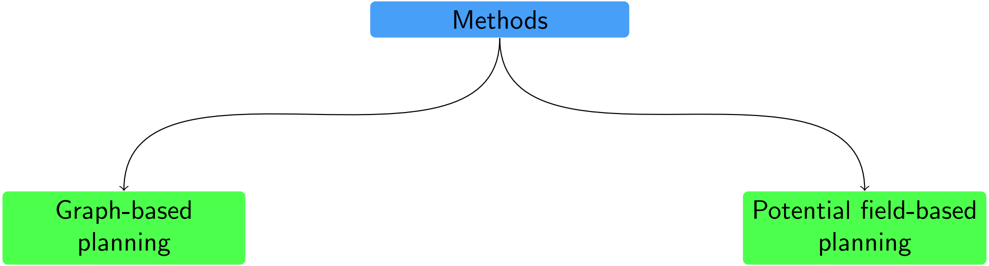


Figure 6.1
Physical space (a) and configuration space (b): (a) A two-link planar robot arm has to move from the configuration *start* to *end*. The motion is thereby constraint by the obstacles 1 to 4. (b) The corresponding configuration space shows the free space in joint coordinates (angle θ_1 and θ_2) and a path that achieves the goal.

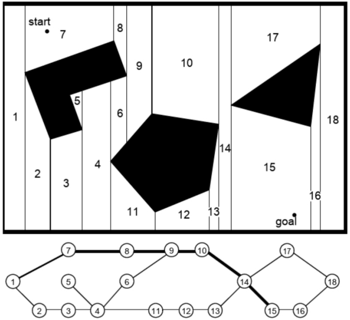
Path Planning Algorithms

Path Planning Methods





Graph Search



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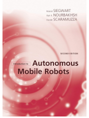

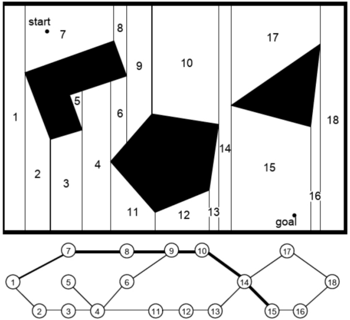

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  - The regions are the nodes in $\mathcal{G}$ and the connections between them are the edges

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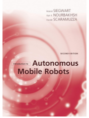

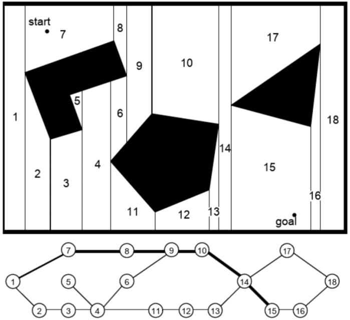

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- To use classical graph search for path planning, **space has to be decomposed into a set of connected regions**
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- The decompositions that we looked at in the last lecture (e.g. the exact cell decomposition) can be used as precursors to path planning using graph search

Graph Search Algorithms

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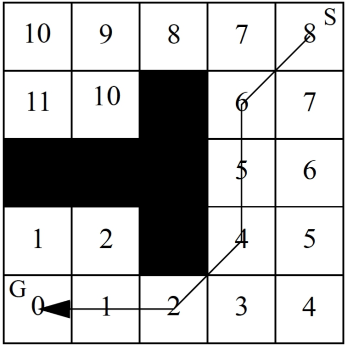
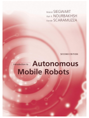
- These algorithms are called **deterministic search algorithm**
- More details about them are discussed in the AI course

Wavefront Algorithm





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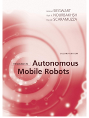

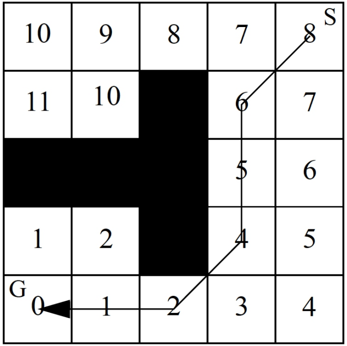

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- The algorithm **starts the search process from the goal** and **stops when a robot's initial position is reached**

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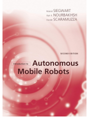

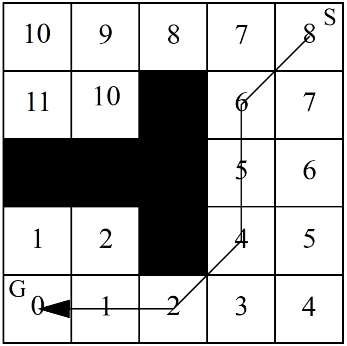

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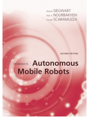
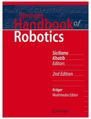
- An important outcome of the wavefront algorithm is an **estimate of the distance from any expanded node to the goal** (represented as a Manhattan distance)

Rapidly Exploring Random Trees (RRTs)





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  - Deterministic search tends to be inefficient — particularly under real-time constraints — and defining useful heuristics is often difficult

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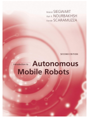

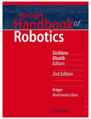

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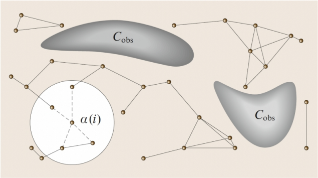

