

Resumo RI 22/23

Real world robotics

- **Transducer** - changes energy forms:
 - Robot <-Transducer-> World
 - Measures something and transforms into electric signals
- Robot -Transducer (Actuators)-> World
- Robot <-Transducer (Sensors)- World
- Robot (robot) means forced labour
- **COBOT** - collaborative robot
 - Safety - around humans
 - Light weight - in order to be portable (suitable for multi tasks)
 - Simplicity - operators do not need background knowledge to work with/teach about them
 - Low expenses - cheap acquisition and maintenance
 - Flexibility - dexterous and flexible (7 DOF)

Actuators

- Actuators + Motors are transducers:
 - Rotative (torque)
 - Linear (force)
- Internal combustion efficiency <30%

Physics

- Mechanical Power (P) = Speed (n) * Torque (M)
 - Measured in Watts (W)
- Electrical Power (P) = Voltage (V) * Current (I)
 - Measured in Watts (W)
- Efficiency => $\text{Power_out} / \text{Power_in}$ (percentage %)
- Torque - “rotation force” => force * distance

Point of work of actuator - interception of actuator curve and load curve

Servo motor

- External behavior is similar to ideal actuator:
 - linear, fast, safe

Gears

Exchange speed for torque.

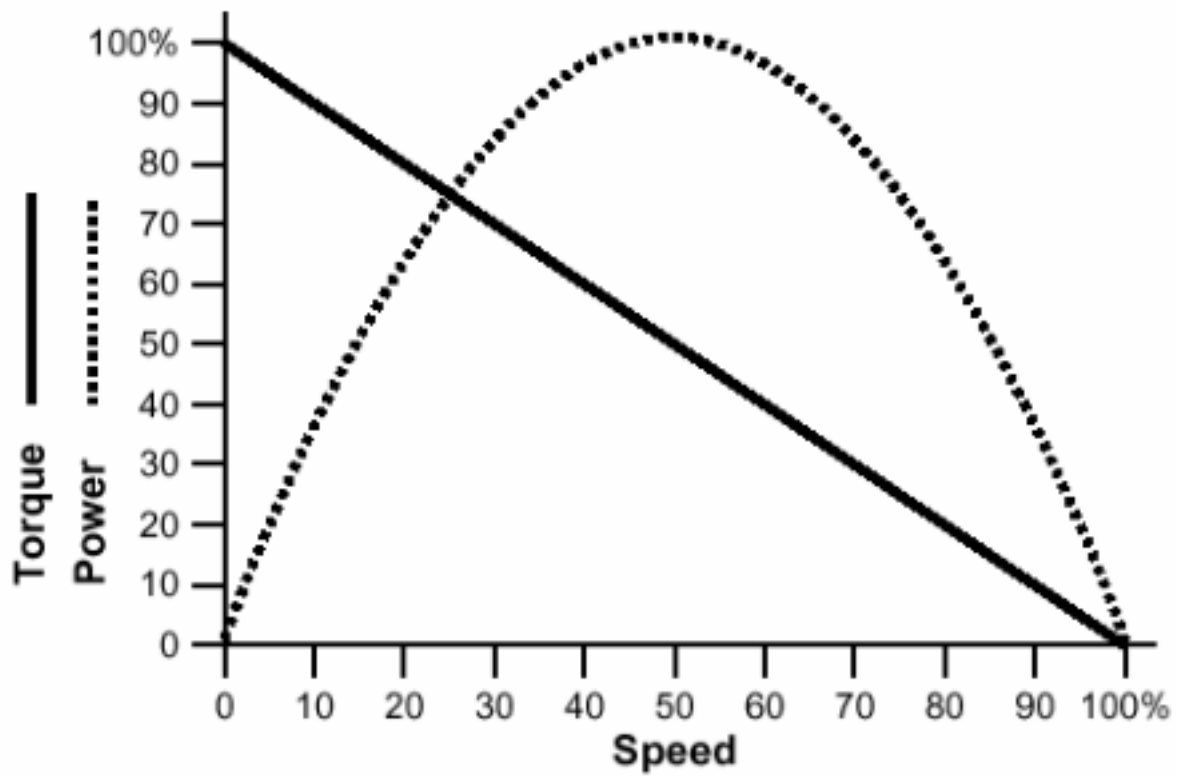
Solenoid

- Electro magnet with air core.
- Simplest electric actuator.

Locomotion

Wheels

- Differential drive - 2 rodas (wheelchair)
- Ackerman - 4 rodas (carro)
- Tricycle - 3 rodas



Plot the curve for the mechanical load and for the motor.

=> Intersection is the working point

Figure 1: power_curve

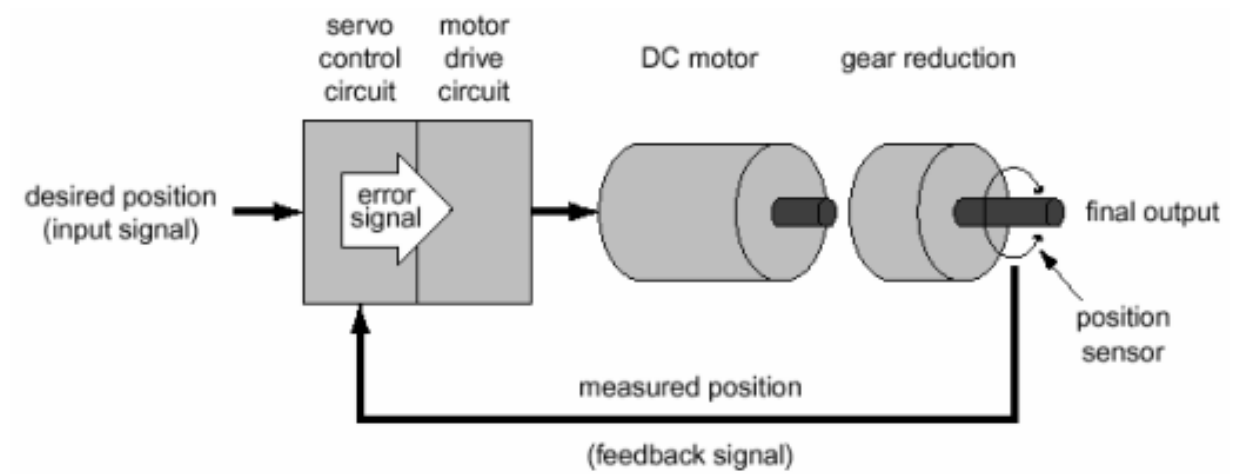
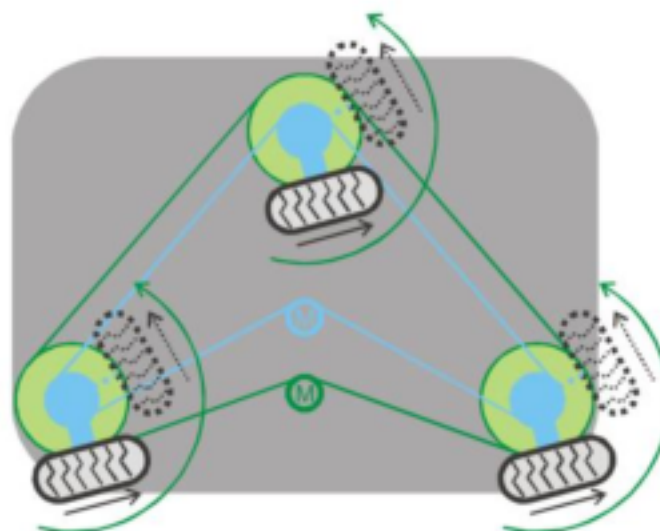


Figure 2: servo_motor



Synchronous
(Quasi omnidrive)

Figure 3: quasi_omnidrive

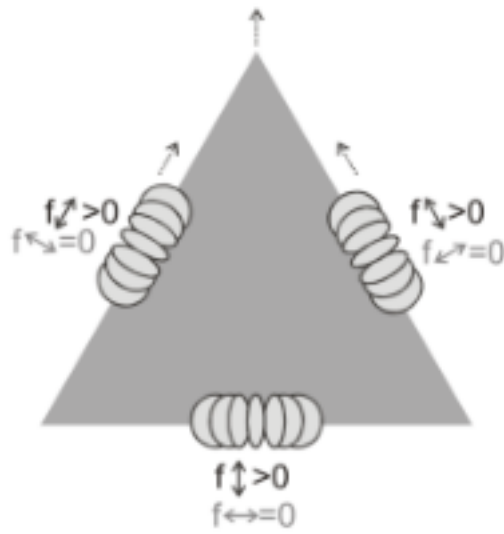


Figure 4: holonomic_drive



Figure 5: mecanum_wheel

◆ State Vector:

$$X_r^T = [x_r \ y_r \ \theta_r \ v_{rt} \ v_{rm} \ \omega_r]$$

◆ Dynamics:

$$\dot{x}_r = v_{rt} \cos \theta_r - v_{rm} \sin \theta_r$$

$$\dot{y}_r = v_{rt} \sin \theta_r + v_{rm} \cos \theta_r$$

$$\dot{\theta}_r = \omega_r$$

$$\dot{v}_{rt} = \alpha(v_{ref} - v_{rt})$$

$$\dot{v}_{rm} = 0$$

$$\dot{\omega}_r = \gamma(\omega_{ref} - \omega_r)$$

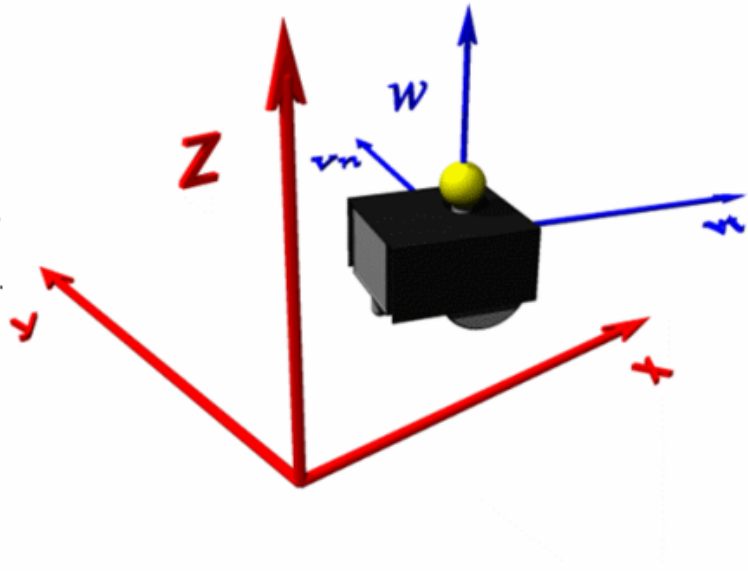
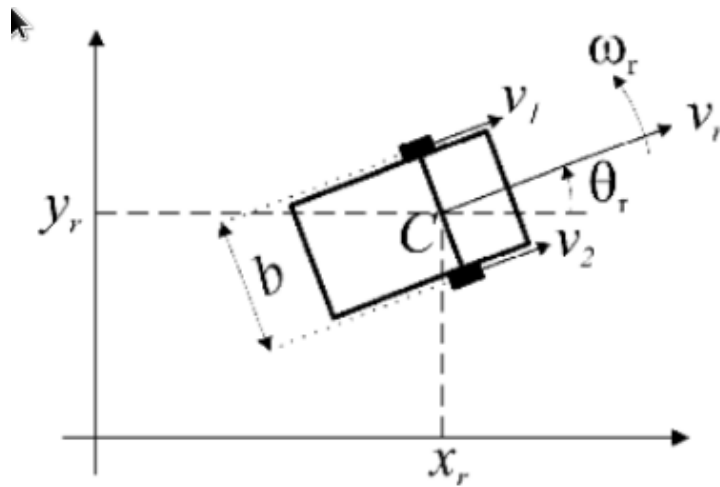


Figure 6: 2d_robot_dynamic_model



$$\begin{cases} v_t = v_r \\ v_t = \frac{(v_1 + v_2)}{2} \\ \omega_r = \frac{(v_1 - v_2)}{b} \end{cases}$$

"Pose" $\Rightarrow (x, y, \theta)$ $\begin{cases} x_r(t+1) = x_r(t) + v_r(t) \cdot \cos \theta_r(t) \cdot \Delta t \\ y_r(t+1) = y_r(t) + v_r(t) \cdot \sin \theta_r(t) \cdot \Delta t \\ \theta_r(t+1) = \theta_r(t) + \omega_r(t) \cdot \Delta t \end{cases}$

Figure 7: diferencia_ground_robot

Omniwheels

Kinematics & Dynamics

Differential ground robot

Manipulators

Joints

Mechanical Joints

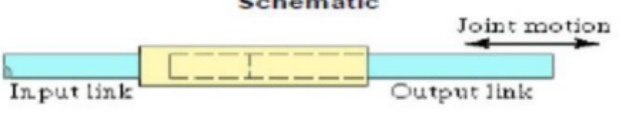
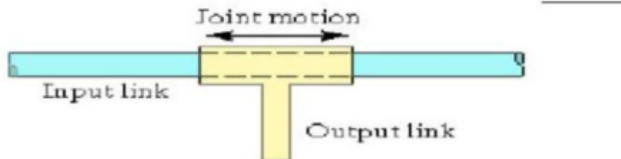
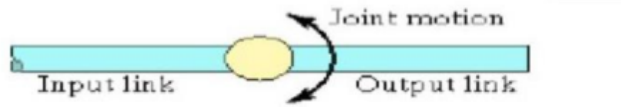
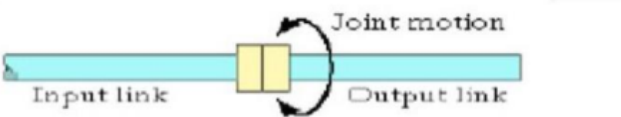
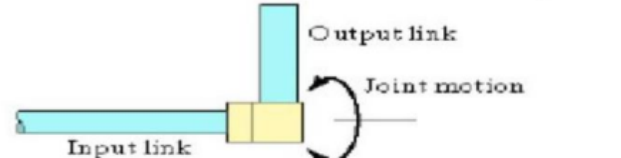
Joint	Description	Schematic
Linear joint	Type L joint; the relative movement between the input link and the output link is a translational sliding motion, with the axes of the two links parallel.	
Orthogonal joint	Type O joint; the relative movement between the input link and the output link is a translational sliding motion, but the output link is perpendicular to the input link.	
Rotational joint	Type R joint; this provides rotational relative motion, with the axis of rotation perpendicular to the axes of the input and output links.	
Twisting joint	Type T joint; this provides rotary motion, but the axis of rotation is parallel to the axes of the two links.	
Revolving joint	Type V joint; the axis of the input link is parallel to the axis of rotation of the joint, and the axis of the output link is perpendicular to the axis of rotation.	

Figure 8: mechanical_joints

Effector (End effector)

Actuator at the end of robot to affect the world.

Sensors

Robot must perceive its physical environment to get information about itself and its surroundings.

- Transducer
- Map physical attribute to measure
- Produce measurements over time
- Sensor “chain” (perception chain likely hardware + software)
- Transducer + electronics + Analog-to-Digital-Converter (ADC) + software

Current sensing methods

- Action oriented perception – Direct link between perception and action

- Expectation-based perception – Sensor interpretation constraining based on world knowledge
- Task-driven attention – Direct perception where information is needed or likely to be provided (focus-of-attention)
- Perceptual classes – Partition world in manageable categories

Accuracy

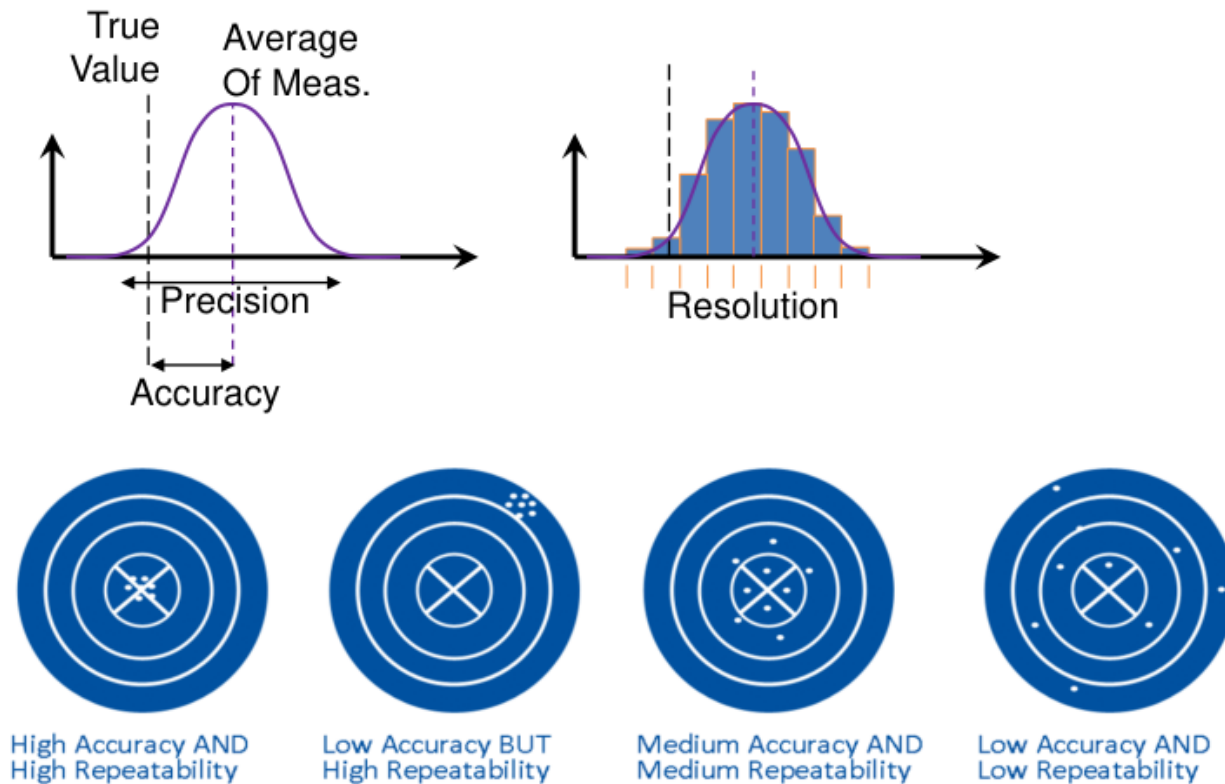


Figure 9: accuracy

Errors

- **Systematic errors:**
 - Always push the measured value in the same direction
 - **Can be reduced by sensor calibration**
- **Non-systematic errors:**
 - Have a more random behavior
 - Cannot be predicted or eliminated by calibration
- **Interference note:**
 - Difference from systematic error
 - Can be measured and corrected by sensor fusion like techniques

Classification of sensors

- **Passive sensors:**
 - Rely on environment to provide the medium for observation
 - Less energy
 - Reduced signal-to-noise ratio
- **Active sensors:**
 - Emits form of energy and measures the impact
 - Restricted environments

- Proprioceptive:
 - Measure system internal values
 - Eg: motor speed, battery status, etc...
- Exteroceptive:
 - Information from the robots external environment
 - Generally considering the robots frame of reference
 - Depend on something external

Potentiometer

- Variable resistance
- Can be used to detect angular or linear position

Encoders/odometry

- Physical principle - record the wheel traversed distance
- Wheel traversed distance is used to estimate robot position and orientation

GPS/DGPS

- Physical principle - triangulation over the distance to several satellites
- Estimates longitude, latitude, and altitude:
 - resolution os 10-15m
- Differential GPS:
 - Extra GPS receivers at known locations
 - Reduces error
 - Resolution of a few centimeters

Proximity sensors - Bumper

- Physical principle - direct contact closes/opens a circuit
- Used to detect collisions
- Binary value
- Reliable but the collision is eminent

Proximity sensors - Infrared

- Physical principle - IR emitter/receiver is used to detect distance or as a barrier
- Used to estimate distance, presence of objects or color
- Several technologies
- Range from 10cm to 1m
- Narrow field of view
- Cheap

Proximity sensors - Sonar

- Physical principle - Emit ultra-sonic chirp, time until echo is received is used to estimate distance
- Time until echo is proportional to the distance until obstacle

Proximity sensors - Laser Range Finder

Similar to sonar but uses lasers.

