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Interactive Communication Systems (ICS)

Bayesian Location Identifier
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Location Tracking is Imprecise

- Location Generators use sensor data to estimate a location
- Sensor data is noisy
- Filters are used to estimate an real position
  despite noise measurement.

- Commonly used filters:
  - Kalman
  - Particle Filters
  - Gaussian Sum Particle Filter

- Idea
  - Use filter outputs to describe position estimates

Particle Filter

- Best explained by an example taken from our AmbiSense lab:

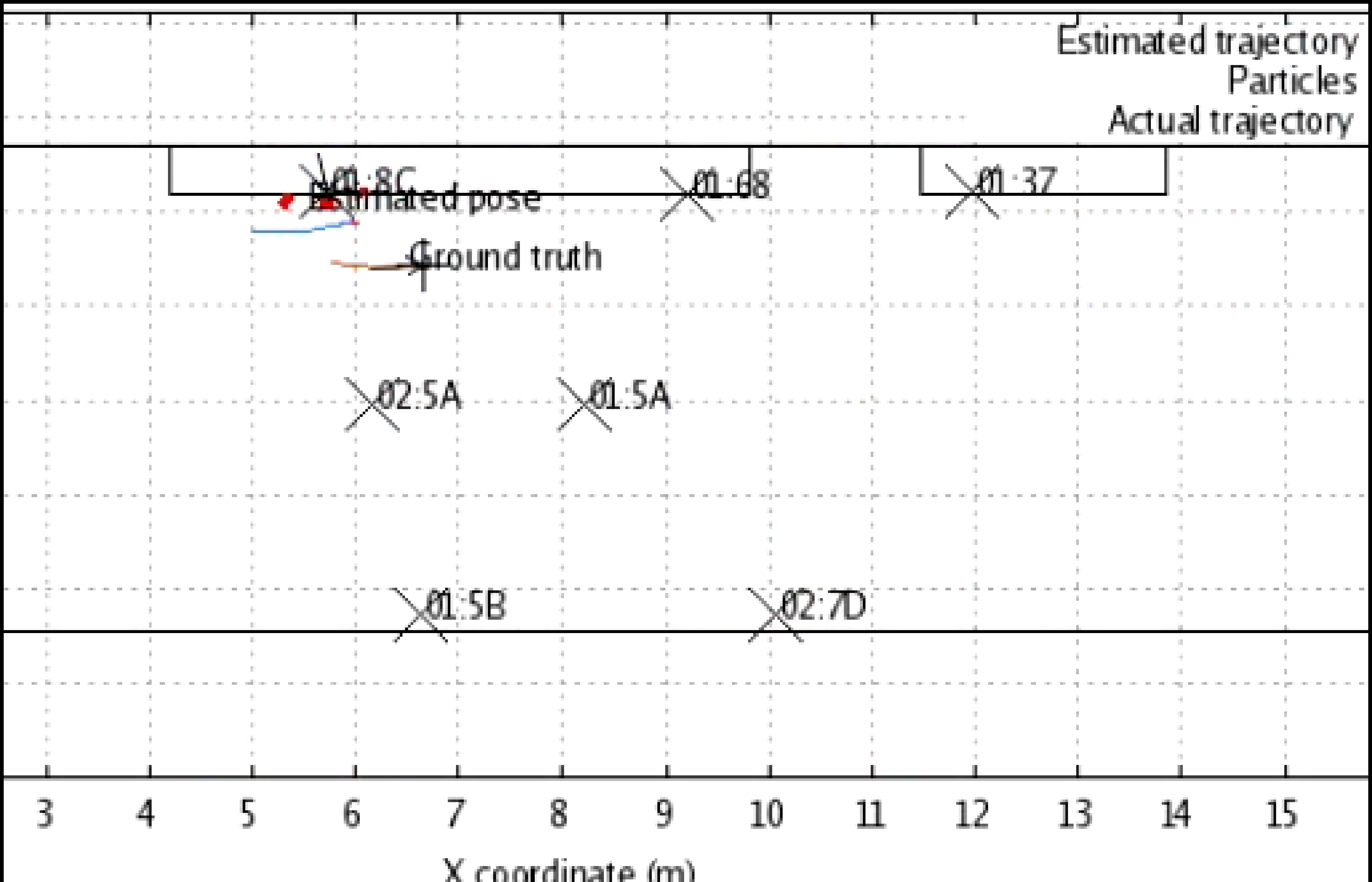
- Experimental setup:
  - Roboter is moving around shelf
  - Roboter location tracking with seven Bluetooth nodes via RSSI
  - Particles are displayes as red dots
  - Ground truth is based on laser measurements

- Uncertainty is given by
  - a set of particles, which represent position estimates

Particle Filters?

