Multi-object filtering methods for multi-target tracking

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School of Engineering and Physical Sciences
Heriot-Watt University

1. Introduction to target tracking
2. Point Processes
3. Modelling multi-object systems
4. Applications

What is Target Tracking?

Target tracking algorithms are methods for determining the positions and velocities of moving objects.

These are fundamental for applications in

- Aerospace defence
- Maritime surveillance
- Space situational awareness

Figure : Tracking ships in Rotterdam harbour (courtesy of TNO).

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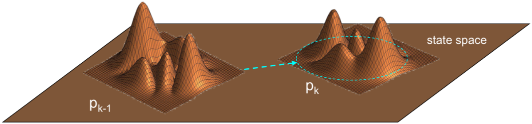
Bayes Filtering/ single-object tracking



Bayes filter

$$p_k(x_k \mid z_{1:k}) \xrightarrow{\text{prediction}} p_{k+1|k}(x_{k+1|k} \mid z_{1:k}) \xrightarrow{\text{data-update}} p_{k+1}(x_{k+1} \mid z_{1:k+1})$$

Kalman filter (Swerling / Stratonovich/ Kalman, late 1950s)

$$N(x_k; m_k, P_k) \xrightarrow{\text{prediction}} N(x_{k+1|k}; m_{k+1|k}, P_{k+1|k}) \xrightarrow{\text{data-update}} N(x_{k+1}; m_{k+1}, P_{k+1})$$

Particle filter (Handschin & Mayne, Imperial 1966/ N. Gordon, Imperial 1993)

$$\{x_k^{(i)}, w_k^{(i)}\}_{i=1}^N \xrightarrow{\text{prediction}} \{x_{k+1|k}^{(i)}, w_{k+1|k}^{(i)}\}_{i=1}^N \xrightarrow{\text{data-update}} \{x_{k+1}^{(i)}, w_{k+1}^{(i)}\}_{i=1}^N$$

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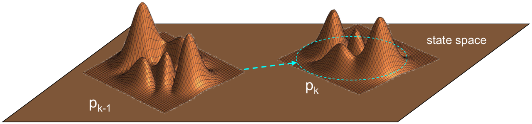

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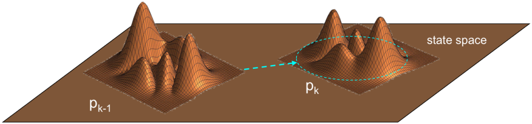

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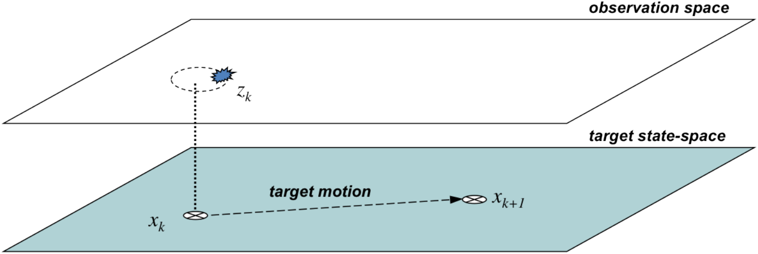
Bayes Filtering: Prediction

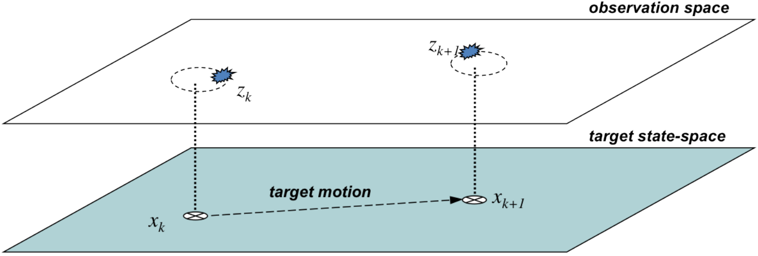


Prediction $p_{k+1|k}(x_{k+1} \mid z_{1:k}) =$

$$\int \underbrace{f_{k+1|k}(x_{k+1} \mid x_k)}_{\downarrow} \, p_k(x_k \mid z_{1:k}) \, dx_k$$

