Multi-sensor multi-target tracking techniques

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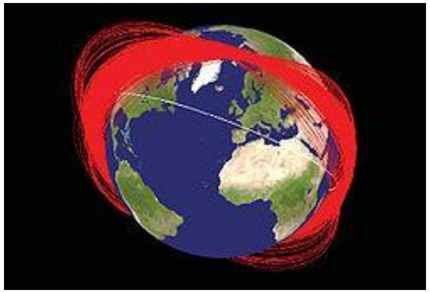
Multi-sensor multi-target tracking techniques for Space Situational Awareness

Motivation: Methods for tracking space debris are essential to prevent damage to expensive space-related infrastructure and to determine cause.

Examples of recent events:

❖ 2009 Russian Kosmos 2251/US Iridium 33 collision.

❖ 2007 Chinese anti-satellite test.



https://en.wikipedia.org/wiki/2007_Chinese_anti-satellite_missile_test

https://en.wikipedia.org/wiki/2009_satellite_collision

Objective: Develop methods for estimation of populations of objects in orbit from sensor data.

Multi-sensor multi-target tracking techniques for Space Situational Awareness

Topics:

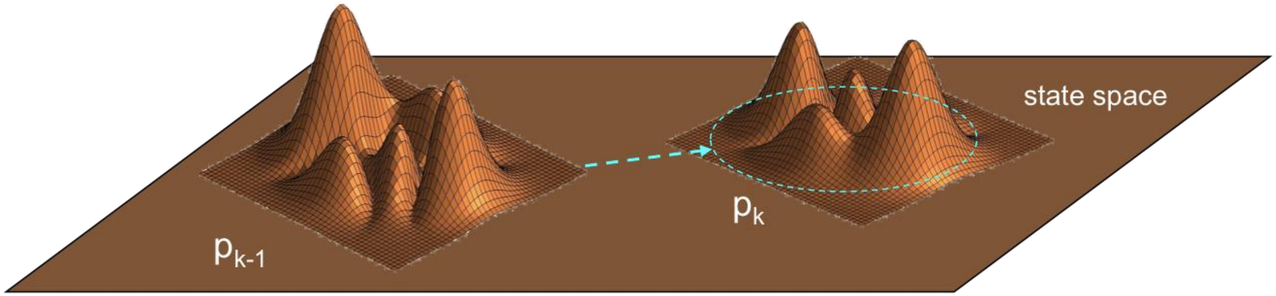
1. **Tracking trajectories of individual objects**
2. **Multi-object estimation**
    - 2a. Modelling systems of multiple objects
    - 2b. Estimating the number and states of objects
    - 2c. Performance assessment
3. **Multi-sensor systems**
    - 3a. Autonomous sensor resource allocation
    - 3b. Multi-sensor fusion and calibration
    - 3c. High-performance computing
    - 3d. Dynamic sensor localisation
4. **Object classification**




What is target tracking?

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

Single-target tracking



Bayes filter (Bayes 1763, Chapman 1928, Kolmogorov 1931)

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

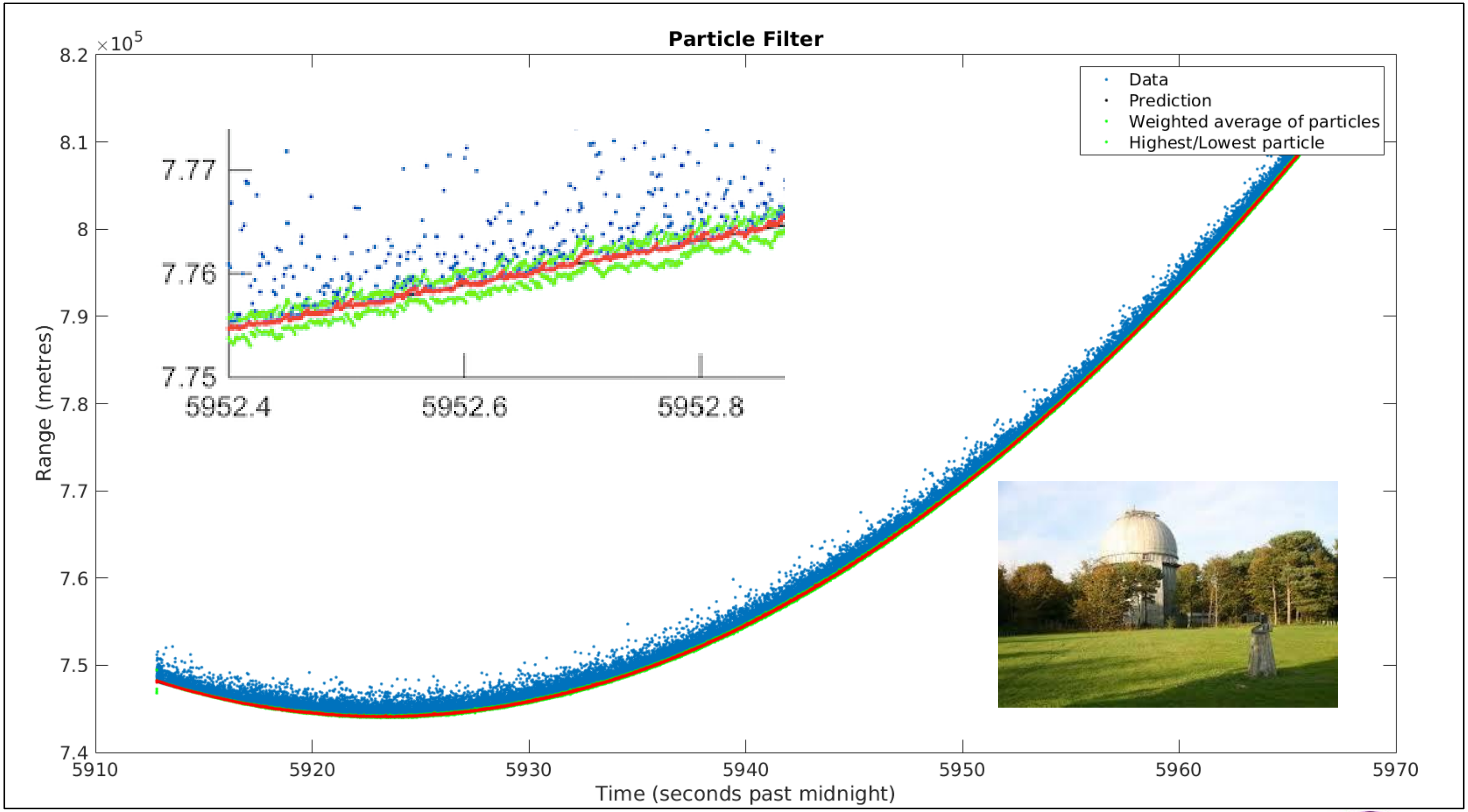
Kalman filter (Swerling / Stratonovich/ Kalman, late 1950s)