Depth sensing

- Stereo-vision:
 - Problem: no features (e.g. parede branca)
 - Sol: **active stereo** - adicionar um laser auxiliar
- Structured light:

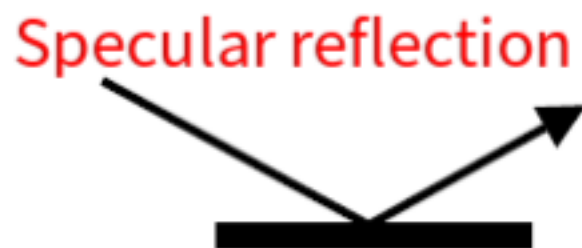
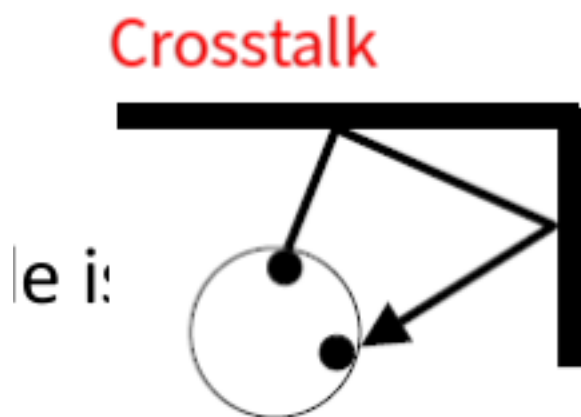
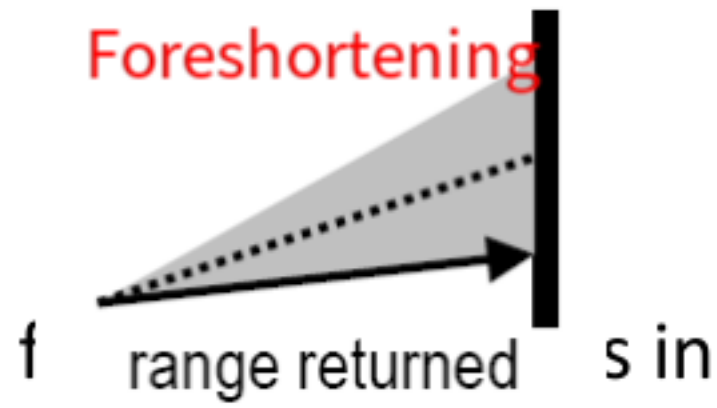


Figure 10: sonar_problems

- Illuminar surface com um padrao
- Camera consegue extrair depth info so com 1 imagem

Robot architectures

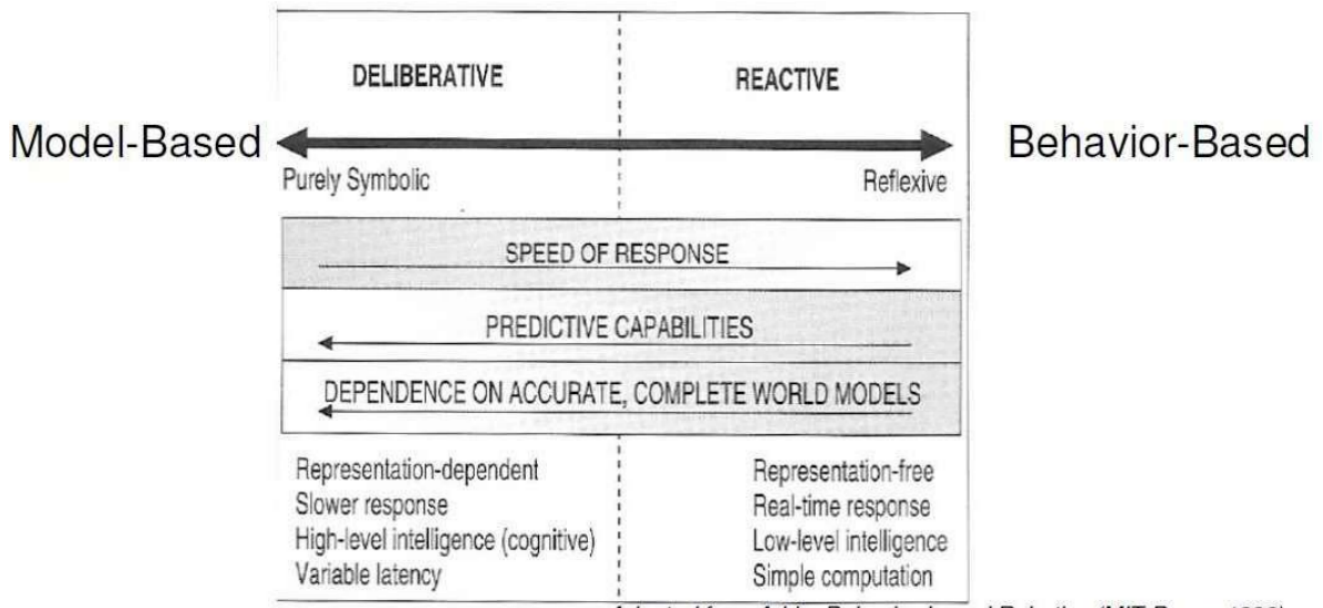


Figure 11: architectures

Hierarchical/Deliberative

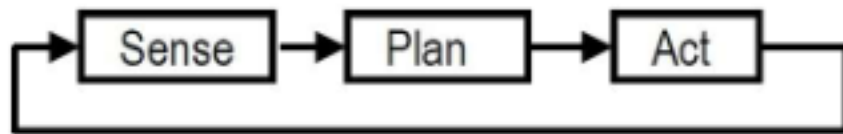


Figure 12: hierarchical_architecture

Reactive

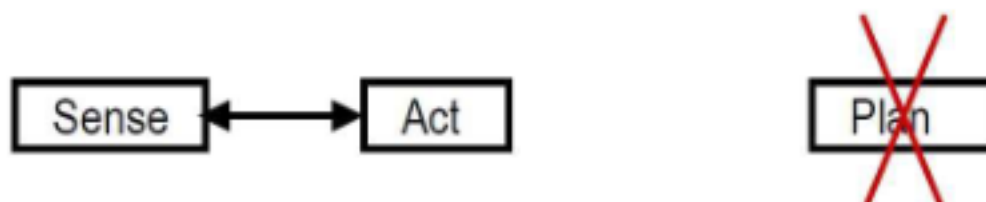


Figure 13: reactive_architecture

- Cheap/low memory processing
- Lack temporal consistency and stability
- No world model - Difficult to localize robot on world

Behavior-based

- Combination of simple behaviors

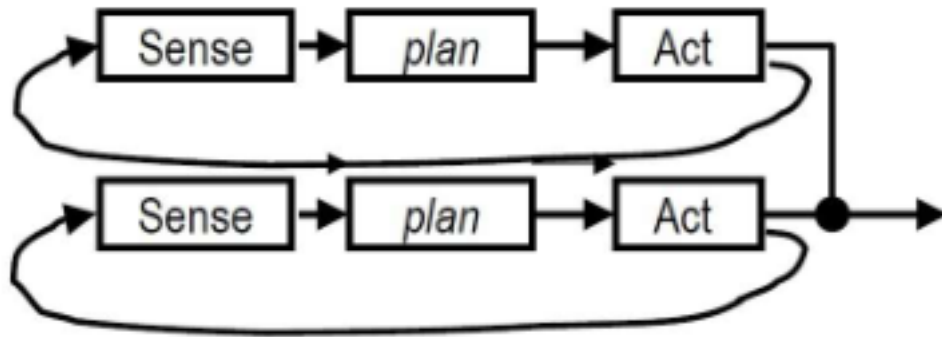


Figure 14: behavior_architecture

- No centralized world model
- Each behavior may store own representation

Hybrid

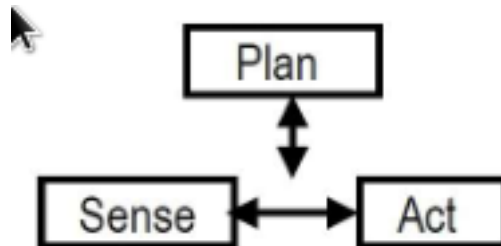


Figure 15: hybrid_architecture

- Combine Reactive and Deliberative approaches
- Mais usado hoje em dia

Localization

- Position estimation
- Pose can't be sensed directly:
 - Usar sensors
 - Geralmente, 1 sensor não chega

Local vs. Global localization

- Position tracking:
 - Initial pose is known
 - Local uncertainty around robot's true pose
- Global localization:
 - Initial pose is unknown
 - Kidnapped robot:
 - * Robot can be teleported to different location

Local techniques aim at compensating odometric errors during robot navigation. They require that the initial location of the robot is approximately known and they typically cannot recover if they lose track of the robot's position. Global techniques can localize a robot without any prior knowledge about its position, i.e., they can handle the kidnapped robot problem, in which a robot is kidnapped and carried to some unknown location. Global localization techniques are more powerful than local ones and can cope with situations in which the robot is likely to experience serious positioning errors.