Markov transition density

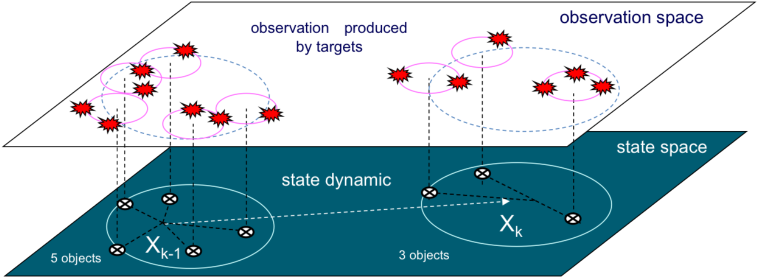
Bayes Filtering: Data Update



Update
$$p_{k+1}(x_{k+1} \mid z_{1:k+1}) = \frac{g_{k+1}(z_{k+1} \mid x_{k+1})\, p_{k+1|k}(x_{k+1} \mid z_{1:k})}{\int \underbrace{g_{k+1}(z_{k+1} \mid x_{k+1})}_{\downarrow}\, p_{k+1|k}(x_{k+1} \mid z_{1:k+1})\, dx_{k+1}}$$

observation likelihood

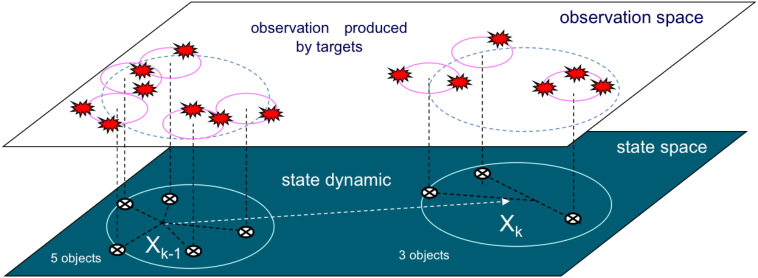
Multi-Target Tracking



The objective in multi-target tracking is to

- Jointly estimate **both** the number of targets and their states.
- Applying single-target methods needs correct associations.

Multi-Target Tracking



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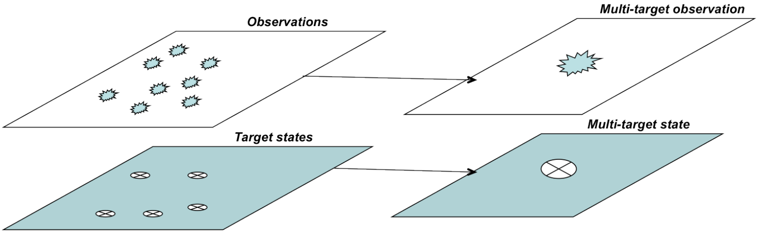
Bayesian Multi-Object Filtering



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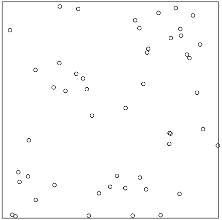
Spatial Point Patterns

A spatial point pattern gives the locations of a set of objects $\mathbf{Y} = \{\mathbf{y}_1, \dots, \mathbf{y}_n\}$ in some region of the space

e.g. $\mathbf{y}_i \in \mathscr{Y}$, where $i = 1, \dots, n$ and $\mathscr{Y} \subseteq \mathbb{R}^{n_y}$

For example:

- 2-dimensional positions of objects in an image from a sensor (i.e. observation space).
- 3-dimensional positions and velocities of objects in some real-world environment (i.e. state space).



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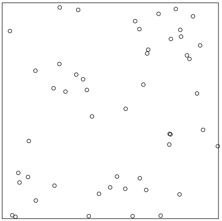

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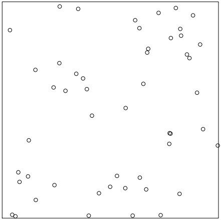

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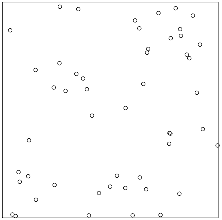

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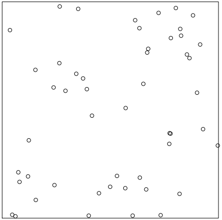

Point Process Representation

A spatial point process is therefore characterised with the following

Table : Point Process Representation

Number of objects	Cardinality probability	Joint spatial density
0	$\rho(0)$	-
1	$\rho(1)$	$p_1(x_1)$
2	$\rho(2)$	$p_2(x_1, x_2)$
3	$\rho(3)$	$p_3(x_1, x_2, x_3)$
4	$\rho(4)$	$p_2(x_1, x_2, x_3, x_4)$
...	...	...
n	$\rho(n)$	$p_n(x_1, x_2, x_3, x_4, \ldots, x_n)$
...	...	...