- RRT is one such algorithm that, at each step, **randomly select a free space node q'** and connects that to already an existing graph segment **if the connection leads to a collision-free path**
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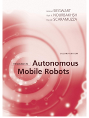

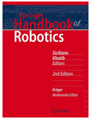

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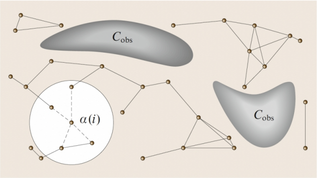

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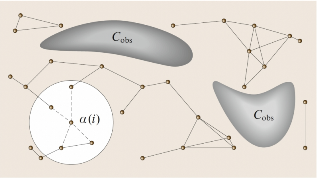

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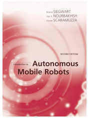
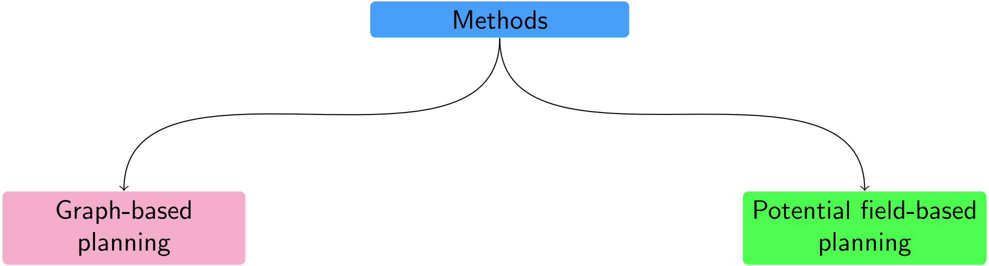
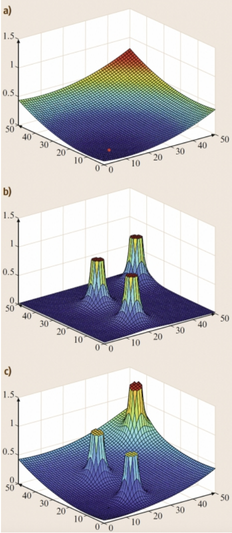
- **RRT is a probabilistically complete algorithm** and **is not optimal**, but is fast and thus usually useful for practical purposes
  - The search typically needs to be repeated multiple times for a solution to be found
- As in some deterministic search algorithms, **the search process can be performed bidirectionally** (starting from both P_s and from P_g) to increase the likelihood of finding a path

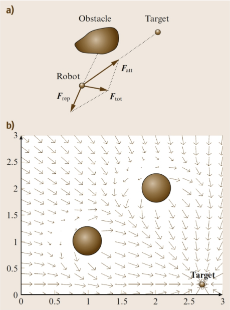
Path Planning Methods





Potential Fields





- Potential field planning is an alternative planning strategy based on which **the robot is treated as being under the influence of a potential field $U(q)$**

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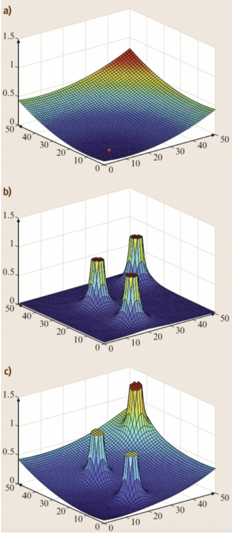
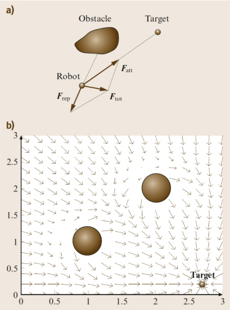
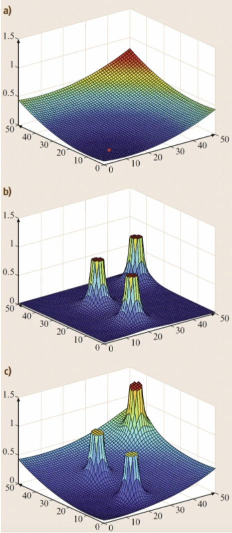
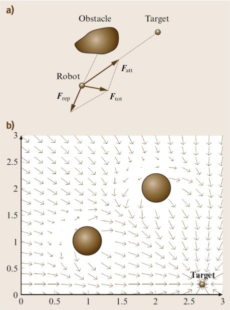




- Potential field planning is an alternative planning strategy based on which **the robot is treated as being under the influence of a potential field $U(\boldsymbol{q})$**
- $U(\boldsymbol{q})$ is created as a combination of attractive and repulsive potentials: $U(\boldsymbol{q}) = U_{attr}(\boldsymbol{q}) + U_{rep}(\boldsymbol{q})$
  - A goal configuration has an attractive potential
  - Obstacles have repulsive potentials

Potential Fields





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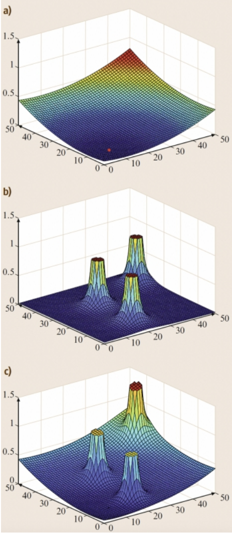