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1)

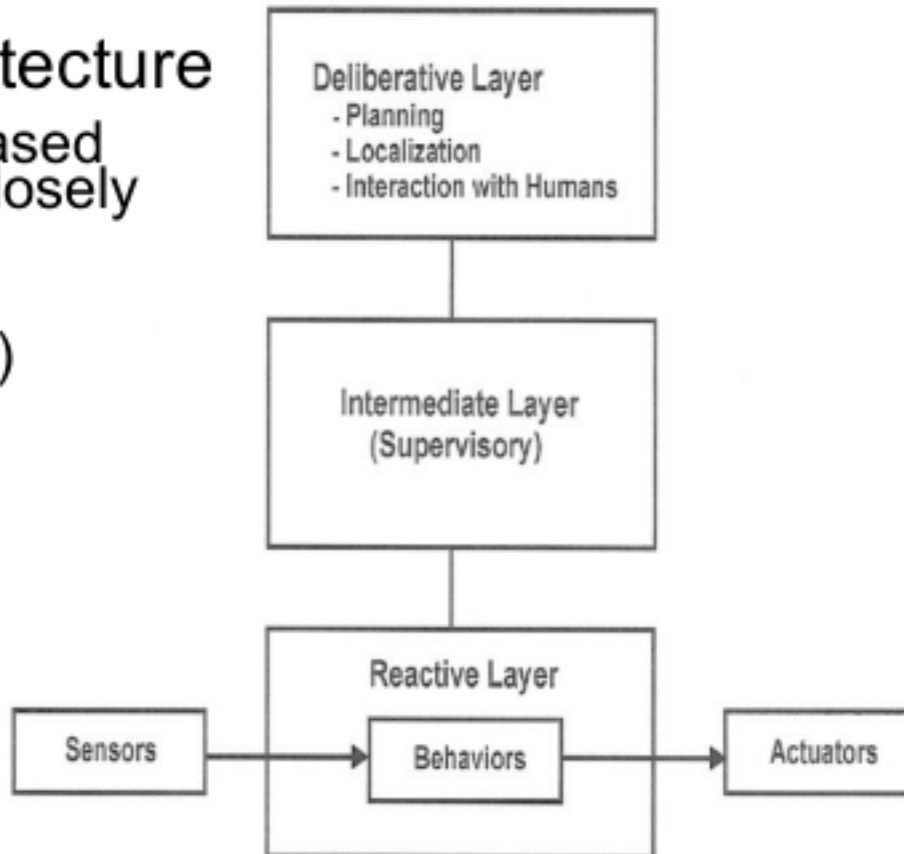


Figure 16: three_layer_hybrid_architecture

Source: “Local and Global Localization for Mobile Robots using Visual Landmarks”, by Stephen Se, David Lowe, Jim Little

Taxonomy for localization

- Static vs. Dynamic Environments
- Passive vs. Active Approaches
- Single-robot vs. Multi-robot

Markov localization

- Probabilistic state estimation
- Belief func - the prob distribution of the estimated pos of the robot for every possible pos.

- Belief is uniform
- First integration of sensor data, result is multimodal
- Convolution with motion model, shifts and flattens belief
- Second integration of sensor data, robot localizes itself
- Moving along

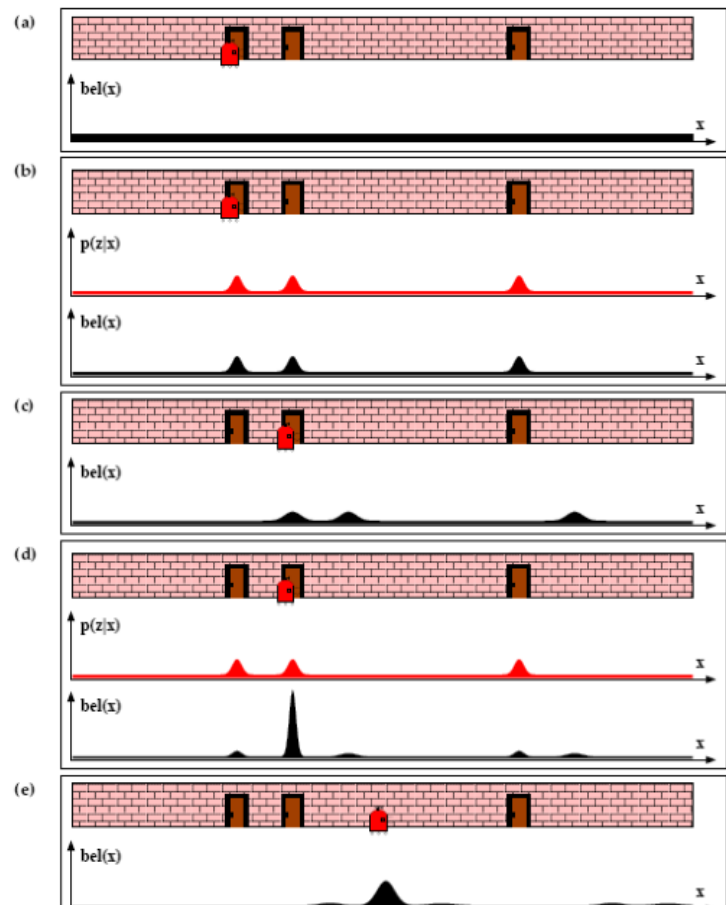


Figure 17: markov_localization

EKF localization

- Caso especial de Markov
- Features are identifiable

Multi-hypothesis tracking

- Extension to basic EKF
- Belief is represented by multiple Gaussians

- Initial belief is a Gaussian distribution
- Motion model is applied
- Sensor data is integrated resulting variance is smaller than variances of belief and sensor model
- Motion uncertainty

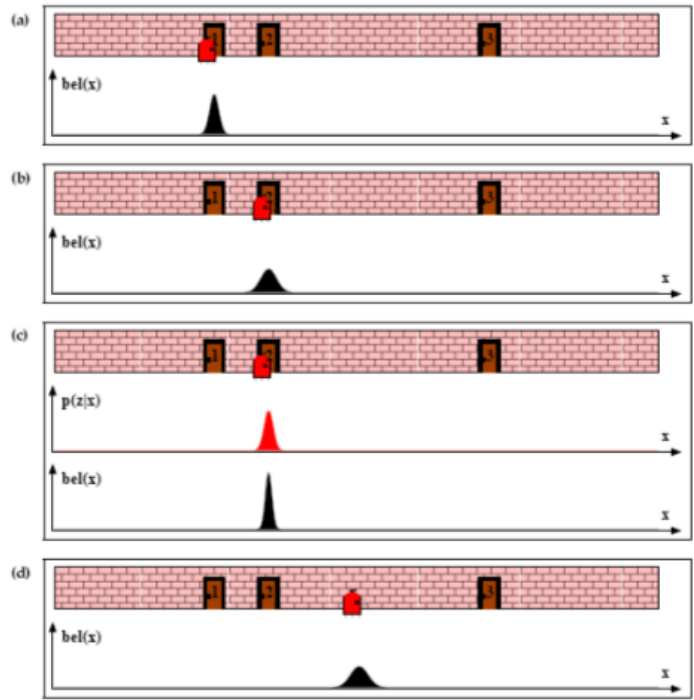


Figure 18: ekf_localization

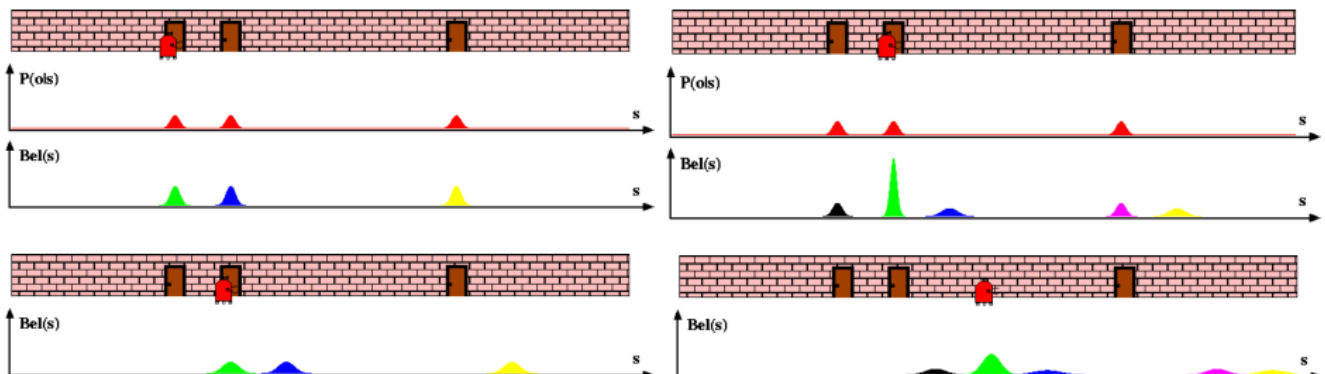


Figure 19: multi_hypothesis_tracking

- a) Belief is uniform
- b) First integration of sensor data, result is multimodal
- c) Convolution with motion model, shifts and flattens belief
- d) Second integration of sensor data, robot localizes itself
- e) Moving along