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

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

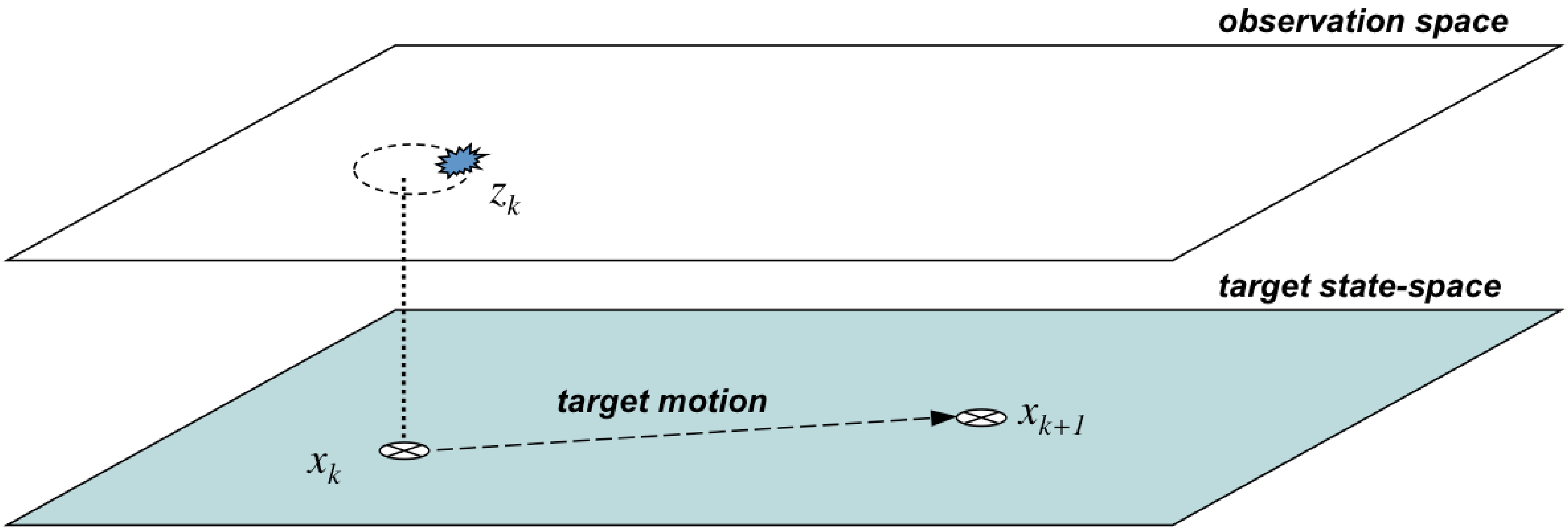
$$\{x_k^{(i)}, w_k^{(i)}\}_{i=1}^N \xrightarrow{\text{prediction}} \{x_{k+1|k}^{(i)}, w_{k+1|k}^{(i)}\}_{i=1}^N \xrightarrow{\text{data-update}} \{x_{k+1}^{(i)}, w_{k+1}^{(i)}\}_{i=1}^N$$

Applications in SSA: laser-ranging at Herstmonceux



Bayesian filtering: prediction

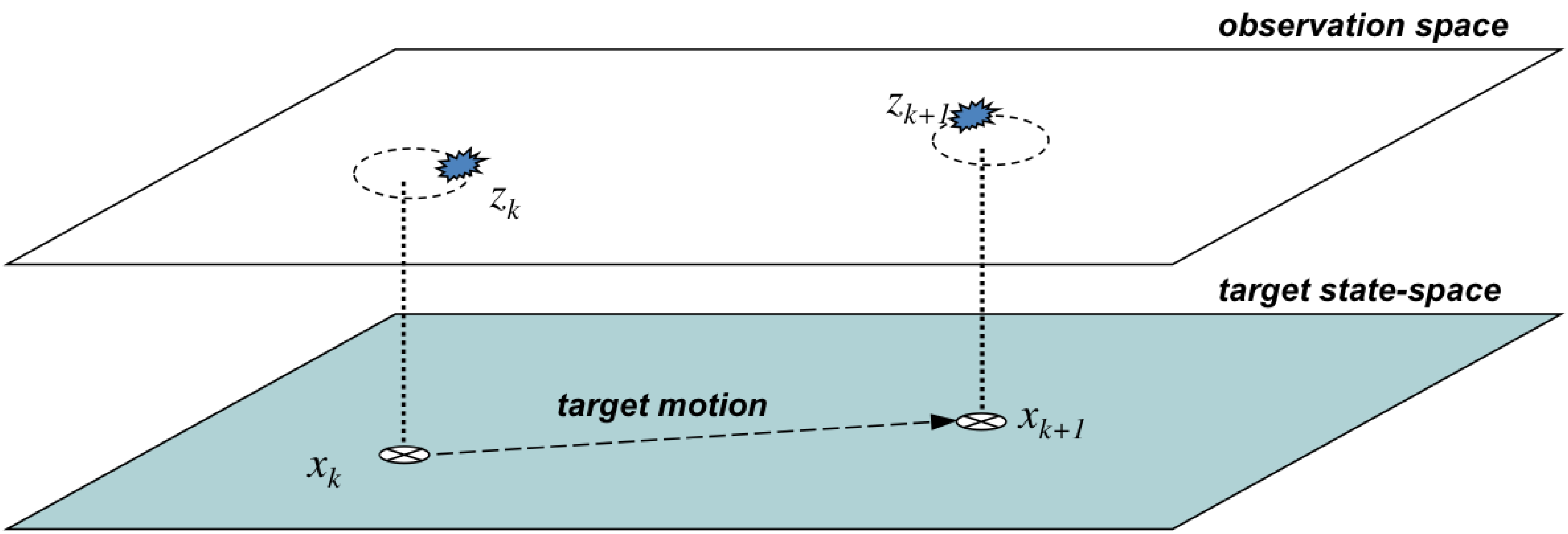
SSA context: orbit prediction with uncertainty



$$p_{k+1|k}(x_{k+1} | z_{1:k}) = \int \overbrace{f_{k+1|k}(x_{k+1} | x)}^{\text{Markov transition density}} p_k(x | z_{1:k})\, dx$$