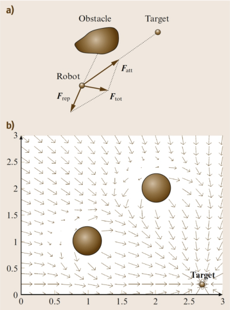

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- Recall that a potential is associated with a **conservative force**, which is expressed as

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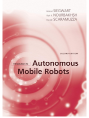
- This means that, at every point $\boldsymbol{q}$, a robot is subject to $F(\boldsymbol{q})$, which dictates the direction in which the robot should move

Attractive Potential



- An attractive potential should **guide a robot towards a given configuration**

- Attractive potentials are typically used only for goal configurations; such a potential can be expressed **as a function of the distance to the goal**

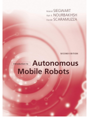
- Let $\|\boldsymbol{q} - \boldsymbol{q}_{goal}\|$ be the Euclidean distance between the current configuration and the goal configuration, and k_a be a positive constant; an example of an attractive potential would then be

$$U_{attr}(\boldsymbol{q}) = \frac{1}{2} k_a \|\boldsymbol{q} - \boldsymbol{q}_{goal}\|^2$$

- The associated force field is then

$$F_{attr}(\boldsymbol{q}) = -\nabla U_{attr}(\boldsymbol{q}) = -k_a(\boldsymbol{q} - \boldsymbol{q}_{goal})$$

Repulsive Potential



- A repulsive potential should **repel a robot from a given configuration**
- Repulsive potentials are typically used for avoiding obstacles, such that they can be expressed **as a function of the distance to obstacles** — each obstacle would have its own repulsive potential
- **Repulsive fields are typically active only within a given region** — faraway obstacles should not affect the motion of a robot
- Let $\|\boldsymbol{q} - \boldsymbol{q}_o\|$ be the minimum distance between $\boldsymbol{q}$ and any point of an obstacle, ρ_0 be a distance threshold, and k_r a positive constant; an example of a repulsive field is then

$$U_{rep}(\boldsymbol{q}) = \begin{cases} \frac{1}{2} k_r \left(\frac{1}{\|\boldsymbol{q}-\boldsymbol{q}_o\|} - \frac{1}{\rho_0} \right)^2 & \|\boldsymbol{q} - \boldsymbol{q}_o\| \leq \rho_0 \\ 0 & \|\boldsymbol{q} - \boldsymbol{q}_o\| > \rho_0 \end{cases}$$

- The associated force field is given as

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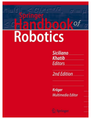
Potential Fields and Local Minima



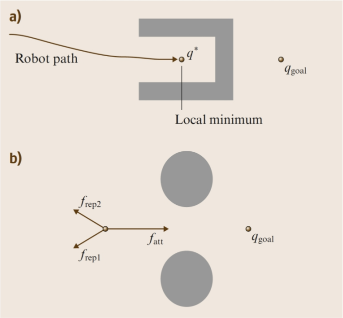
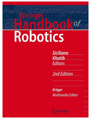
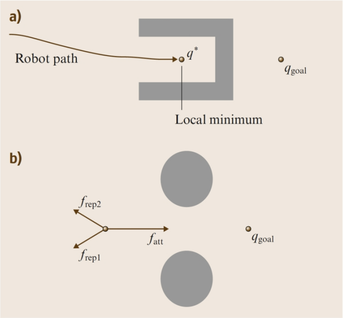


Fig.7.9a,b Two examples of the local minimum problem with potential functions

- Given the interplay between attractive and repulsive potentials, it can happen that the resulting force at a given point adds to $\mathbf{0}$ — **a robot gets stuck at a local minimum** in such a case

Potential Fields and Local Minima





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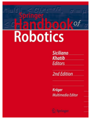
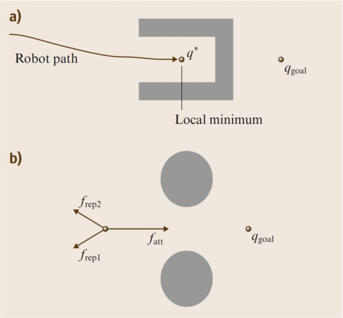
Potential Fields and Local Minima





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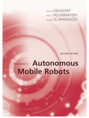
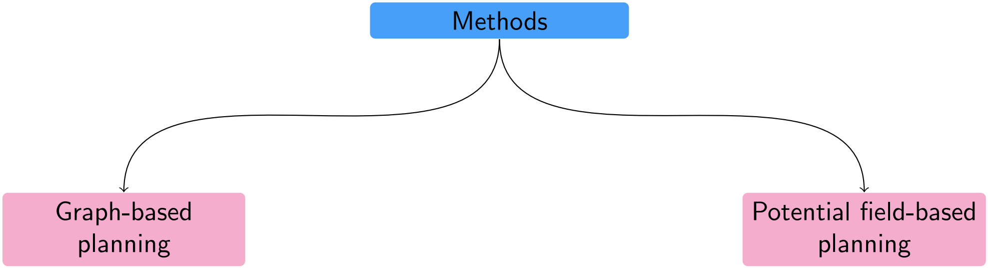
- Given the interplay between attractive and repulsive potentials, it can happen that the resulting force at a given point adds to $\mathbf{0}$ — **a robot gets stuck at a local minimum** in such a case
- Thus, on their own, **a potential field is not a complete path planner**
- One strategy to escape local minima is to employ **random walks** — this turns a potential field into a randomised planner