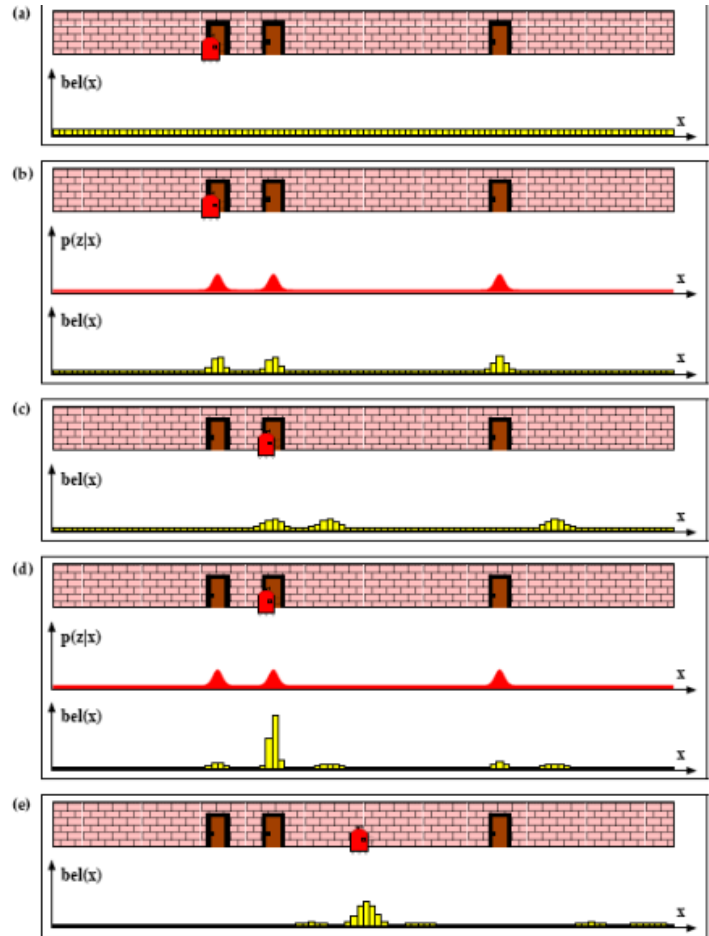


Figure 20: grid_localization

Grid localization

- Same but with histograms

Monte Carlo Sampling

- Pose particles drawn at random and uniformly
- Importance factor assigned to each particle, set of particles hasn't changed
- After resampling and incorporating robot motion
- New measurement assigns new importance factors
- New resampling and motion

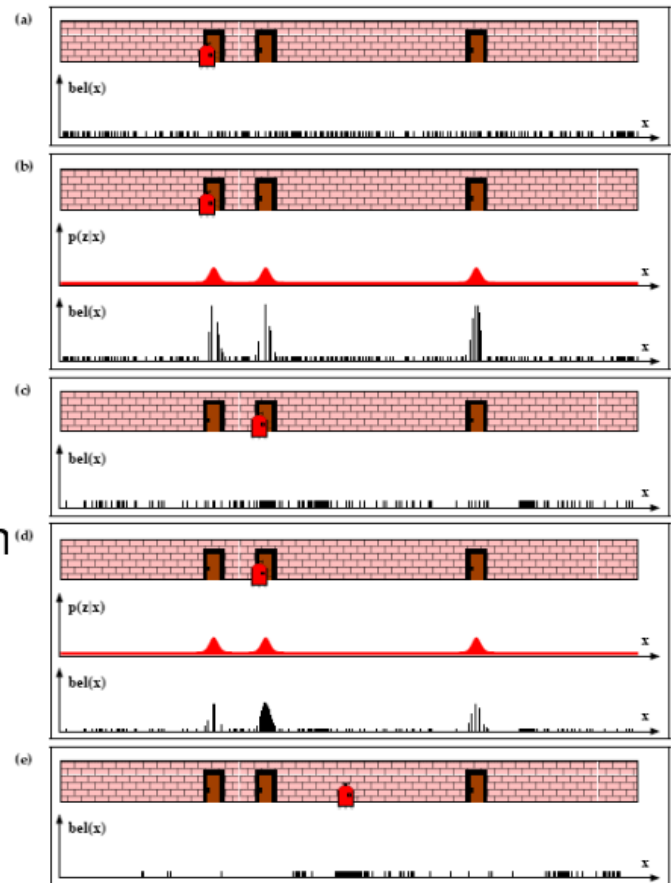


Figure 21: monte_do_carlos

- Começa com barrinhas random
- Dá ressample para concentrar particles onde há mais importantes
- Particles num sítio ficam mais importantes quando o robot vê coisas nesse sítio.

Mapping

- The process of building an internal estimate of the metric map of the environment.

Dempster-Schafer theory

- Belief func em vez de probabilities:
 - Main difference from probabilities is that uncertainties in the reading count as belief mass for **dontknow**
- Frame of Discernement - set of propositions:
 - In occupancy grid FOD = {Occupied, Empty}
 - Sensor reading may be considered ambiguous
- Belief function properties
 - $Bel = m(\{Occupied\}), m(\{Empty\}), m(dontknow)$
 - $dontknow = \{Occupied, Empty\}$

Belief function for sonar

- Region that supports evidence of having an obstacle
 - $m(\text{occupied}) = \text{evidence}$
 - $m(\text{empty}) = 0$
 - $m(\text{dontknow}) = 1 - \text{evidence}$
- Region that supports evidence of being empty
 - $m(\text{occupied}) = 0$
 - $m(\text{empty}) = \text{evidence}$
 - $m(\text{dontknow}) = 1 - \text{evidence}$
- The main difference from probabilities is that uncertainties in the reading count as belief mass for dontknow

Figure 22: sonar_example

SLAM

- Cycle through localization and mapping

Uncertainty

- Mapping between observations and the map is unknown
- Picking wrong associations causes divergence

Position thingy

Motion + observation model

- Motion model - describes the relative motion of the robot
- Observation (or sensor) model - relates measurements with robot's pose

Navigation

- How do I get where I want to go

Challenges

- Path planning problem:
 - robot has a map
 - knows own and target positions
- Localization problem:
 - robot has a map
 - knows target position
 - doesn't know own position