Bayesian filtering: update

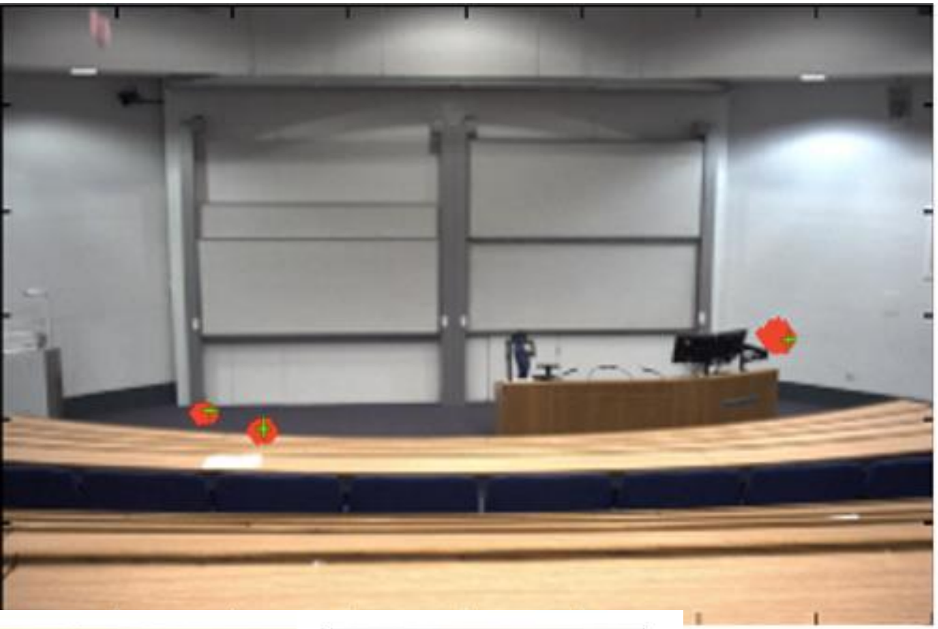
SSA context: sensor models for telescopes, radar, optical sensors



Conditional likelihood

$$p_{k+1}(x_{k+1} | z_{1:k}) = \frac{g_{k+1}(z_{k+1} | x_{k+1}) p_{k+1|k}(x_{k+1} | z_{1:k})}{\int g_{k+1}(z_{k+1} | x) p_{k+1|k}(x | z_{1:k}) dx}$$

Application: Tracking from cameras



Stereo update:

$$p_k(x_k \mid z^{[1]}_{1:k}, z^{[2]}_{1:k}) = \frac{g^{[1]}_k(z^{[1]}_k \mid x_k)\, g^{[2]}_k(z^{[2]}_k \mid x_k)\, p_{k|k-1}(x_k \mid z^{[1]}_{1:k-1}, z^{[2]}_{1:k-1})}{\int g^{[1]}_k(z^{[1]}_k \mid x)\, g^{[2]}_k(z^{[2]}_k \mid x)\, p_{k|k-1}(x \mid z^{[1]}_{1:k-1}, z^{[2]}_{1:k-1})\, dx}$$

IEEE TRANSACTIONS ON SIGNAL PROCESSING 1

A Unified Approach for Multi-Object Triangulation, Tracking and Camera Calibration

Jeremie Houssineau, Daniel E. Clark, Spela Ivekovic, Chee Sing Lee, and Jose Franco

EPSRC Engineering and Physical Sciences Research Council

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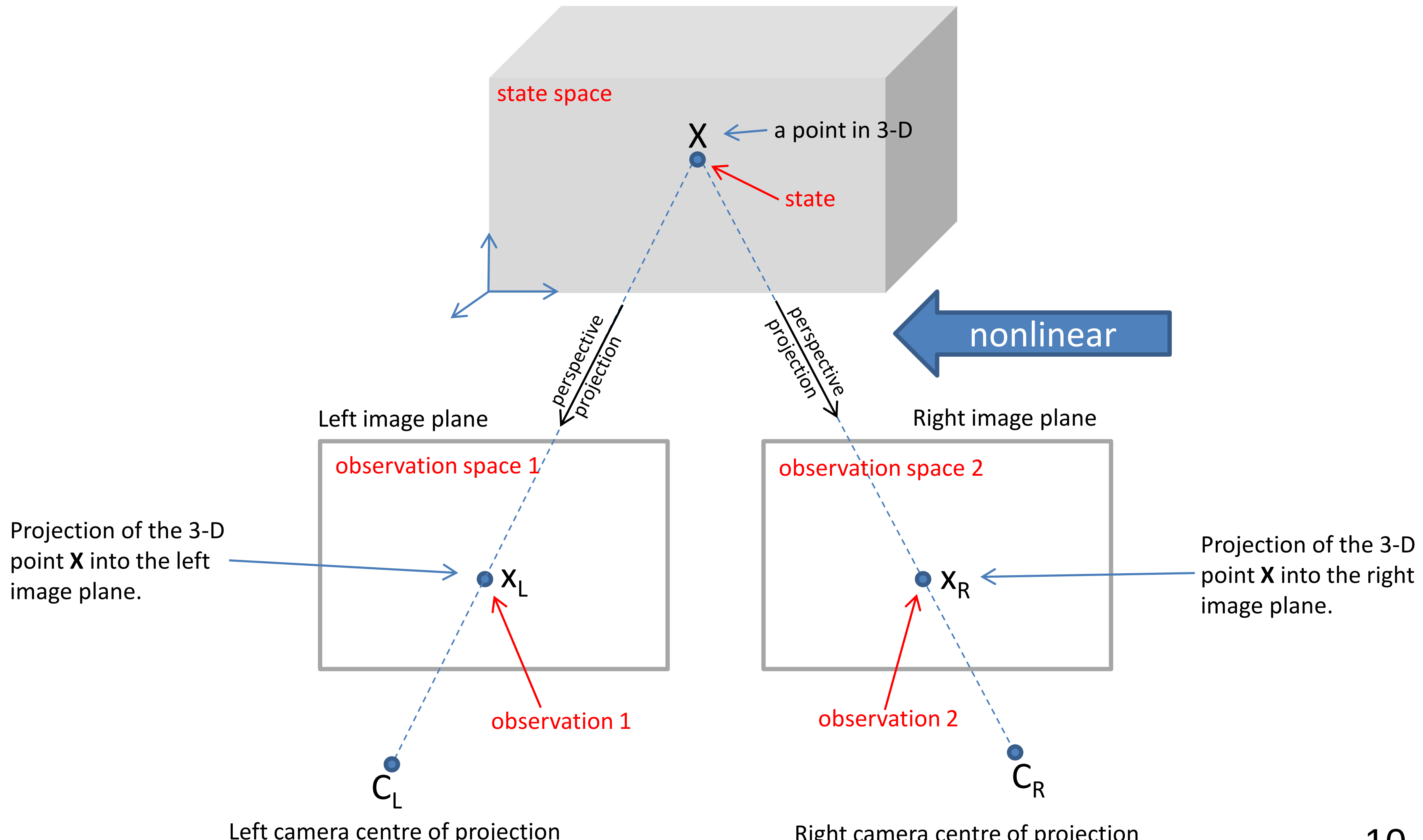
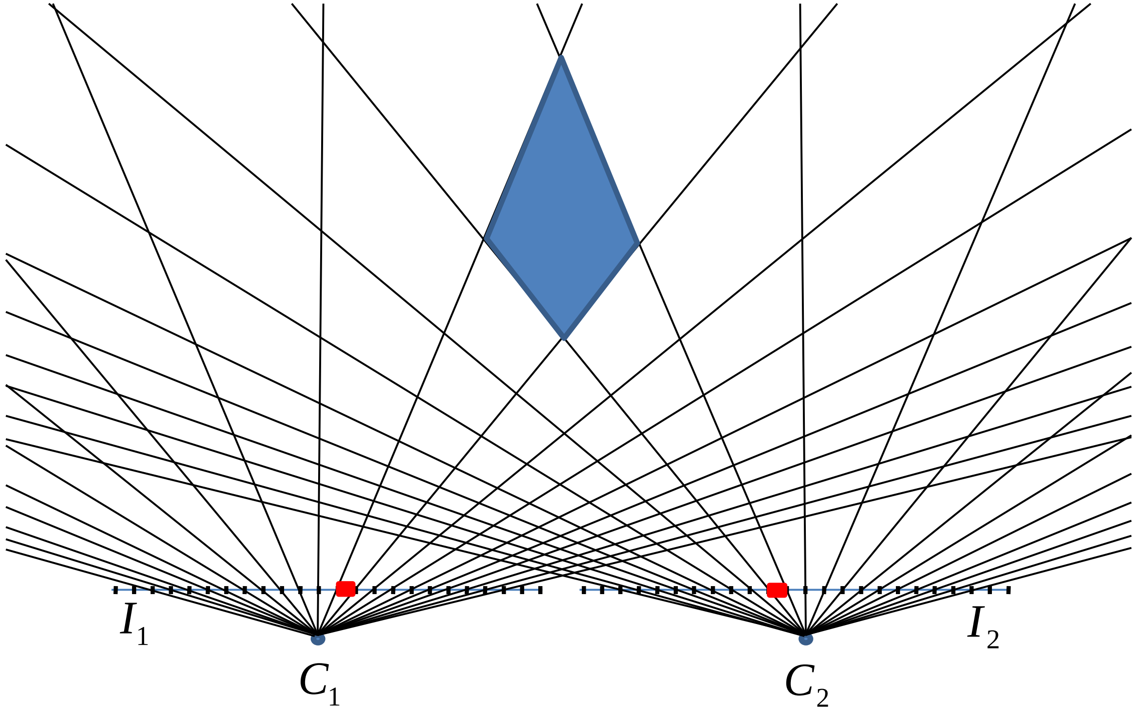
Tracking from cameras