Point processes

Definition (Probability generating functional - Moyal 1962)

The probability generating functional G_Φ of a process Φ can be written for $w \in \mathscr{U}(\mathbf{X})$ as

$$G_\Phi(w) = J_\Phi^{(0)} + \sum_{n \geq 1} \frac{1}{n!} \int w(x_1) \ldots w(x_n) J_\Phi^{(n)}(x_1, \ldots, x_n) d^n x.,$$

where $J_\Phi^{(0)}$ is the probability for the population to be empty and where $d^n x$ stands for $dx_1 \ldots dx_n$.

THE GENERAL THEORY OF STOCHASTIC POPULATION PROCESSES

BY

J. E. MOYAL

Australian National University, Canberra, Australia [1]

Point processes

Example (Probability generating functional -Moyal 1962)

Taking the k^{th}-order variation of $G_\Phi(w)$ in the directions $\{\xi_1, \ldots, \xi_k\}$, we have,

$$\delta^k G_\Phi(w; \xi_1, \ldots, \xi_k) = \sum_{n \geq k} \frac{1}{(n-k)!} \int \xi_1(x_1) \ldots \xi_k(x_k) w(x_{k+1}) \ldots w(x_n) J_\Phi^{(n)}(x_1, \ldots, x_n) d^n x.$$

We can recover the Janossy densities $J_\Phi^{(n)}(x_1, \ldots, x_n)$ and factorial moments $M_\Phi^{(n)}(x_1, \ldots, x_n)$ with

$$J_\Phi^{(n)}(x_1, \ldots, x_n) = \delta^k G_\Phi(0; \xi_1, \ldots, \xi_k),$$
$$M_\Phi^{(n)}(x_1, \ldots, x_n) = \delta^k G_\Phi(1; \xi_1, \ldots, \xi_k).$$

THE GENERAL THEORY OF STOCHASTIC POPULATION PROCESSES

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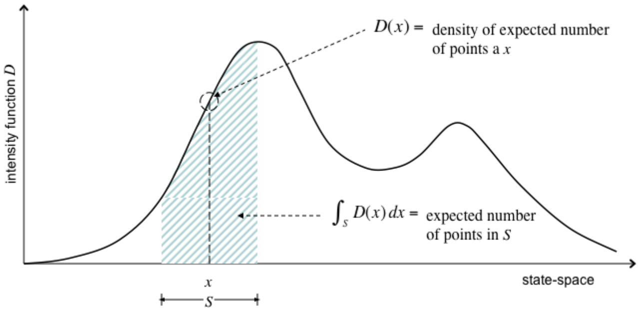
Point Process Intensity

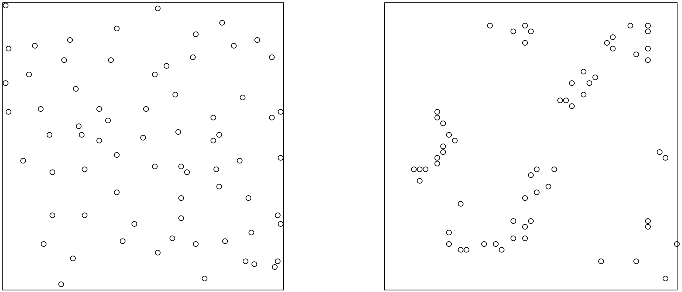
The intensity function of a point process is the average density of points (expected number of points per unit area).