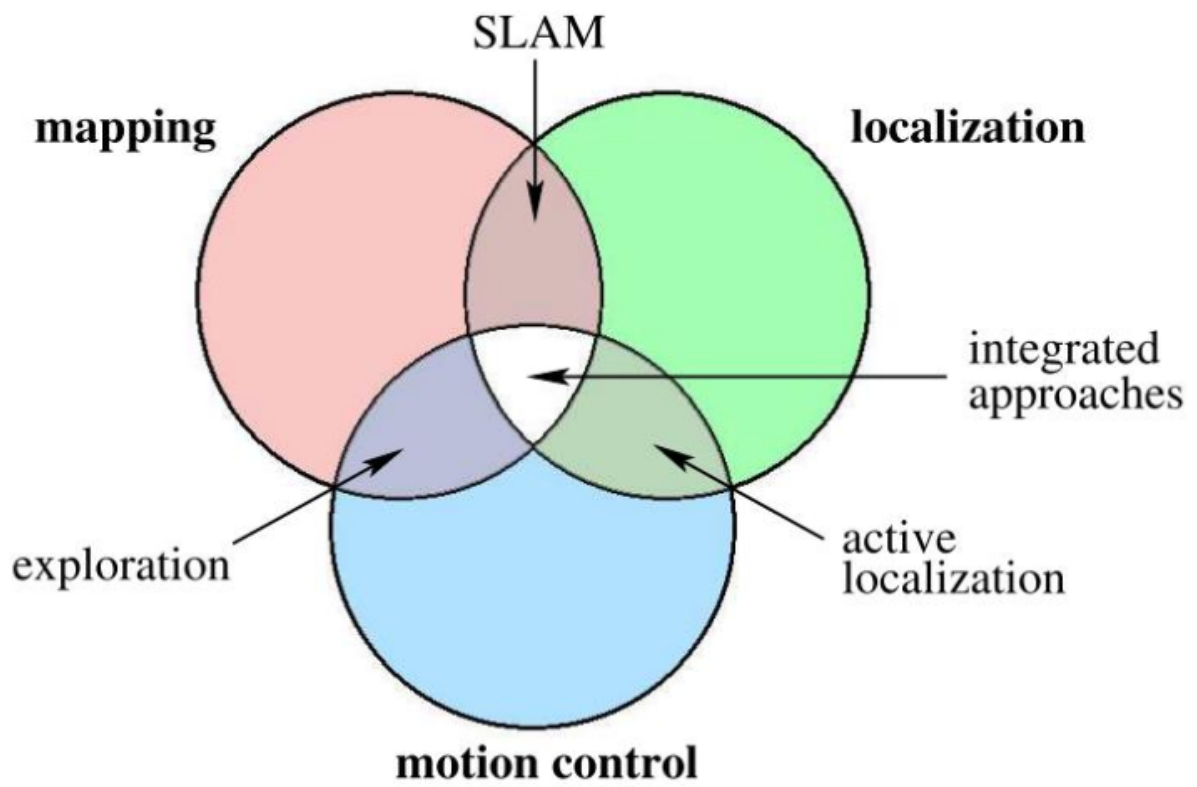


Figure 23: slam

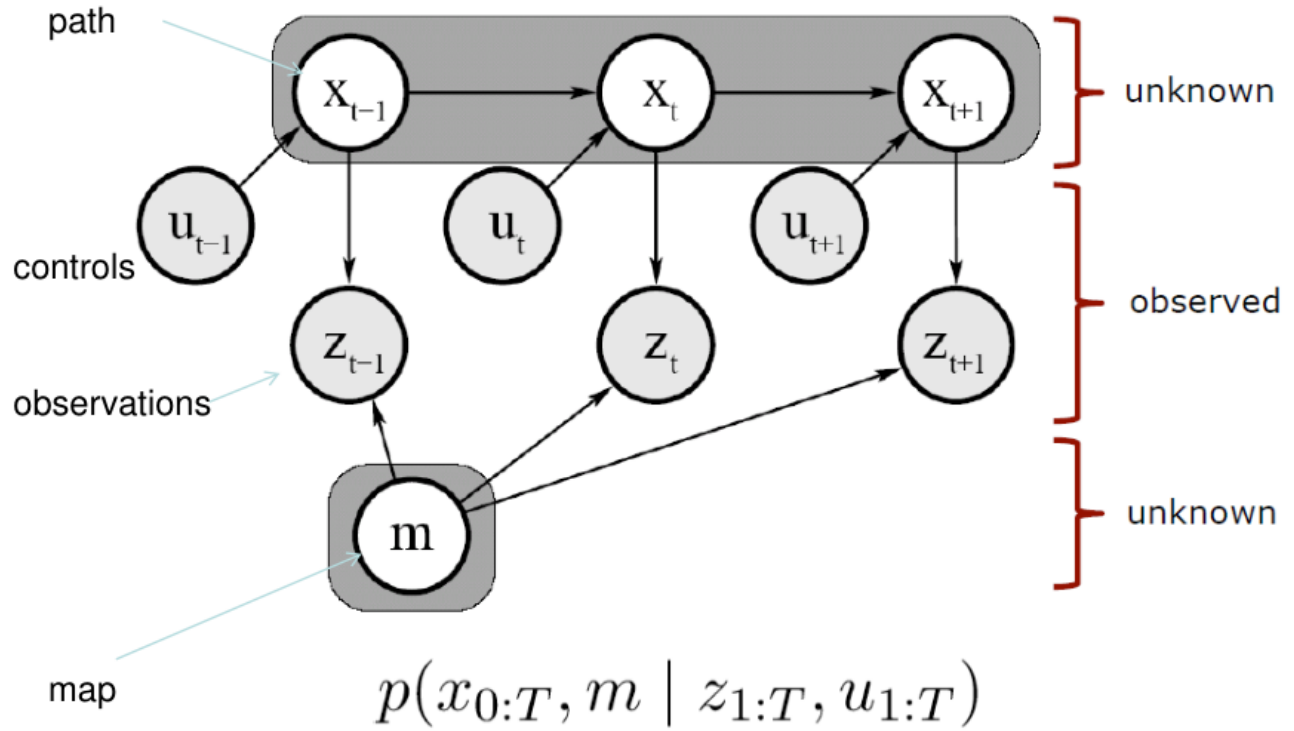


Figure 24: position_problem_slam

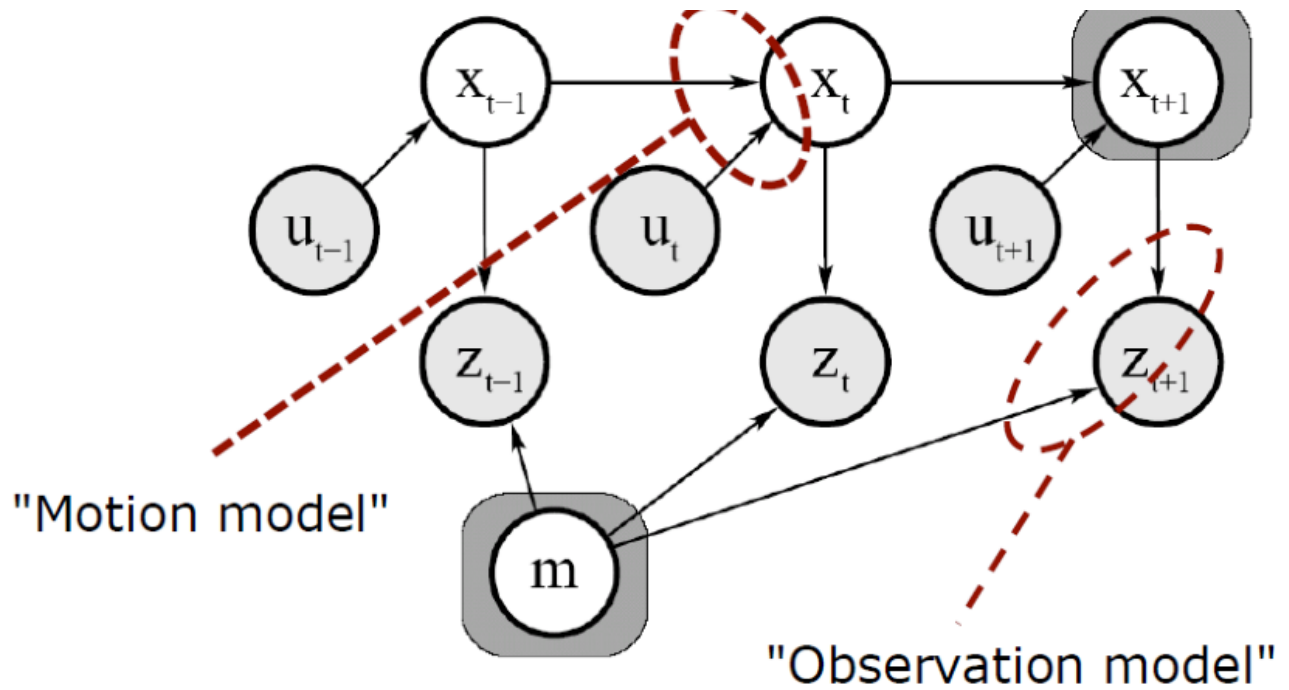


Figure 25: motion_observation_model

- Coverage problem:
 - robot has a map
 - knows own position
 - doesn't know target position
- Mapping problem
 - robot doesn't have a map
 - may know own position
- SLAM:
 - robot doesn't have a map
 - robot doesn't know own position

Metric Maps and Topological Maps

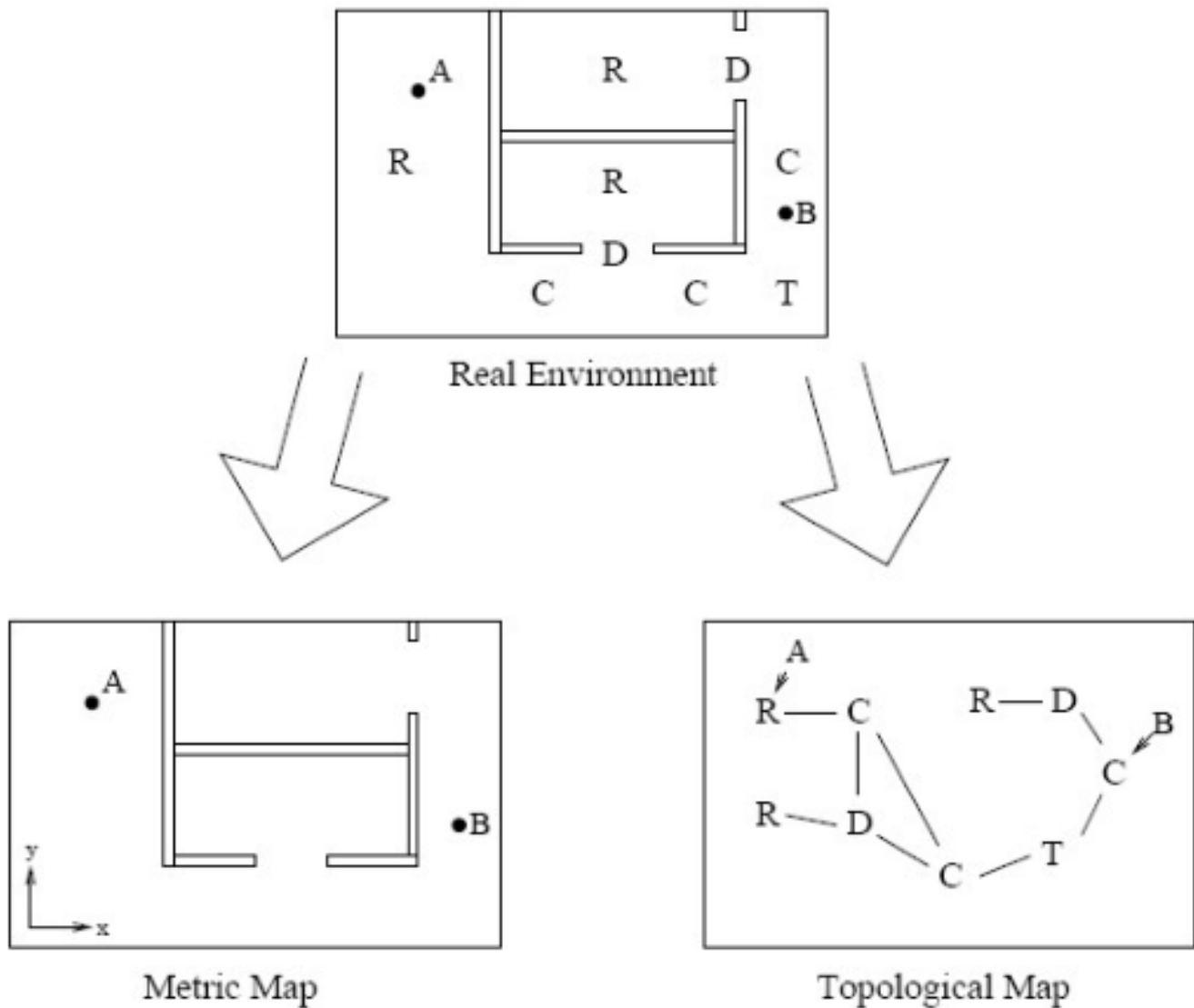


Figure 26: metric_topological_maps

Visibility graph

- Nodes are obstacles angles
- Edges connect nodes that are visible from each other