- Best explained by an example filmed in our AmbiSense lab:

[http://www.ambisense.org]


Estimated trajectory
Particles
Actual trajectory
01:8C
Estimated pose
01:68
01:37
Ground truth
02:5A
01:5A
01:5B
02:7D
3
4
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15
X coordinate (m)

Kalman Filtering (citing Wikipedia)

- Uses on Gaussian distributions to describe uncertainty.
- The Kalman filter model assumes the true state at time k is evolved from the state at (k − 1) according to

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k$$

  - where F_k is the state transition model which is applied to the previous state x_{k-1};
  - B_k is the control-input model which is applied to the control vector u_k;
  - w_k is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance Q_k.

$$\mathbf{w}_k \sim N(0, \mathbf{Q}_k)$$

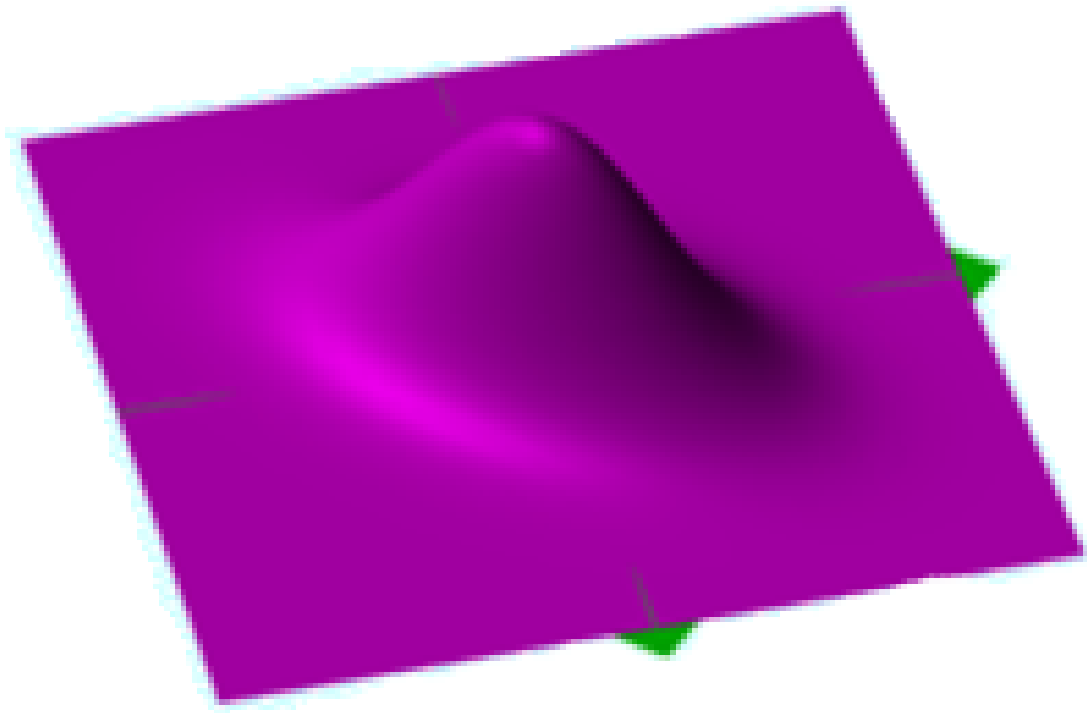
- At time k an observation (or measurement) z_k of the true state x_k is made according to

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k$$

  - where H_k is the observation model which maps the true state space into the observed space
  - and v_k is the observation noise which is assumed to be zero mean Gaussian white noise with covariance R_k.

Kalman Filter output

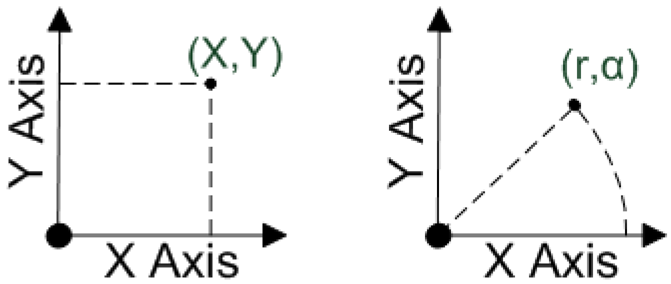
- Algorithmic details are not important…
- We only like to understand the filter output, which is simple:
  - multi-variable Gaussian probability density function with
  - position estimate z_k and covariance matrix R_k



http://en.wikipedia.org/wiki/Covariance_matrix

Related Datum, Coordinate Systems, Transformation Matrix

- Position is estimated relative to another PIDF-LO, e.g.
  - Longitude, lattidue, height
  - Civic address
  - WLAN access point identified by MAC address
- Supporting two coordinate Systems
  - Cartesian
  - Polar



- In addition, coordinates are transformed with

$$T(\vec{x}) = \mathbf{A}\vec{x}$$

  - *T* is a linear transformation mapping $\mathbf{R}^n$ to $\mathbf{R}^m$ for vector *x.*
    A is the transformation matrix.
  - **A** supports rotation, scaling, shearing, refraction, affine transformation, perceptive projection, …

Summary: Bayesian Location Identifier

- Position estimates are always imprecise…
- Idea
  - use filter outputs to describe measurements of locations
  - Describe them with Bayesian statistics…
  - Our solution is based on a solid scientific foundation…

- Filter outputs are easy to understand
- Apps can do with this data anything they want to…
  - Who knows what kind of applications will be invented?

- Potential Improvements:
  - Add a time field.
  - Requesting sensor data having a request time stamp (for fusion)
  - Compressed representation of particles