Mobile Robots and Autonomous Vehicles

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1 State of the Art, Technologies

ITS:intelligent transportation systems
ADAS:advanced driver-assistance systems

Required technological breakthroughs

- Motion & action autonomy v/s Shared control:
  ⇒ Adapted to Dynamic & Open Environments populated by Human Beings
- Increased robustness & safety (sensing & control):
  ⇒ Dealing with incompleteness & uncertainty (Bayesian models)
- Intuitive Programming & Human Robot Interaction:
  ⇒ Self-learning capabilities & behavior models + Multi-modal interaction
- Real-time & Cost constraints:
  ⇒ Miniaturization & Efficient Embedded systems

Real dynamic world is too complex for being fully modeled using classical tools (complexity, incompleteness and uncertainty). Therefor, it is necessary to introduce **probabilistic Reasoning Approaches** in traditional decisional & Control Robot Architectures.

1.1 How to control Robot actions in a Dynamic world populated by Human Beings ?

- **Real world**: Dynamic Human Environment
- **Sense** :Sensing the environment using various sensors
- **Interpret**: Interpreting the dynamic scene using context & semantics
- **Plan & Decide**: Planning robot motions + Deciding of the most appropriate action to be executed (with a Goal in mind)
- **Act & Interact**: Acting & Interacting in the Real world (Safety & Acceptability)

1.1.1 Sense

Main Difficulty

- Huge heterogeneous sensory data
- Sensing errors & Uncertainty
- Real-time processing

Main Functions

- Localization & Mapping (SLAM)
- Static & Mobile Objects Detection

Main Models & Algorithms

- Bayesian Filtering
- Feature based & Grid based approaches

1.1.2 Interpret

Main Difficulty

- Uncertainty & Huge volume of sensory data to be processed
- Real-time processing
- Reasoning about various knowledge: history, context, semantics, prediction models

Main Functions

- Detection & Tracking of Mobile Objects (DATMO)
- objects classification (recognition)
- prediction & Risk Assessment: avoiding future collisions

Main Models & Algorithms

- Bayesian Perception Paradigm
- Behaviors modeling & learning
- Bayesian approaches for Prediction & Risk Assessment

1.1.3 Plan & Decide

Main Difficulty & Functions

- On-line Motion Planning under various constraints: time, kinematic, dynamic, uncertainty, collision risk, social
- Decision making under uncertainty using contextual data: history, semantics, prediction

Main Models & Algorithms

- Iterative Risk-based Motion Planning: e.g. Risk-RRT
- Decision making using Contextual data & Bayesian networks

1.1.4 Act & Interact

Main Difficulty & Functions

- Robot navigation while taking into account both Safety & Social constraints
- Human in the loop !

Main Models & Algorithms

- Human-Aware Navigation paradigm: safety & social filters
- Intuitive Human-Robot Interaction

1.2 Sensing technologies

Proprioceptive Sensors	Exteroceptive Sensors
Wheel Encoder	IR Transceiver
Torque Sensor	Humidity Sensor
Accelerometer	Tactile Sensor
Inclinometer	Microphone
Gyroscope	Temperature Sensor
Voltagemeter	Light Sensor
	Camera
	Radio
	Antenna
	Force Sensor
	RFID Reader
	Magnetometer

Artificial Signatures

1.3 Social Filter

Approach: Representing "Personal Space" & "Interaction Space" as motion constraints for the robot (using Mixture of Gaussians)

2 Bayes & Kalman Filters

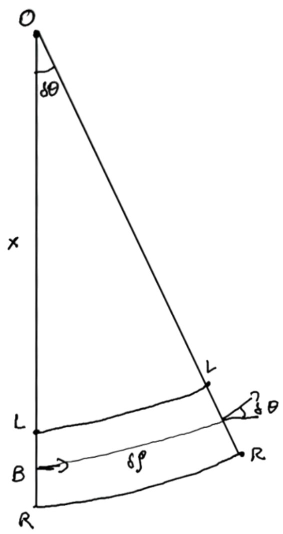
Localization is an estimation problem, the goal is to estimate a state (Position and orientation) by updating the probability distributional function when the sensor data arrive.
Proprioceptive sensor:

$$s_{i+1} = f\left(s_i, u_{i+1}\right)$$

Exteroceptive sensor:

$$z_i = h\left(S_i\right)$$

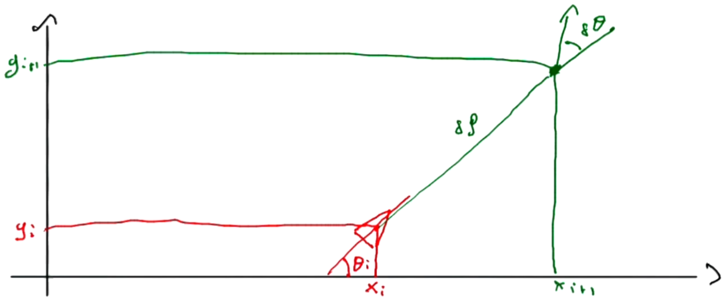
2.1 Study case: Differential drive



$$S_{i+1} = \begin{bmatrix} x_{i+1} \\ y_{i+1} \\ \theta_{i+1} \end{bmatrix} \quad S_i = \begin{bmatrix} x_i \\ y_i \\ \theta_i \end{bmatrix} \quad u_{i+1} = \begin{bmatrix} \alpha_{i+1}^R \\ \alpha^L i+1 \end{bmatrix}$$

$$S^R = R^R \alpha_{i+1}^R \quad \delta\rho = \frac{S^R + S^L}{2} \quad \delta\theta = \frac{s^R - s^L}{B}$$

$$S^L = R^L \alpha_{i+1}^L$$



$$\left[\begin{array}{l} x_{i+1} = x_i + \delta\rho\cos\theta_i \\ y_{i+1} = y_i + \delta\rho\sin\theta_i \\ \theta_{i+1} = \theta_i + \delta\theta \end{array}\right.$$

2.2 Sensor statistical models

Exteroceptive sensor:
One dimension

$$\begin{aligned} z &= h(S) + w \\ w &= N\left(0, \sigma_w^2\right) \\ P(w) &= \frac{1}{\sqrt{2\pi}\sigma_w} \exp\left(-\frac{w^2}{2\sigma_w^2}\right) \\ P(z) &= \frac{1}{\sqrt{2\pi}\sigma_w} \exp\left(-\frac{[z-h(s)]^2}{2\sigma w^2}\right) \end{aligned}$$

multiple dimension

$$w = N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}_n, R\right)$$

$$P(z) = \frac{1}{(2\pi)^{1/2}\sqrt{det(R)}} \exp\left[-\frac{1}{2}[z-h(s)]^\top R^{-1}[z-h(s)]\right]$$

R is the covariance matrix
Proprioceptive sensor:
One dimension

$$\begin{aligned} & P\left(S_{i+1} \mid S_i, u_{i+1}^m\right) \quad u = u^m + v \\ & s_{i+1} = f\left(s_i, u_{i+1}\right) \cong f\left(s_i, u_{i+1}^m\right) + \frac{\partial f}{\partial u} v \\ & V = N\left(0, \sigma_v^2\right) \\ & S_{i+1} = N\left(f\left(s_i, u_{i-1}^m\right), \left(\frac{\partial F}{\partial u}\right)^2 \sigma_\nu^2\right) \end{aligned}$$

Multiple dimension

$$\begin{aligned} V &= N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}_n, Q\right) \\ S_{iH1} &= N\left(f\left(s_i, u_{in}^m\right), F_u Q F_u^\top\right) \\ F_u &= \frac{\partial f}{\partial u} \end{aligned}$$

2.3 Recall probability

Markov assumption: A stochastic process has the Markov property if the conditional probability distribution of future states of the process depends only upon the present state
Theorem of Total Probability

$$P(A) = \sum_B P(A, B)$$

Bayes theorem

$$P(A \mid B) = \frac{P(A,B)}{P(B)} = \frac{P(B \mid A)P(A)}{P(B)}$$
$$P(B \mid A) = \frac{P(A,B)}{P(A)}$$

$$P(A \mid B,C) = \frac{P(B \mid A,C)P(A \mid C)}{P(B \mid C)}$$
$$P(A \mid C) = \sum_{B} P(A \mid B,C)P(B \mid C)$$

Bayesian estimators:

+ Kalman filter (KF): linear model and Gaussian noise

+ Extended Kalman filter (EKF): non-linear model (low nonlinearities, approximation of order 1) + Gaussian noise

+ Unscented Kalman filter (UKF): non-linear model (linearization of order 2) + Gaussian noise