Tracking from cameras

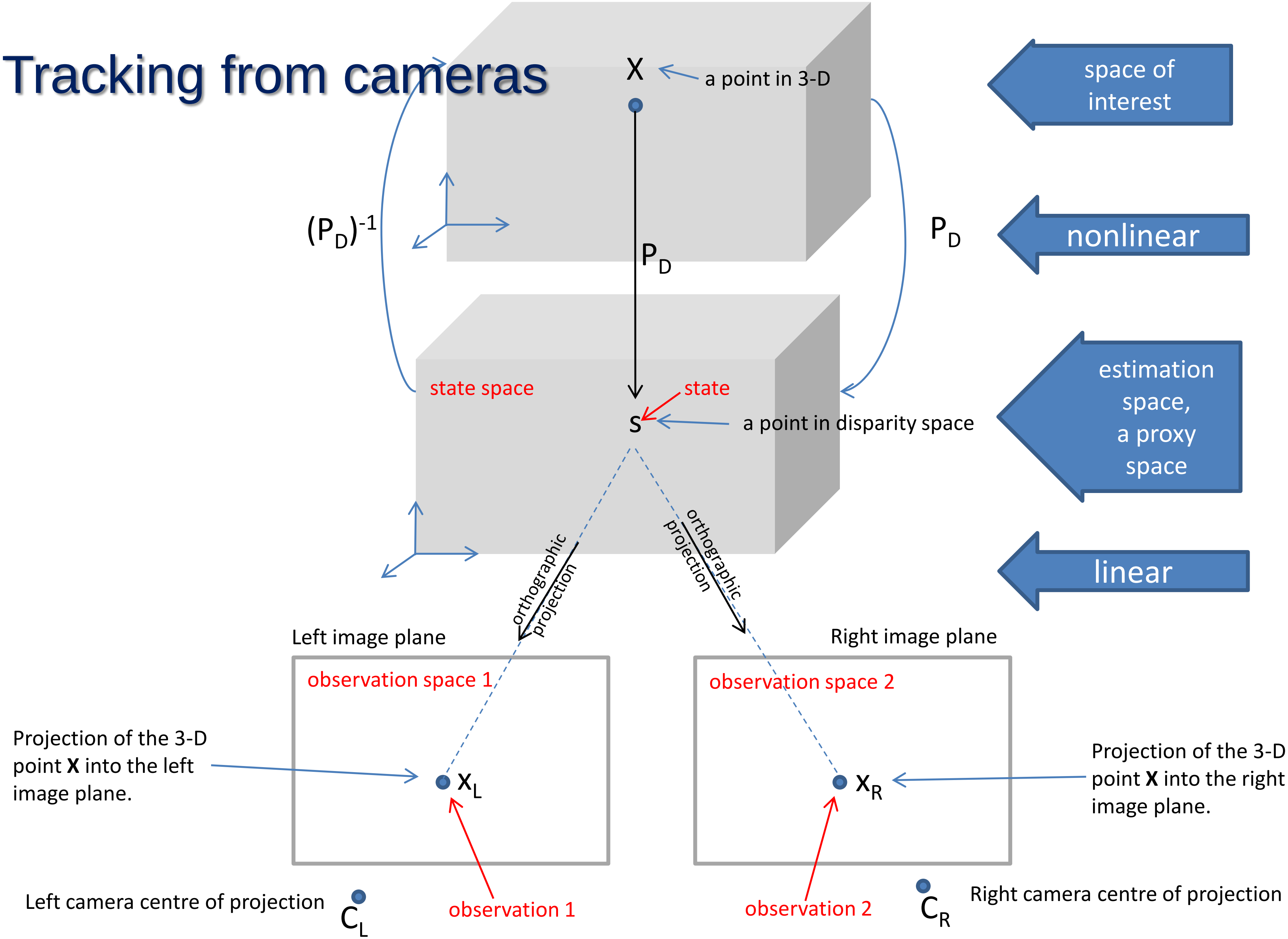


The variance of the target position changes with the distance from the cameras:

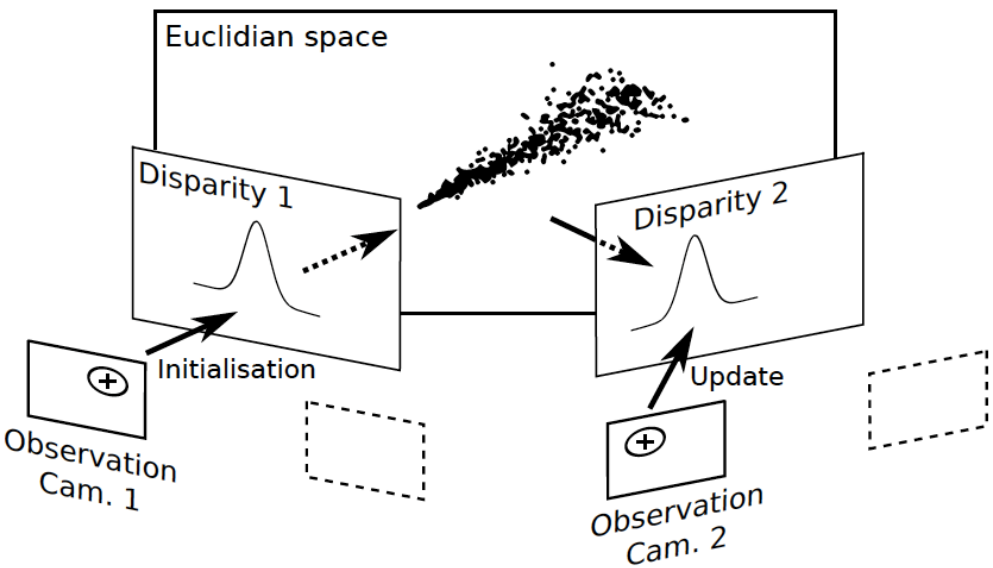
-The pdf becomes highly non-Gaussian (Kalman filter variants fail).

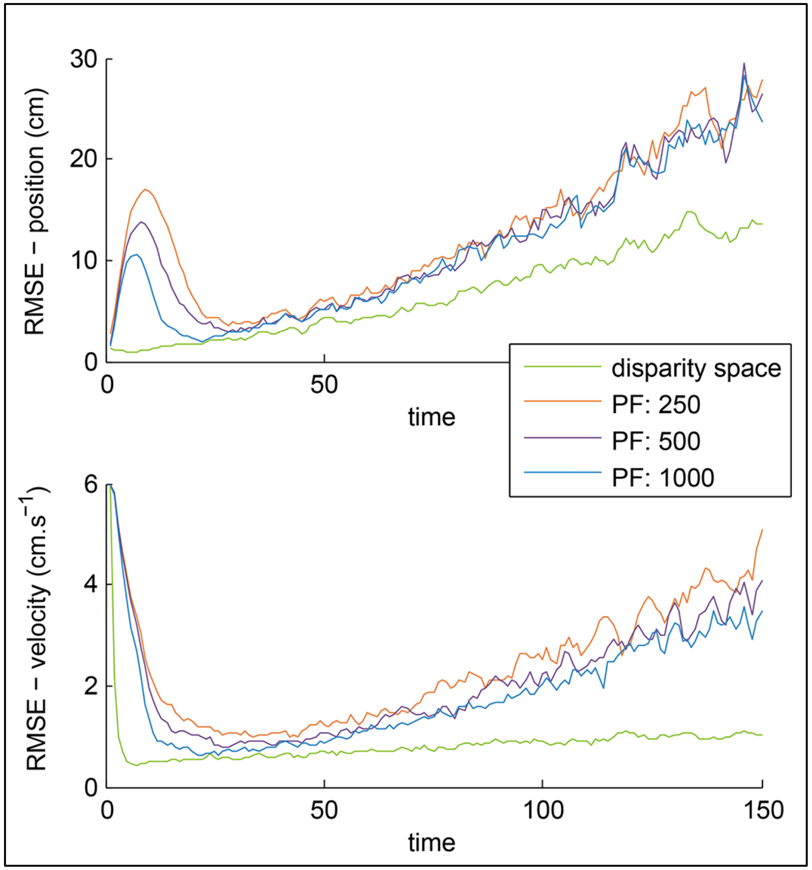
-The pdf is sparse in depth (particle filters fail).