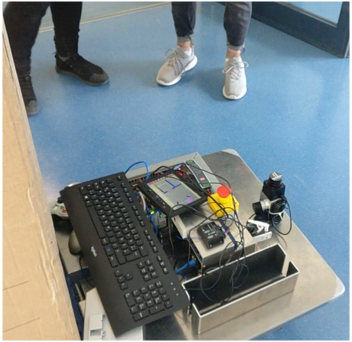
Path Planning Methods





Local Obstacle Avoidance

Local Obstacle Avoidance for Unknown Obstacles



- Path planning can generate collision-free paths for known obstacles in the map, but **a robot should also have an ability to handle unknown and dynamic obstacles**
  - Very few environments are completely static — most are dynamic at least to some extent

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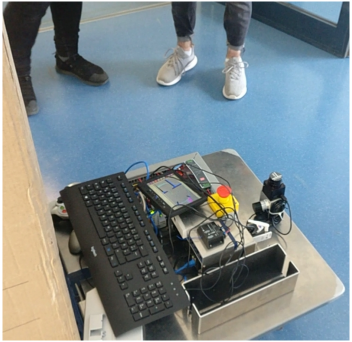

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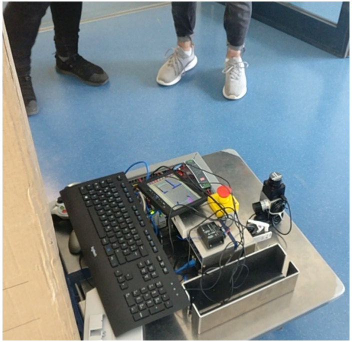

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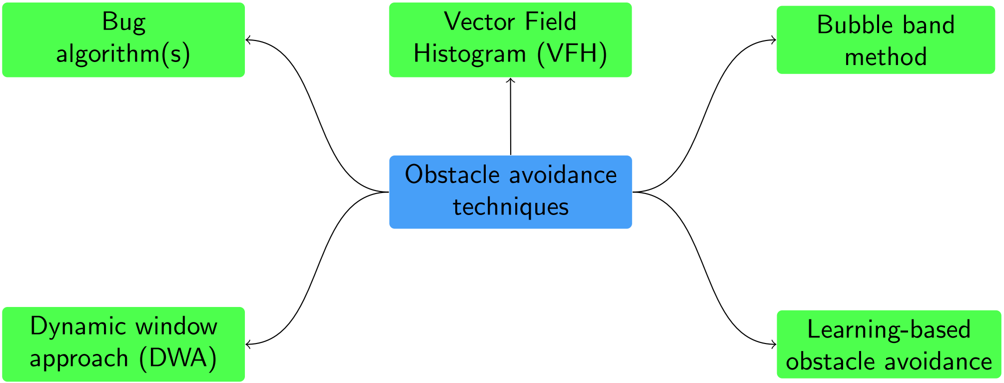
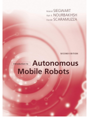
  - Very few environments are completely static — most are dynamic at least to some extent
- Local obstacle avoidance needs to **take the current sensor measurements into account** so that appropriate avoidance maneuvers can be performed
- Traditional obstacle avoidance strategies are defined for **static obstacles** — dynamic obstacles (such as people) pose a different level of challenge and **are most effective in conjunction with an obstacle motion model**

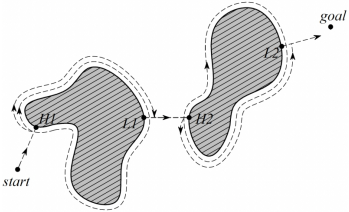
Obstacle Avoidance Techniques

There is a large variety of obstacle avoidance techniques in the literature; we will take a closer look at some of them on the following slides



Bug1 Algorithm





- The Bug1 algorithm is perhaps the simplest obstacle avoidance strategy

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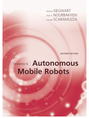

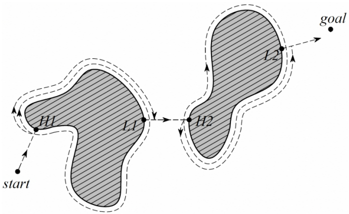

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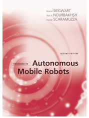
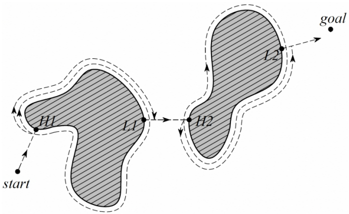
- The algorithm performs two steps:

Bug1 Algorithm





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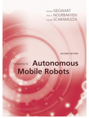

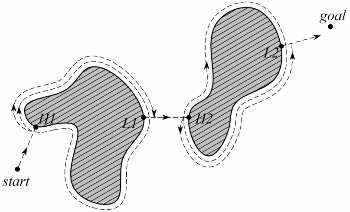

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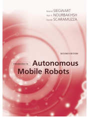

