→ Localization

A single sensor measurement is usually insufficient to determine the pose.

Goal: Localize robot in known map.

Inputs: Map of environment, perceptions and actions of robot.

Output: Estimated position on map.

↳ Markov localization

Probabilistic state estimation is applied to the localization problem through Bayes filters.

Past and future are independent. Pose is given by a belief function.

Splitting actuation and measurement:

prediction phase: update previous estimate only based on actuation. Incorporates only motion model

correction phase: correct prediction based on measurements. Incorporates sensor model, based on Bayes formula.

It combines a map of the environment with a sensor model that describes how the robot's sensors respond to environment.

↳ Kalman filter localization

A case of Markov localization.

Belief, motion model and sensor model are represented by Gaussians (mean and covariance).

Has a prediction and correction phase as well.

- Extended Kalman filters: assume next state and measurement can be non linear.
- Extension to extended: belief is represented by multiple Gaussian filters.

↳ Gaussian localization

Good uncertainty representation for tracking (not global localization). Not good for hard spatial constraints. Linearization can be an issue (depends on uncertainty and non linearity). Features must be sufficient.

↳ Grid localization.

Grid decomposition of the pose space.
Histogram filter to represent position belief.

Choosing the resolution for the grid cell is a key point. (resolution changes computation and info loss).

Can be used to solve the global localization problem, can process raw measurements, not bound to unimodal distribution.

A grid to represent a 2D pose is cubic, each plane representing a possible robot orientation.

↳ Monte Carlo localization

Based on random (educated) guesses drawn into the pose space (particles), belief is given by a set of particles.

Measurement is used to determine the importance weight of particles.

Weights are used to influence a random selection of particles (heavier particles are more likely to be selected). Number of particles is key.

Can be used to solve global position, not bound to unimodal distributions.