Tracking from cameras



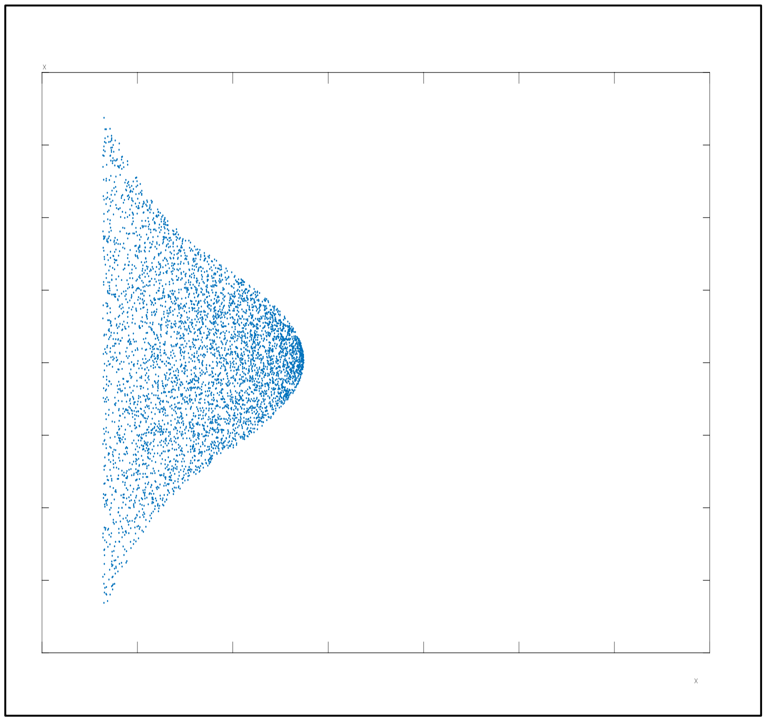
Tracking from cameras

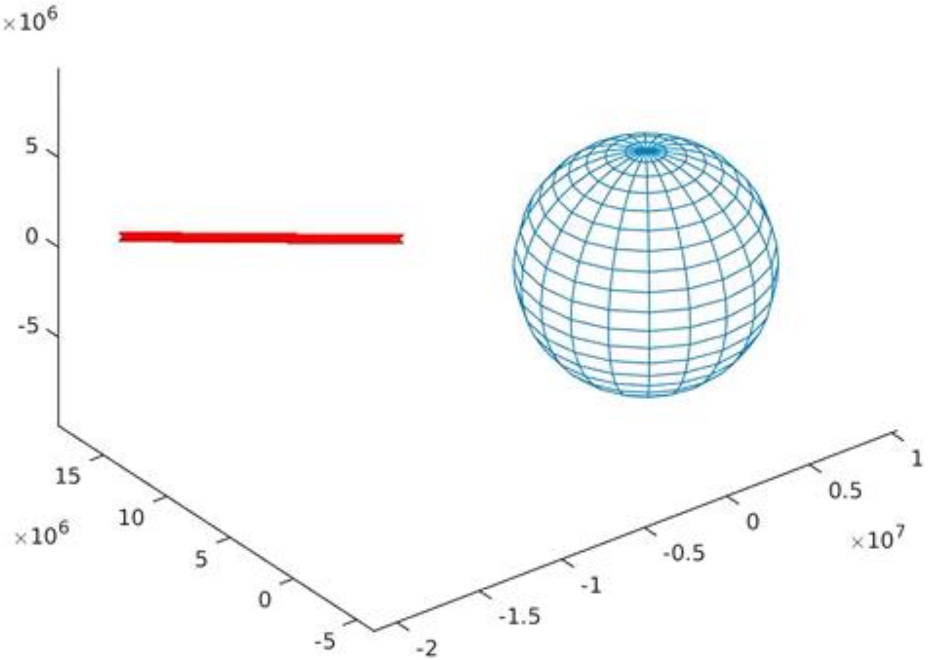




Tracking orbiting objects

Initial orbit determination with admissible region and orbital estimation





A Spherical Co-ordinate Space Parameterisation for Orbit Estimation

Jose Franco, Emmanuel D. Delande
School of Engineering and Physical Sciences
Heriot-Watt University
Edinburgh, UK

Carolin Frueh
School of Aeronautics and Astronautics
Purdue University
West Lafayette, IN, USA

Jeremie Houssineau, Daniel E. Clark
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Heriot-Watt University
Edinburgh, UK

[dstl] EPSRC Engineering and Physical Sciences Research Council

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Applications in SSA: weather radar

Target detection and estimation in clutter with blind regions

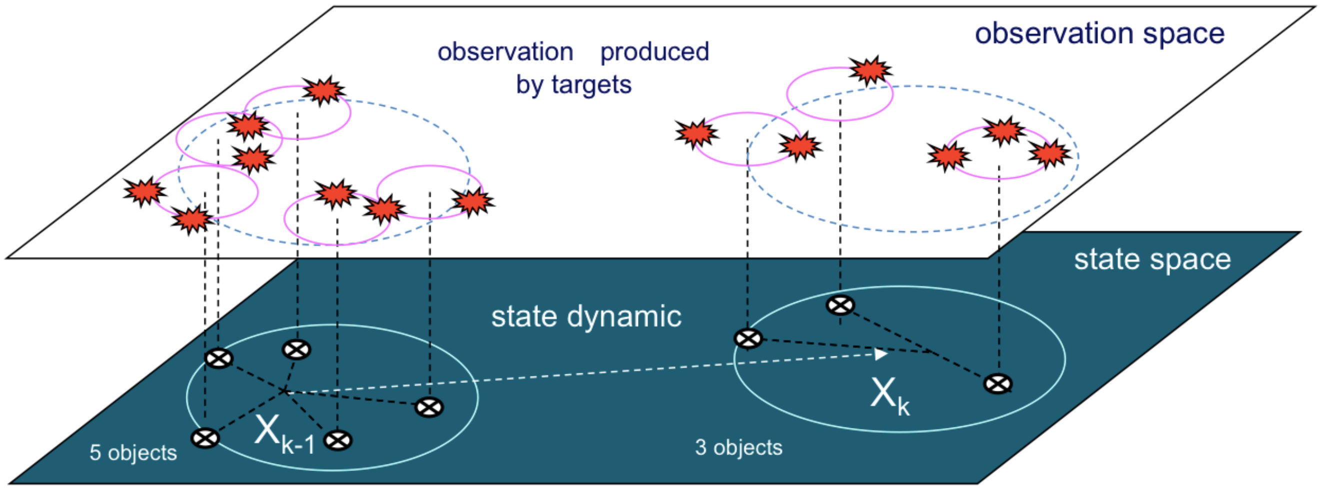
Chilbolton Advanced Meteorological Radar

- Fully steerable meteorological 3Ghz radar with a Doppler capability
- Modified in 2010 to carry out Space Situational Awareness (SSA) operations
- Low Earth Orbit (LEO) object tracking

Image Credit:
http://www.metoffice.gov.uk/

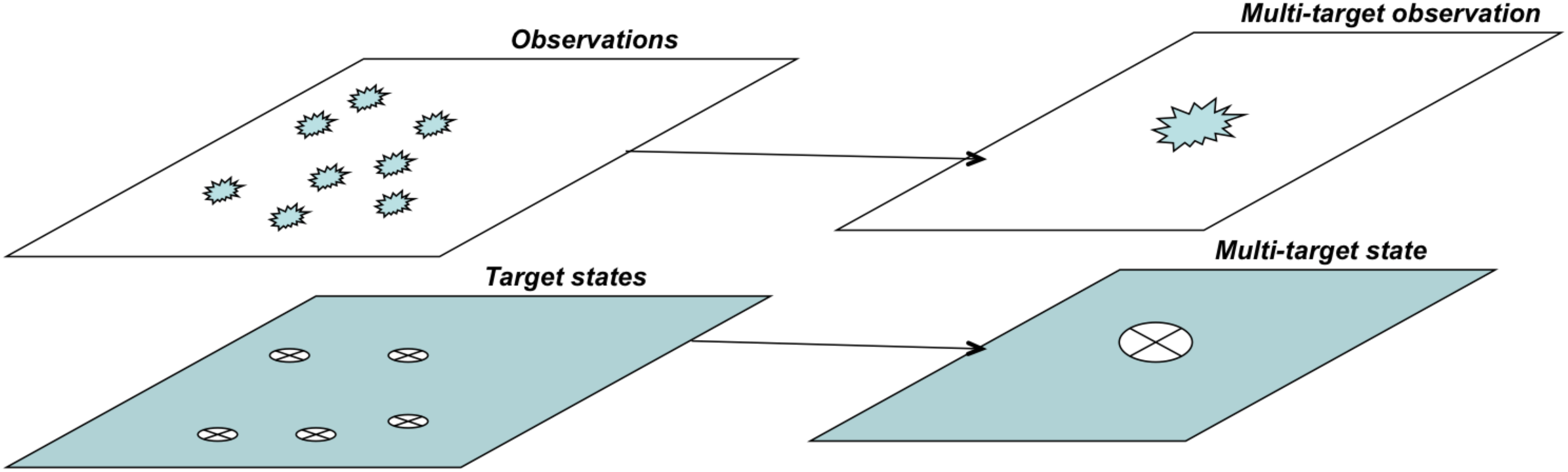
Andrey Pak (VIBOT) CAMRa Data Processing July 17, 2015 2 / 4