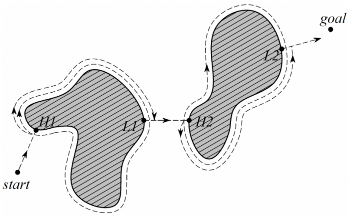

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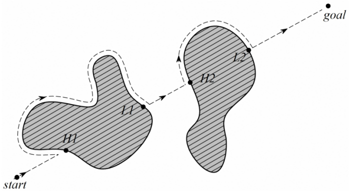
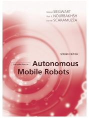
  2. Follow the obstacle contour to the point closest to the goal and then leave the obstacle to move towards the goal
- Bug1 is a **naive and inefficient obstacle avoidance strategy**, as the full obstacle contour needs to be traversed so that a departure point is identified

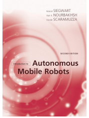
Bug2

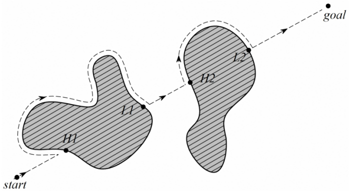


- Bug2 constitutes a more efficient version of Bug1



Bug2





- Bug2 constitutes a more efficient version of Bug1
- The idea behind Bug2 is to **follow the obstacle's contour until reaching a point from which there is a direct path to the goal**; at this point, the robot leaves the obstacle and starts moving towards the goal

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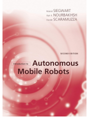
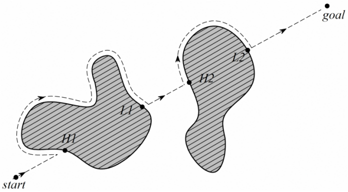
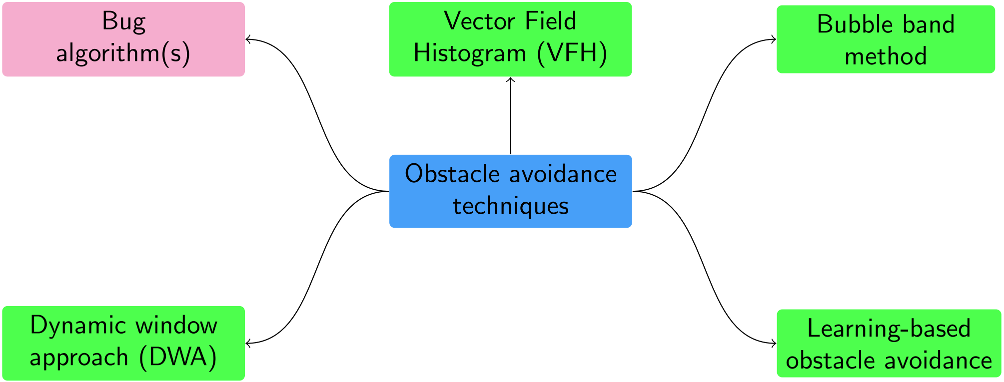


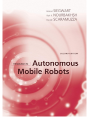


- Bug2 constitutes a more efficient version of Bug1
- The idea behind Bug2 is to **follow the obstacle's contour until reaching a point from which there is a direct path to the goal**; at this point, the robot leaves the obstacle and starts moving towards the goal
- Some non-convex obstacle shapes may lead to a suboptimal or oscillatory behaviour of the bug algorithms

Obstacle Avoidance Techniques



Vector Field Histogram (VFH)



- A vector field histogram is an obstacle avoidance method that uses a local map based on recent sensor measurements

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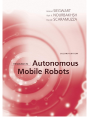

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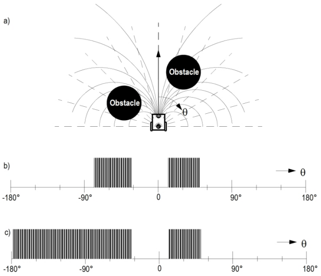

Figure 6.17
Example of blocked directions and resulting polar histograms [54]. (a) Robot and blocking obstacles. (b) Polar histogram. (b) Masked polar histogram.

- The method **creates a discrete histogram that encodes the probability that there is an obstacle at a given direction from the robot**

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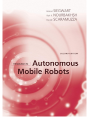

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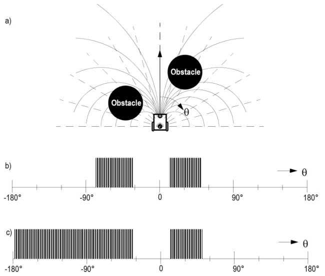

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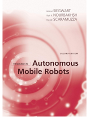
Example of blocked directions and resulting polar histograms [54]. (a) Robot and blocking obstacles. (b) Polar histogram. (b) Masked polar histogram.

- The method **creates a discrete histogram that encodes the probability that there is an obstacle at a given direction from the robot**
- Given the histogram, **candidate passages that would fit the robot are found**, and a direction of motion is **identified based on a cost function** of the form:

$$J = w_1 h + w_2 \gamma + w_3 \Delta h$$

- Here $w_{1,2,3}$ are positive constants, h is the orientation towards the goal, γ is the change in wheel orientation that would be necessary to move in the candidate orientation, and Δh is the necessary orientation change to achieve h

Vector Field Histogram (VFH)



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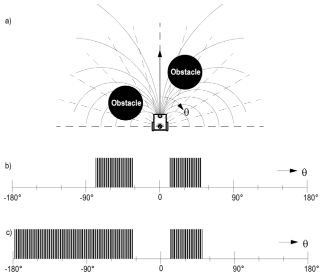