Intensity function $\equiv$ Probability Hypothesis Density (PHD); notation $D(x)$



Point Process Intensity (Cont'd)

- The intensity may be constant across the region (homogeneous)
- or some regions may have higher intensity than others (inhomogeneous):



(samples from: homogeneous PP - left; inhomogeneous PP - right)

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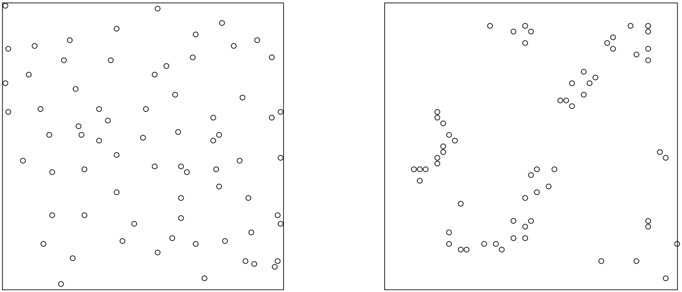

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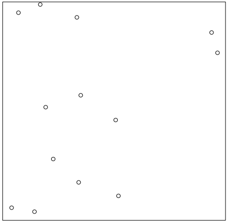
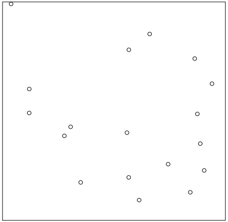
Point Process Superposition

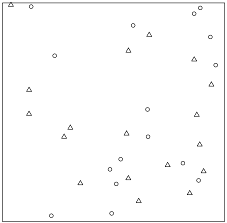
- Often we observe different (independent) point patterns in the same region originating from different point processes (e.g. false and true target detections).
- We can model this phenomenon as the superposition of independent point processes.



X_1



X_2



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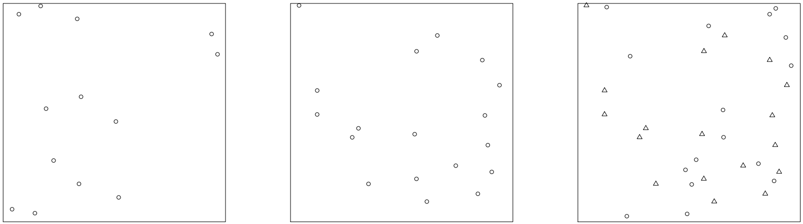
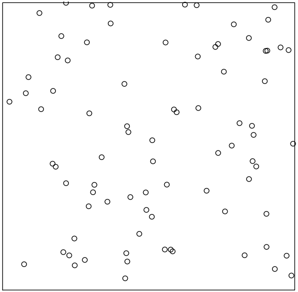


X_1 X_2 $X_1 \cup X_2$

Poisson point process

The Poisson point process with Poisson rate $\lambda > 0$ has the following properties

- The expected number of objects in the region is λ.
- The locations of the points are independent and identically distributed according to some spatial distribution $s(x)$.
- Intensity function of a Poisson point process $D(x) = \lambda \cdot s(x)$.



Samples from a homogeneous Poisson point process with rate 100

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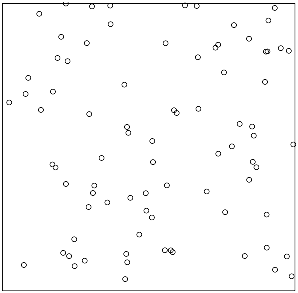

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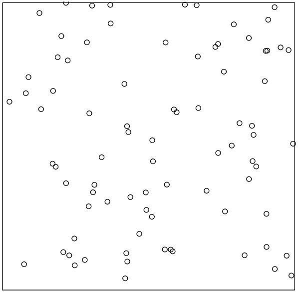

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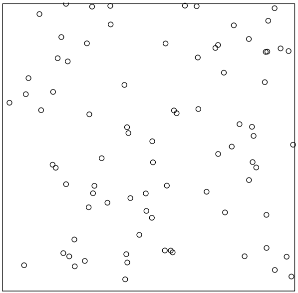

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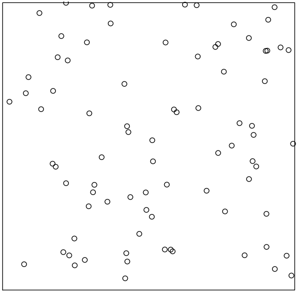

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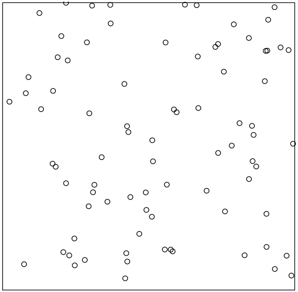

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PHD filtering - Poisson-based multi-target tracker

(Loading video)

Figure : Object tracking in sonar images

The first industrial application of the PHD filter was for oil pipeline tracking for BP (2006) in SeeByte Ltd.