Multi-target tracking



The objective in multi-target tracking is to jointly estimate both the number of targets and their states.

Multi-object filtering

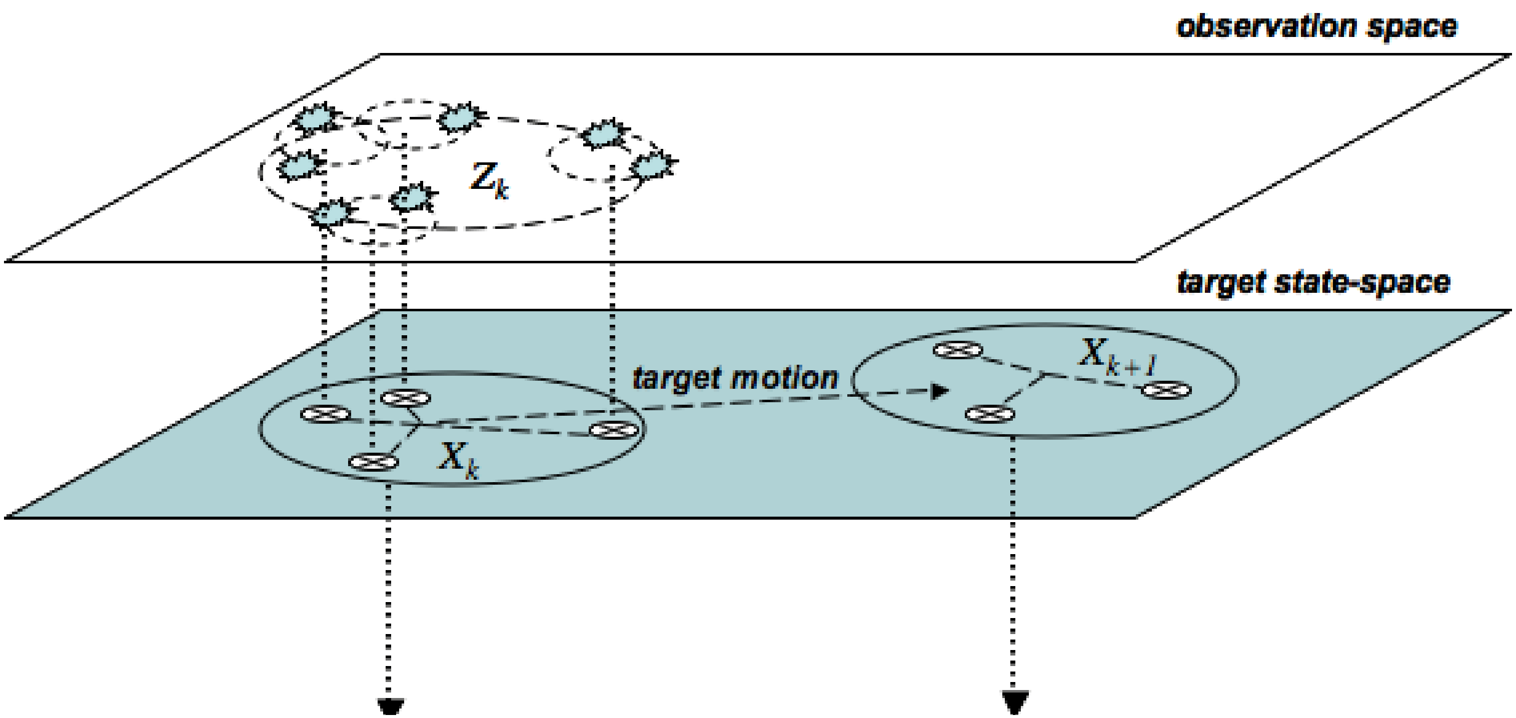


$$p_k(X_k \mid Z_{1:k}) \xrightarrow{\text{prediction}} p_{k+1|k}(X_{k+1|k} \mid Z_{1:k}) \xrightarrow{\text{data-update}} p_{k+1}(X_{k+1} \mid Z_{1:k+1})$$

Multitarget Bayes Filtering via First-Order Multitarget Moments

RONALD P. S. MAHLER
Lockheed Martin

Multi-object filtering: prediction



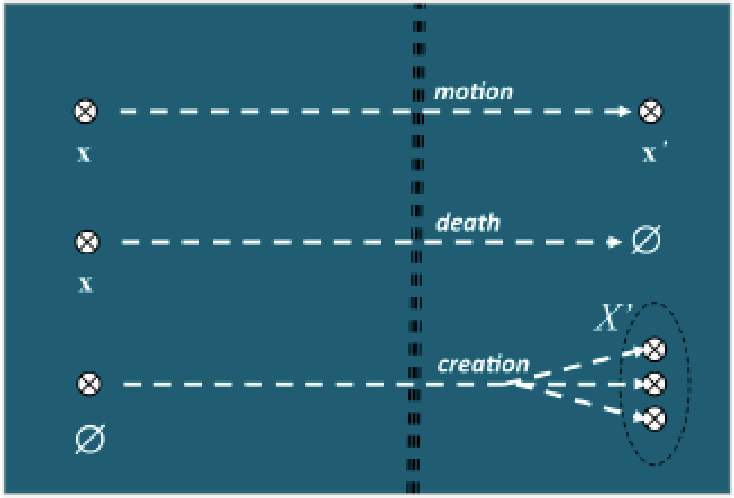
$$p_k(X_k \mid Z_{1:k}) \xrightarrow{\text{prediction}} \underbrace{p_{k+1|k}(X_{k+1} \mid Z_{1:k})}$$

$$\downarrow$$

$$\int \underbrace{f_{k+1|k}(X_{k+1} \mid X_k)}_{\text{multi-target Markov transition}} \; p_k(X_k \mid Z_{1:k}) \, \delta X_k$$