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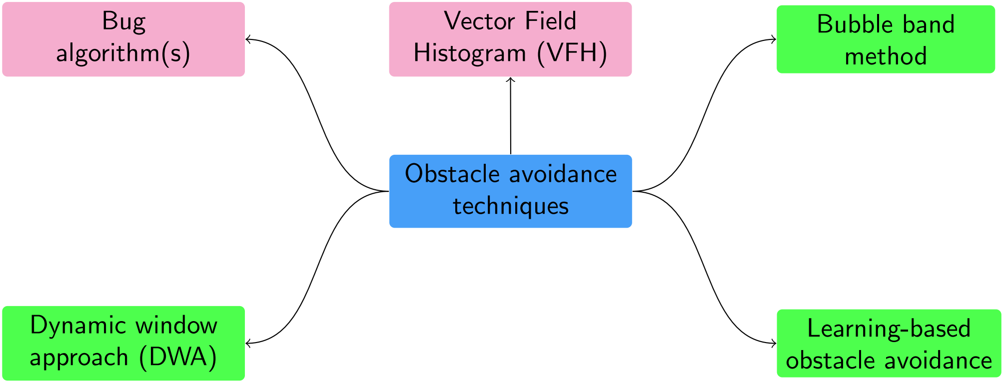
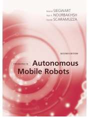
- An extended VFH method assumes **motion along straight lines and arcs**, and creates a **masked histogram** that prevents motion directions that would pass through the obstacles

Obstacle Avoidance Techniques



Bubble Band Method



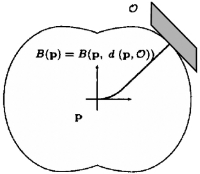


Figure 6.18
Shape of the bubbles around the vehicle. Courtesy of Raja Chatila [165].

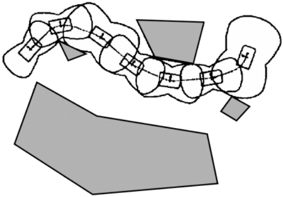
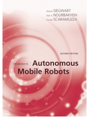
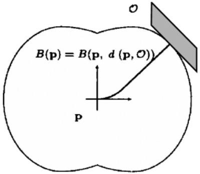


Figure 6.19
A typical bubble band. Courtesy of Raja Chatila [165].

- The bubble band method **models the robot as a bubble**, where a bubble is **the maximum reachable space without collisions around a configuration q**

Bubble Band Method





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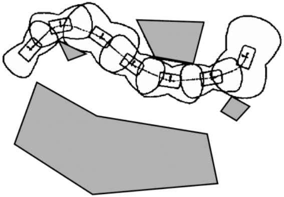

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A typical bubble band. Courtesy of Raja Chatila [165].

- The bubble band method **models the robot as a bubble**, where a bubble is **the maximum reachable space without collisions around a configuration q**
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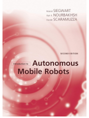
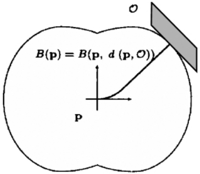
Bubble Band Method





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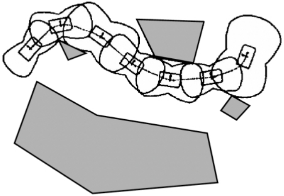

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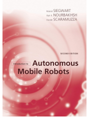

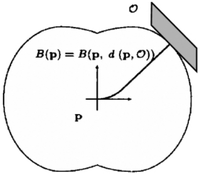

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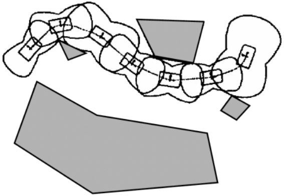

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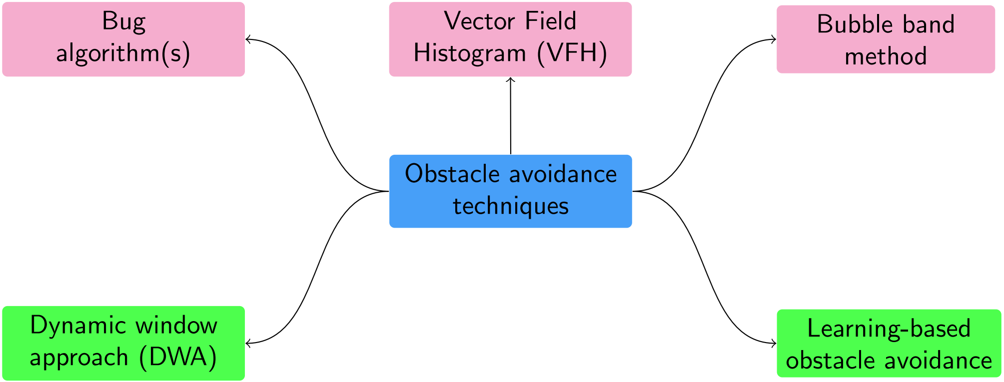
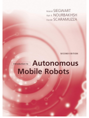
- The bubble band method is thus **a path and motion planning method**

Obstacle Avoidance Techniques



Dynamic Window Approach (DWA)



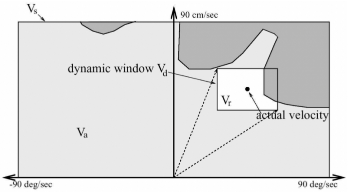


Figure 6.21
The dynamic window approach (courtesy of Dieter Fox [130]).
The rectangular window shows the possible speeds (v, ω) and the overlap with obstacles in configuration space.