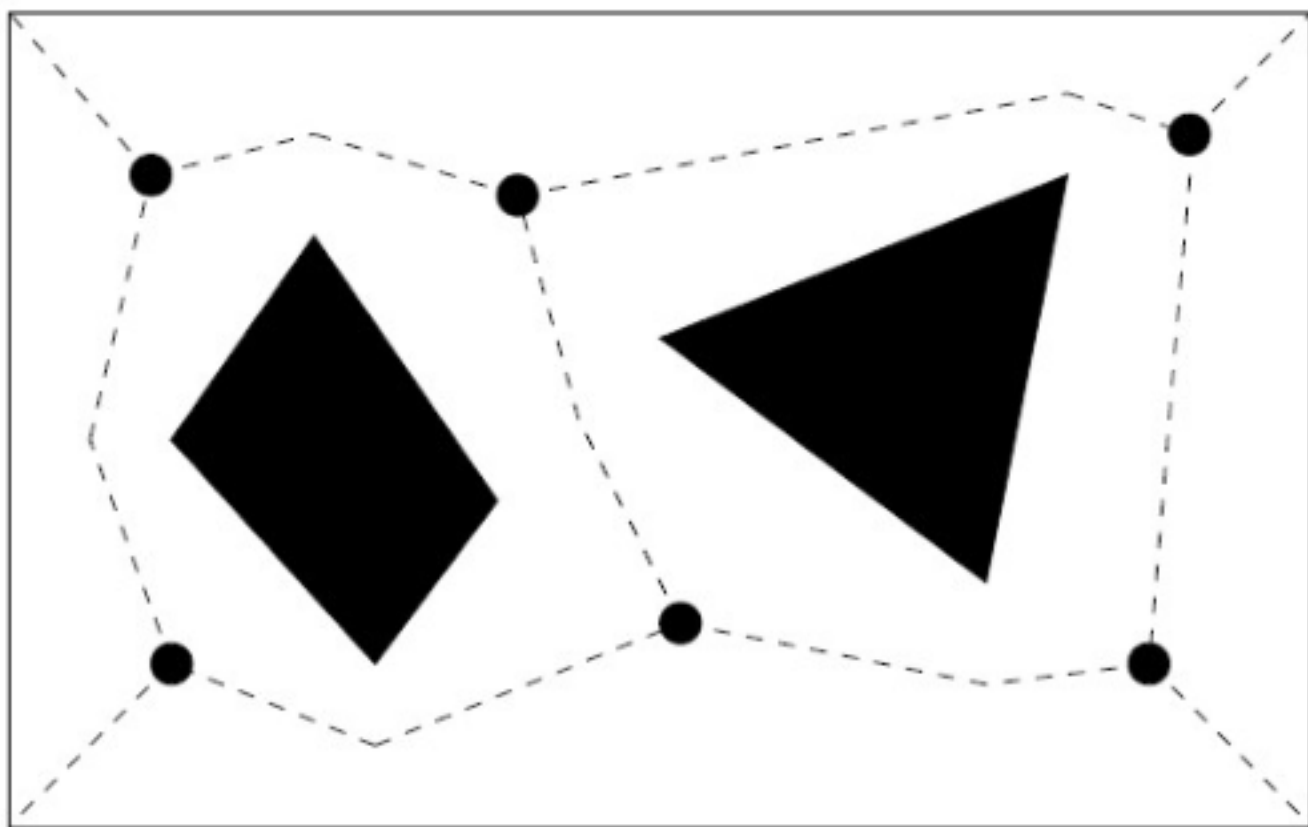


Figure 28: voronoi_diagram

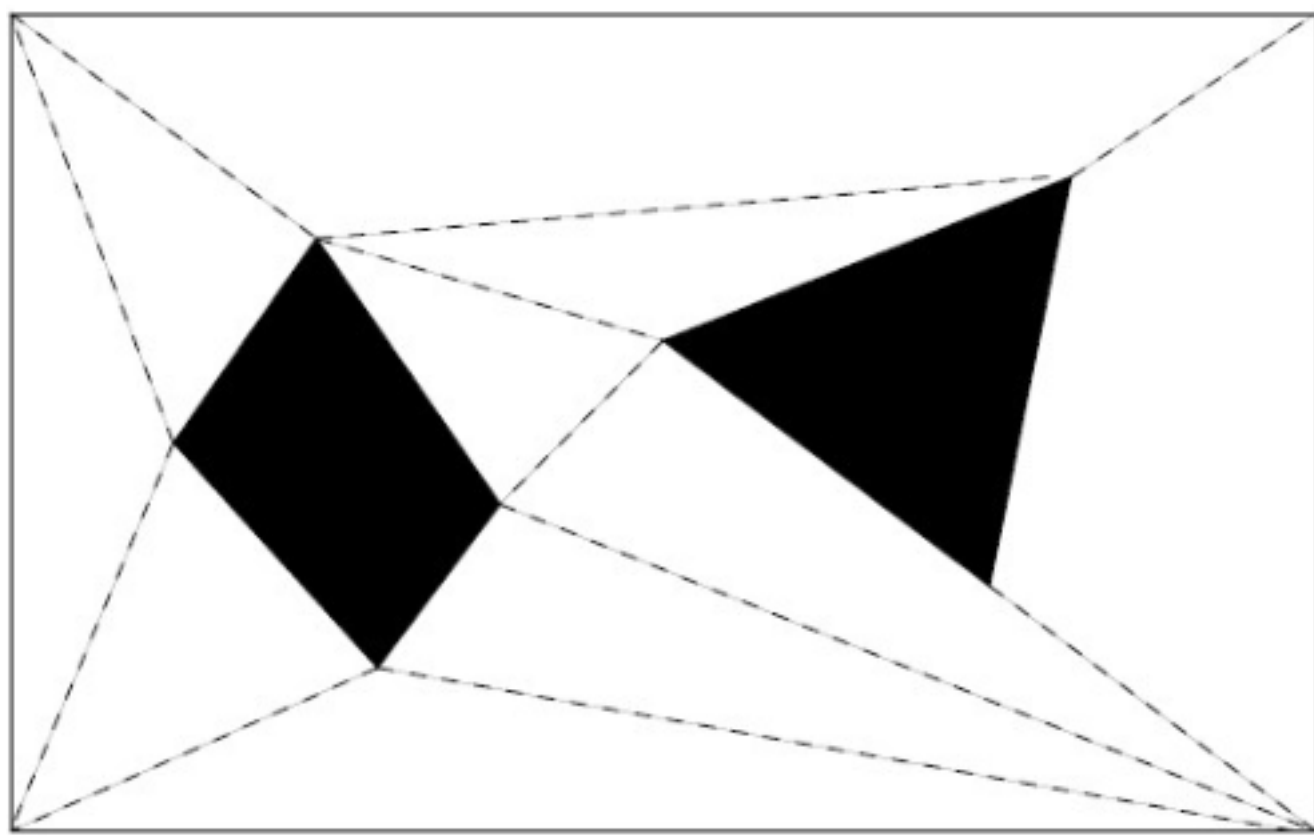


Figure 29: exact_cell_decomposition

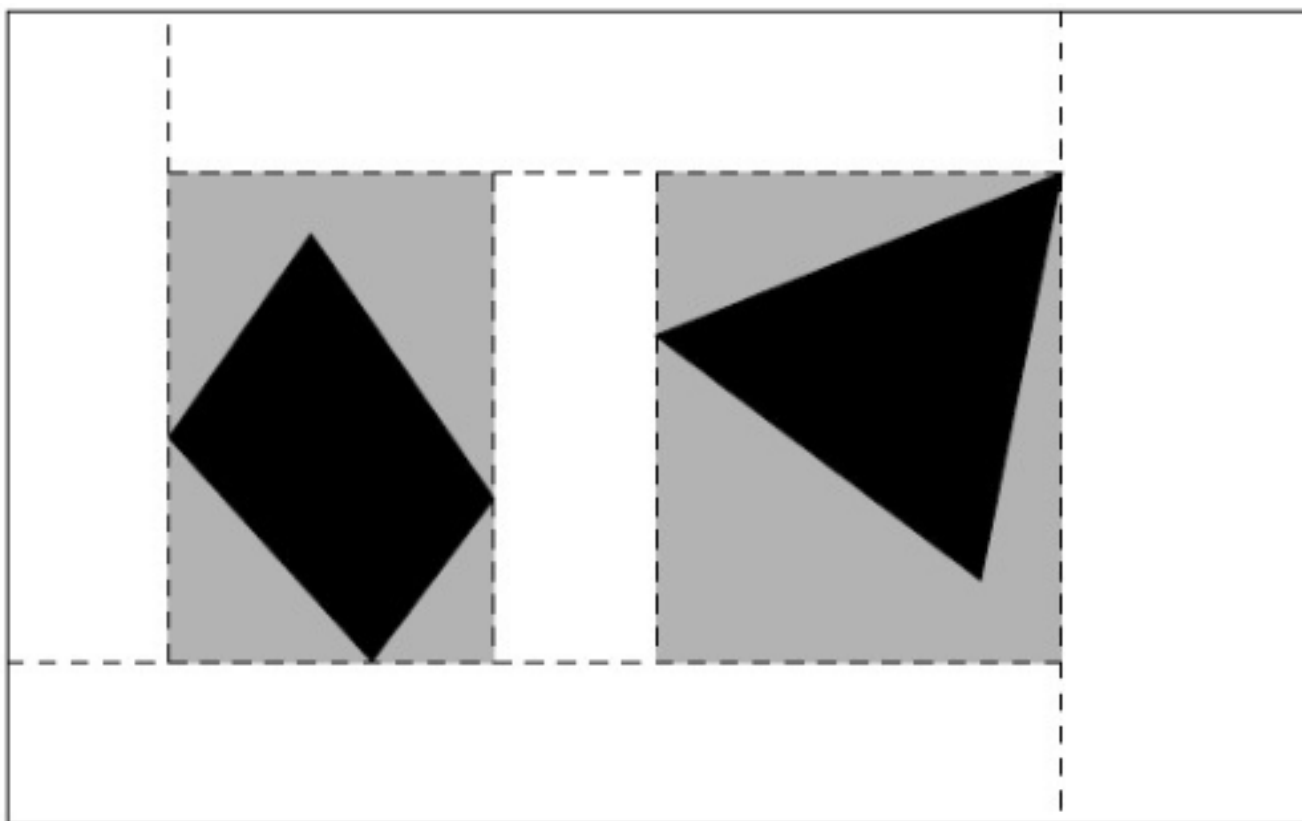


Figure 30: rectangular_cell_decomposition