Multi-object modelling for target detection & tracking

Figure : http://www.nollywoodone.com/latest-additions/9009-the-u-s-military-s-real-time-google-street-view-airborne-spy-camera-can-track-an-entire-city-in-1-800mp.html

Populations of objects modelled with *point processes*

Multi-object modelling for target detection & tracking

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Populations of objects modelled with *point processes*

- Target population;
- Target interactions;
- Target measurements;
- Missed detections;
- False alarms;
- Target appearing/disappearing;
- ...

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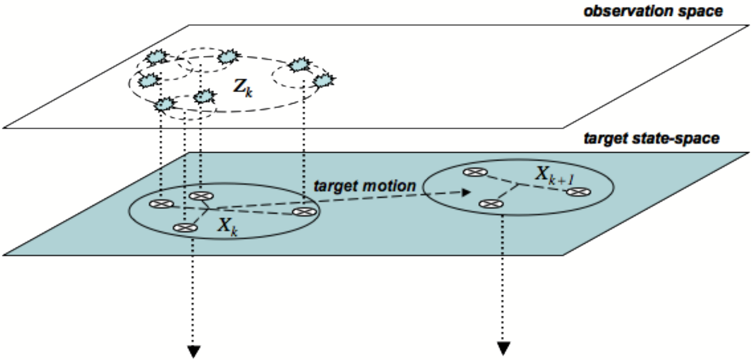
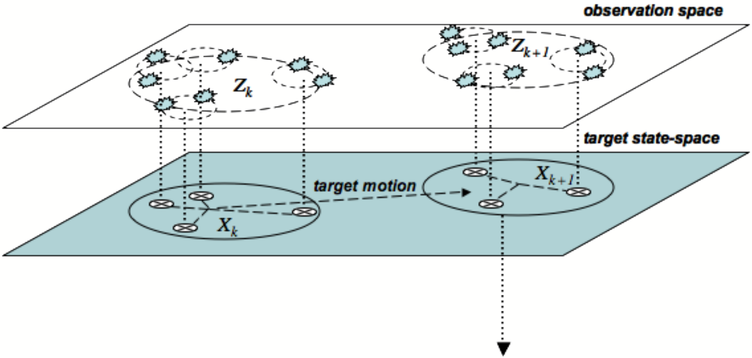
Multi-object Bayes filtering: prediction



The evolution of the multi-object process is specified with the composite functional

$$G(h) = G_k\left(G_{k+1|k}(h|\cdot)\right)$$

Multi-object Bayes filtering: update



The joint functional describing the relation between targets and measurements is specified through the functional

$$G(v, w) = G_k\left(vG_L(w|\cdot)\right).$$

Higher-order statistics of point processes

Recent developments in multi-object filtering allow:

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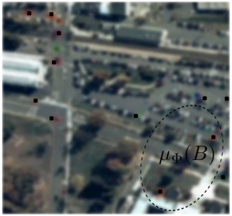
- Exploitation of higher-order statistics on point processes, notably the *region-based variance in target number*.



What is going on inside B?

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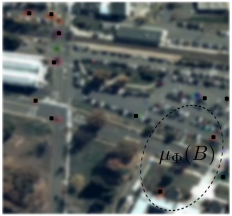

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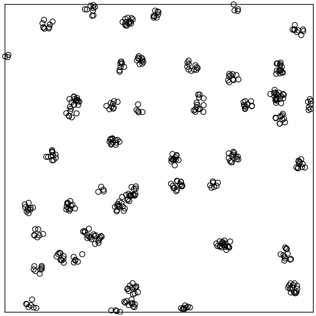
Sensor control using variance