- The dynamic window approach enables obstacle avoidance **by considering kinematic constraints**

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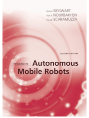

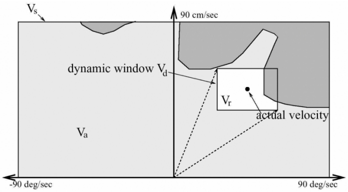

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- The dynamic window approach enables obstacle avoidance **by considering kinematic constraints**
- There are multiple variations of the technique, but they can roughly be divided into:
  - **Local DWA**, which only considers local obstacle information
  - **Global DWA**, which also includes global environment information in its planning process

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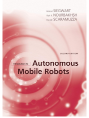

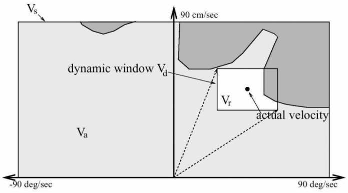

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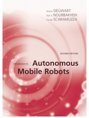
  - **Local DWA**, which only considers local obstacle information
  - **Global DWA**, which also includes global environment information in its planning process
- DWA in not just a method for path planning, but also for **motion planning**
  - Prediction of the effects of the robot's motion — based on a motion model — are thus done by the algorithm

Local Dynamic Window Approach



- The local DWA assumes circular motion with linear velocity v and angular velocity ω, such that it tries to **find instantaneous velocities that would bring the robot closer to the goal without causing an obstacle collision**

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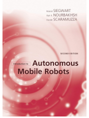

- The local DWA assumes circular motion with linear velocity v and angular velocity ω, such that it tries to **find instantaneous velocities that would bring the robot closer to the goal without causing an obstacle collision**
- The approach performs two steps at every iteration (i.e. at every step of the control algorithm):
  1. Finding a dynamic window of **feasible velocities** that a robot can reach within the next control step
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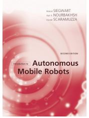

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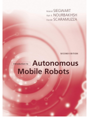
  1. Finding a dynamic window of **feasible velocities** that a robot can reach within the next control step
  2. Reducing the dynamic window by only considering **admissible velocities**, namely those that guarantee that no obstacle collision will occur
- From the admissible set, v and ω are chosen so that they **keep the robot as away from obstacles**, **are as aligned with the goal**, and **are as fast** as possible
  - This is achieved using an objective function of the form

$$J(v, \omega) = w_1 h(v, \omega) + w_2 s(v, \omega) + w_3 d(v, \omega)$$

where $w_{1,2,3}$ are positive constants, h is the heading, s the speed, and d the closest distance to an obstacle

Global Dynamic Window Approach



- The global DWA is an extension of the local DWA approach that additionally considers global environment information

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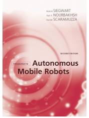

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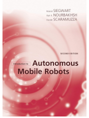

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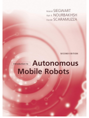

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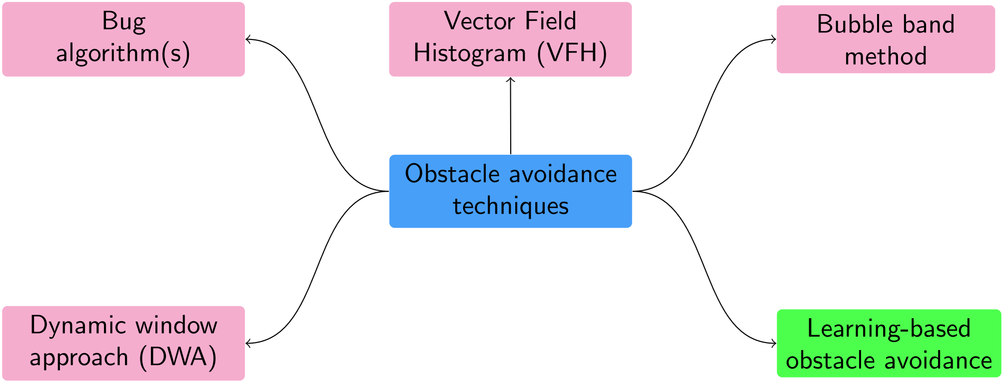
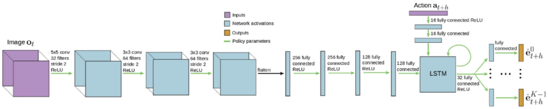
- **The size of the region covered by the local occupancy grid is dynamically changed** so that the goal can always be found from the robot's current position
- The global DWA **reverts to the local DWA** when the robot is surrounded by obstacles and a path to the goal cannot be found using the wavefront algorithm

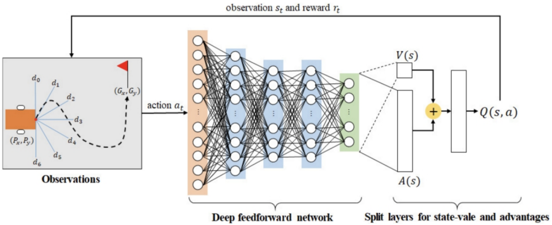
Obstacle Avoidance Techniques



Learning-Based Obstacle Avoidance



G. Kahn, P. Abbeel and S. Levine, "BADGR: An Autonomous Self-Supervised Learning-Based Navigation System," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 1312–1319, Apr. 2021.