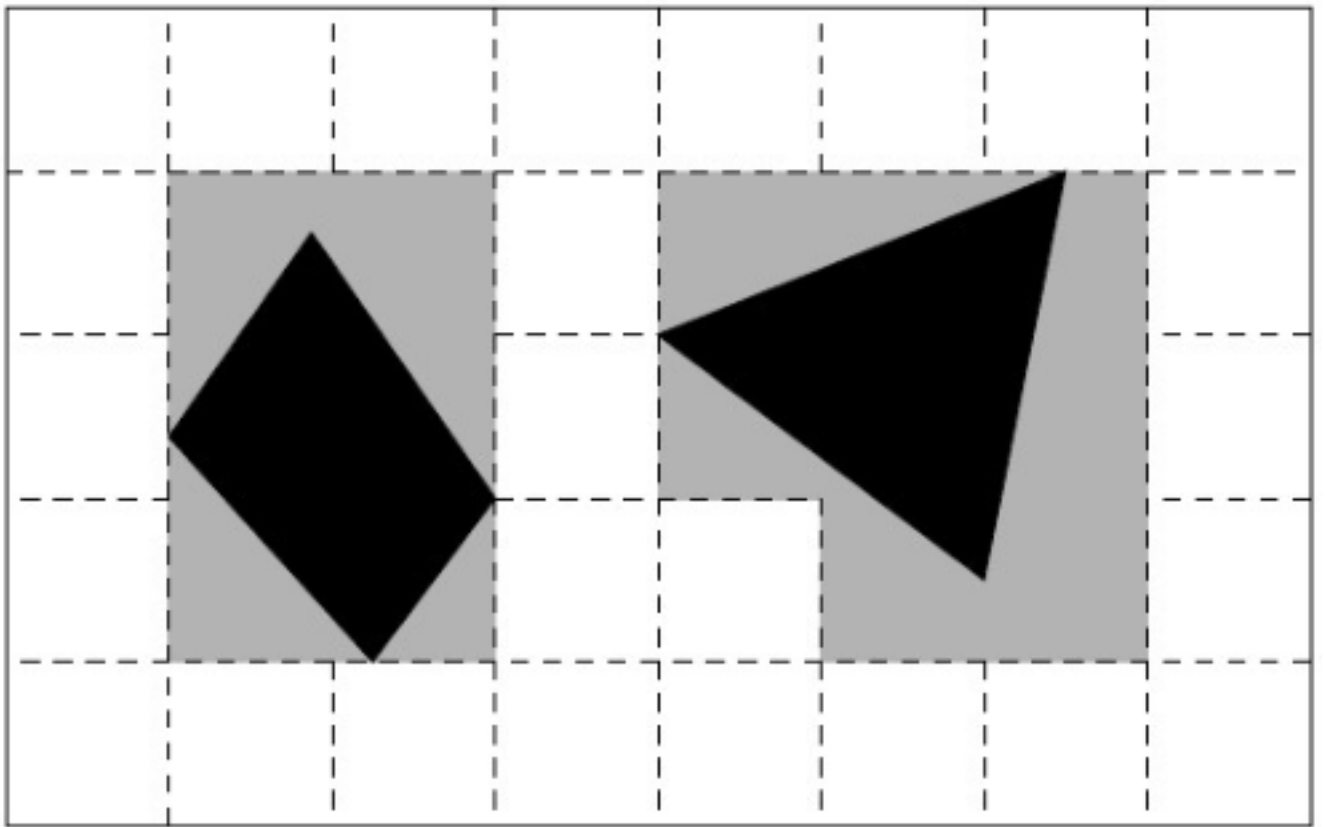


Figure 31: regular_cell_decomposition

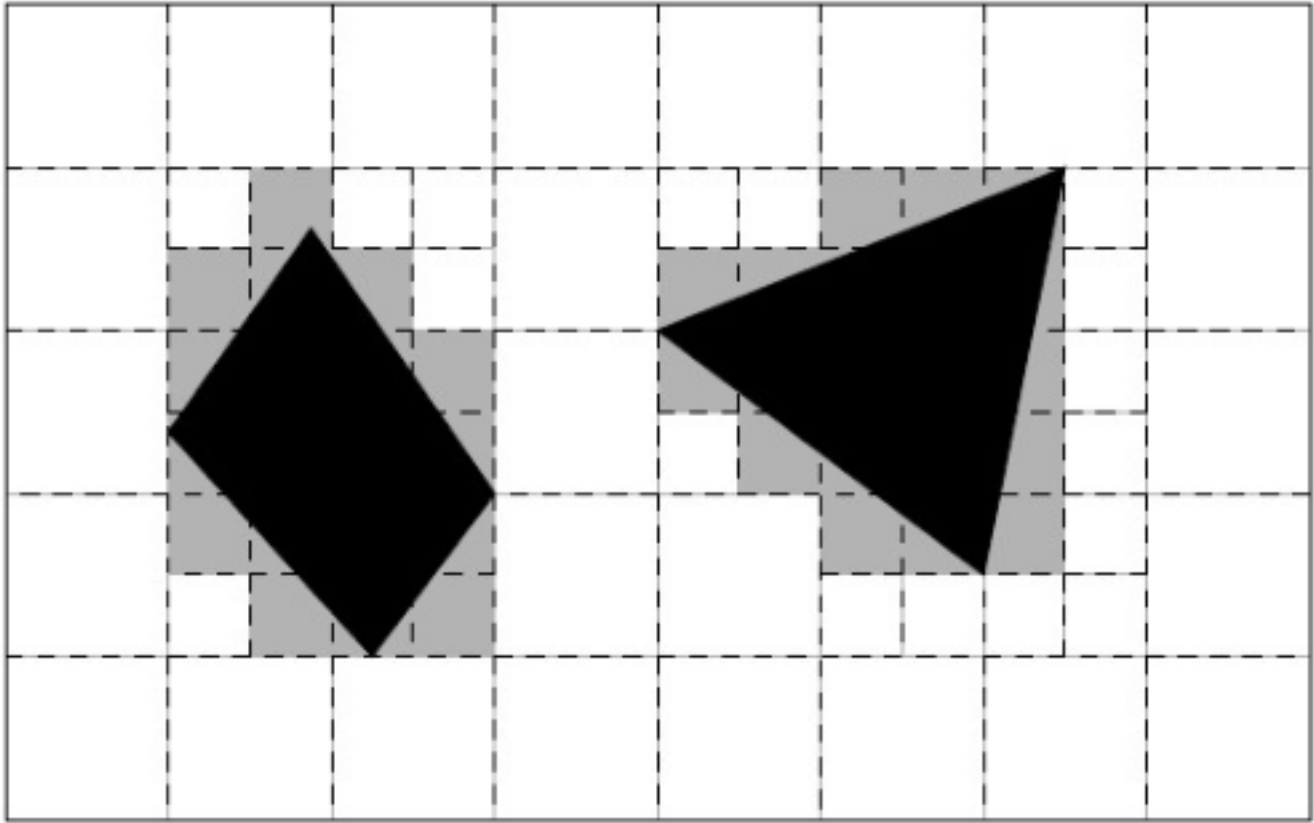


Figure 32: quadtree_cell_decomposition

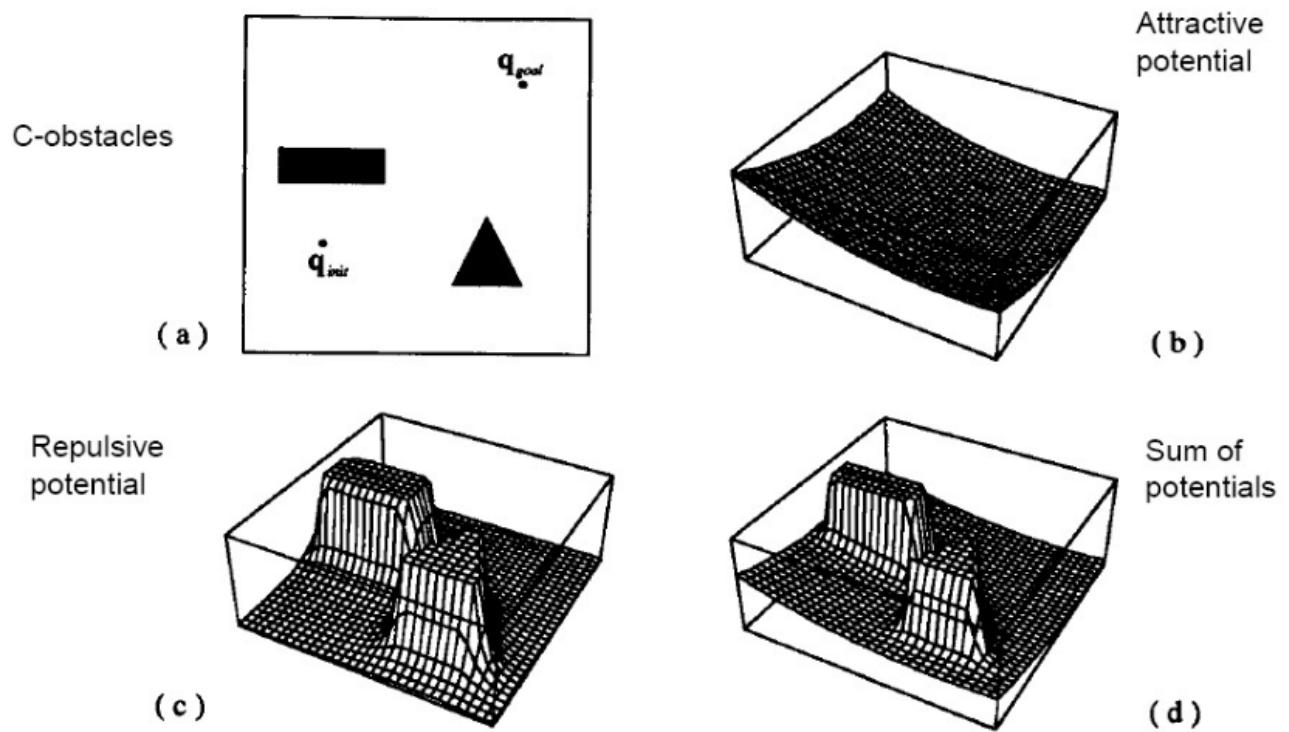


Figure 33: potential_field_local_planning