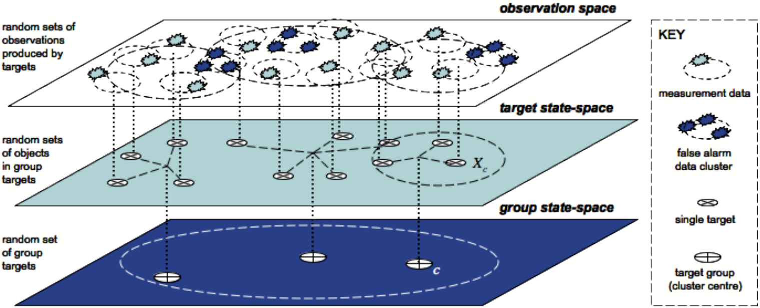
Example: Cluster Processes

Cluster Processes are formed with the composition of functionals, eg. $G(\psi) = G_1(G_2(\psi))$.



Multi-Group Multi-Object Bayes Filtering

Group-Target State Variable: $\mathbb{X} = \{(c_1, X_1), \ldots, (c_n, X_n)\}$



$$p_k(\mathbb{X}_k \mid Z^{(k)}) \xrightarrow{\text{prediction}} p_{k+1|k}(\mathbb{X}_{k+1} \mid Z^{(k)}) \xrightarrow{\text{data-update}} p_{k+1}(\mathbb{X}_{k+1} \mid Z^{(k+1)})$$

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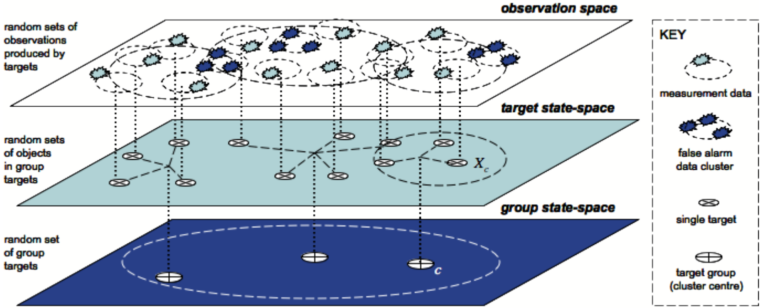

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Tracking Multiple Group Targets

Camera calibration (sensor registration)

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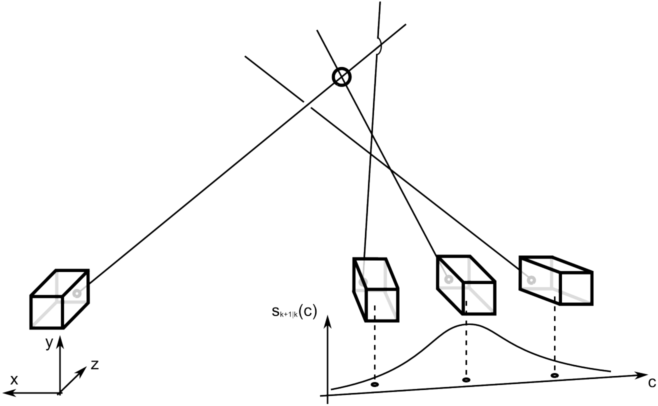
Measurements from the displaced camera are conditional on the calibration parameters.



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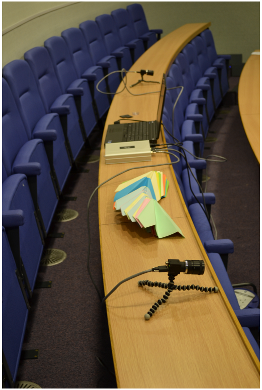
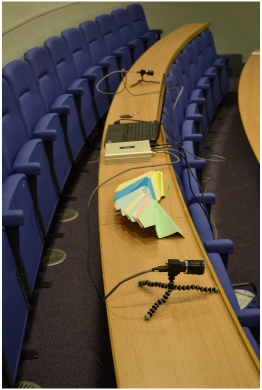


Estimating calibration parameters via tracking of paper airplanes

Camera calibration (sensor registration)