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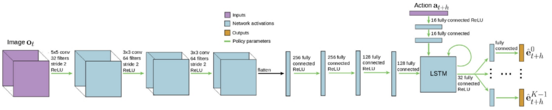

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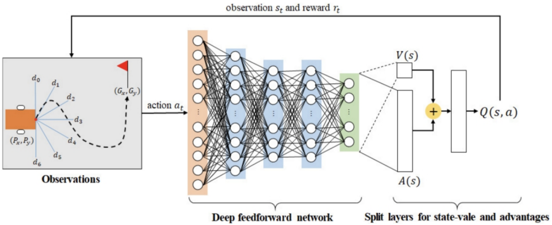

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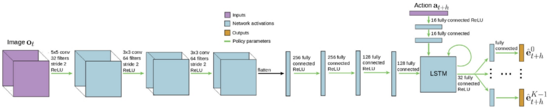

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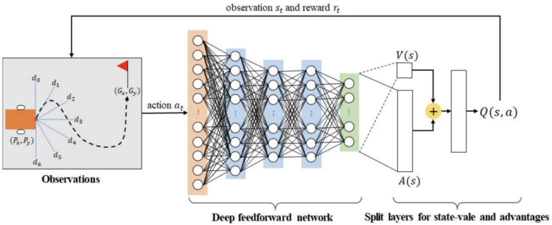

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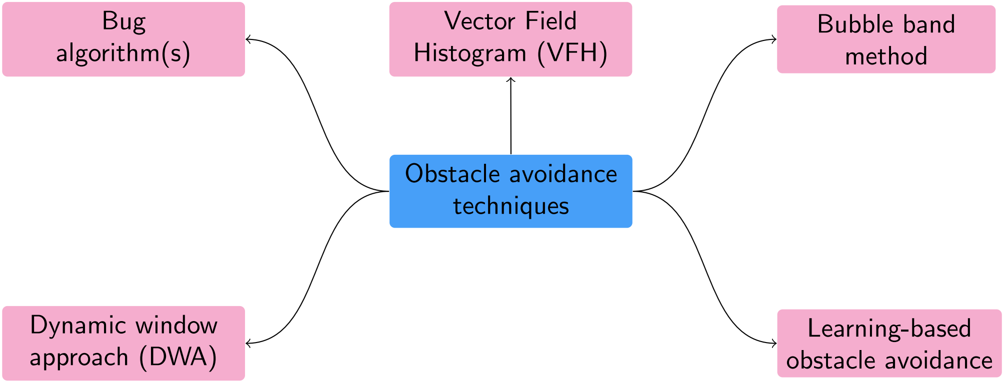
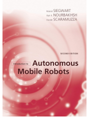
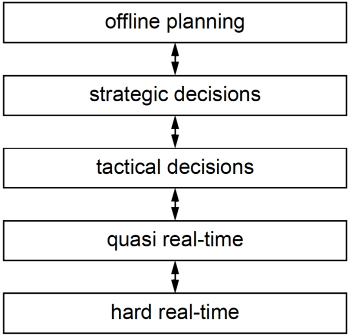
- In recent years, there have been attempts to use learning algorithm that **acquire local navigation behaviours that map sensor measurements to motions** — often using **learned neural network-based policies**
- The development and exploration of such methods is, however, still an ongoing process — **model-based techniques still dominate navigation applications**

Obstacle Avoidance Techniques



Temporal Considerations





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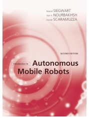

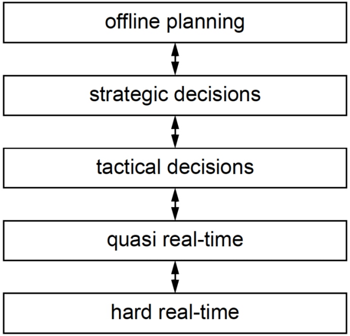

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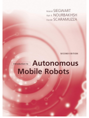

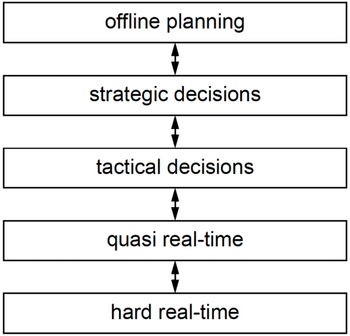

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  - operations where some latency (due to sensor processing or planning) can be tolerated (e.g. planning a path to a goal)
- Temporal constraints are taken into account within a **navigation architecture**

Summary

- Path planning is the problem of finding a collision-free path that brings a robot from its initial location to a goal
- There are various (offline) path planning algorithms, which can be observed as belonging to two major categories: graph-based search and potential field planning
- Path planning algorithms find a path in a known map, but online obstacle avoidance is also required for dealing with environmental changes; there are many obstacle avoidance methods in the literature, most of which perform both path and motion planning (e.g. DWA)
- Machine learning-based approaches aim to replace the dependency on (simple) robot models by acquiring navigation behaviours from data
- Navigation architectures need to take into account timing constraints on the operation of a robot, particularly for functionalities that have hard real-time constraints