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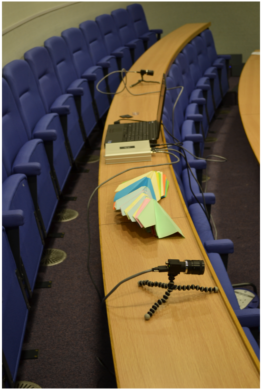

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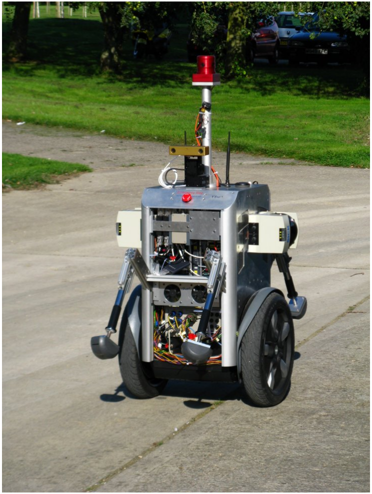
Simultaneous localisation and mapping (SLAM)

Estimate the motion of a vehicle in an unknown environment, while concurrently estimating the configuration of the environment.

- Parent process is the vehicle location
- Daughter process is map, conditioned on vehicle location



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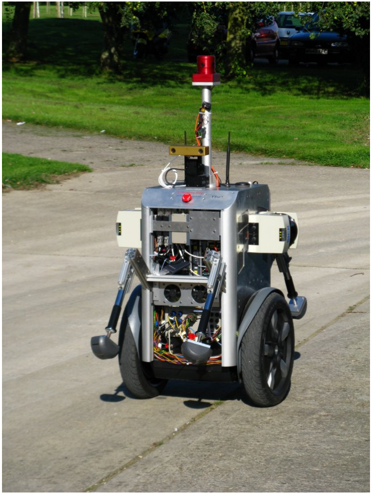

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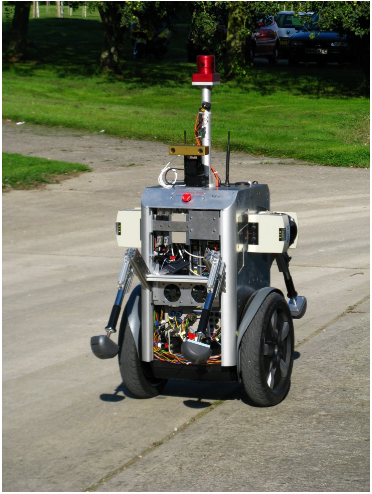

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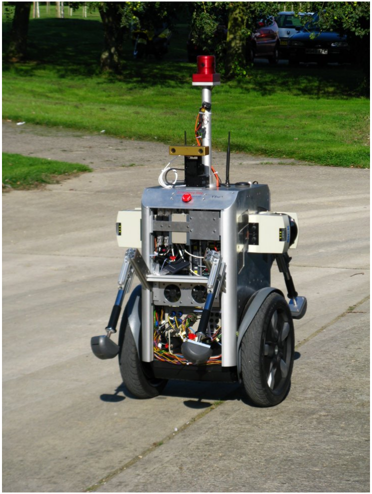

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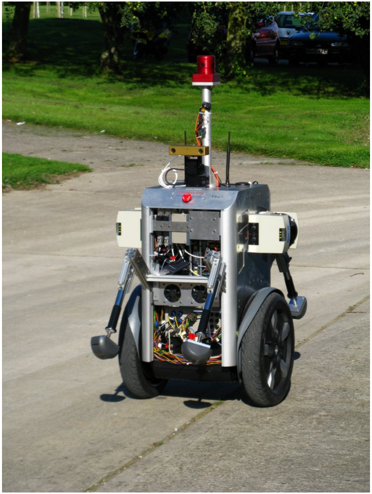
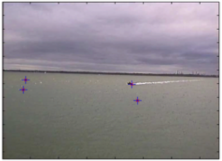
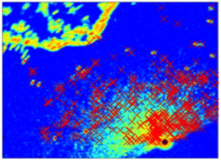
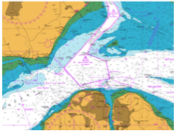


Simultaneous localisation and mapping (SLAM)

Multi-sensor fusion -maritime surveillance (CDE with BAE Systems, DSTL)

EO/radar data fusion using PHD filter estimation.

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