Multi-object filtering: prediction

SSA requirements: identification of new objects, object breakup



$$X_k = S_{k|k-1}(X_{k-1}) \cup \Gamma_k$$

$$f_{k|k-1}(X_k \mid X_{k-1})$$

Multi-object transition density

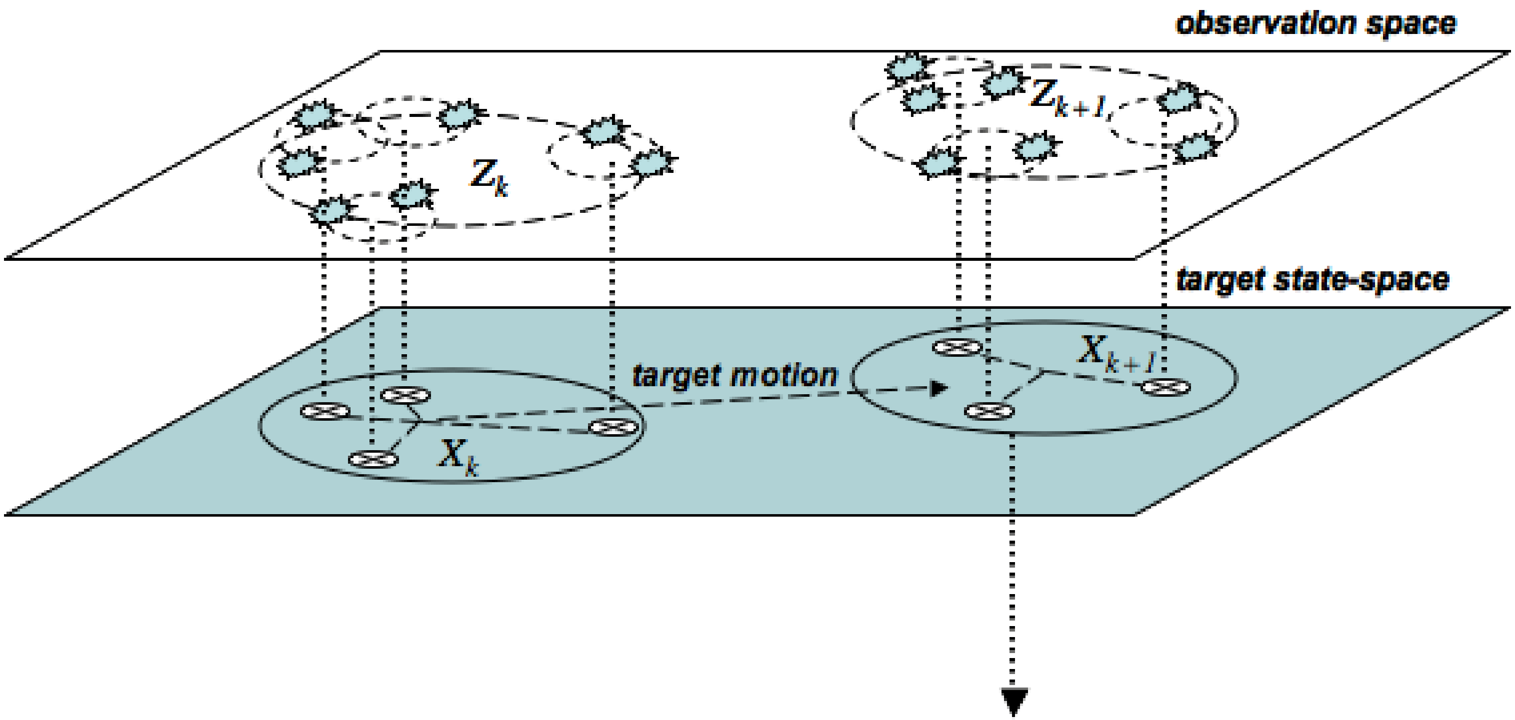
Multi-object Markov model needs to account for:

- Motion of existing targets.
- Possibility of target death.
- Appearance of new targets.

The CPHD Filter with Target Spawning

Daniel S. Bryant, Emmanuel D. Delande, Steven Gehly, Jérémie Houssineau, Daniel E. Clark, Brandon A. Jones

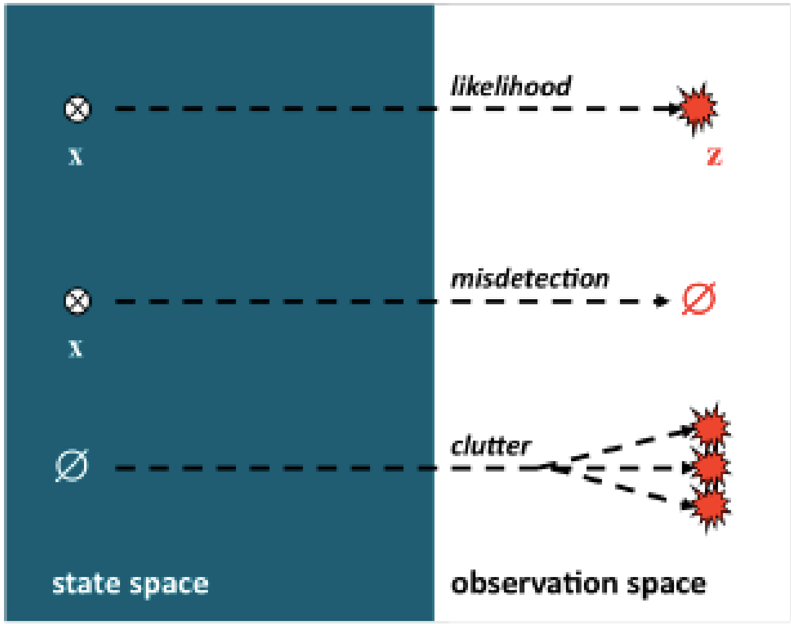
Multi-object filtering: update



$$p_{k+1|k}(X_{k+1} \mid Z_{1:k}) \xrightarrow{\text{data-update}} \underbrace{p_{k+1}(X_{k+1} \mid Z_{1:k+1})}_{\big\downarrow}$$

$$\frac{g_{k+1}(Z_{k+1} \mid X_{k+1})\, p_{k+1|k}(X_{k+1} \mid Z_{1:k})}{\int \underbrace{g_{k+1}(Z_{k+1} \mid X_{k+1})}_{\text{multi-object likelihood}}\, p_{k+1|k}(X_{k+1} \mid Z_{1:k})\, \delta X_{k+1}}$$

Multi-object filtering: update



$$Z_k = \Theta_k(X_k) \cup K_k$$

$$g_k(Z_k|X_k)$$

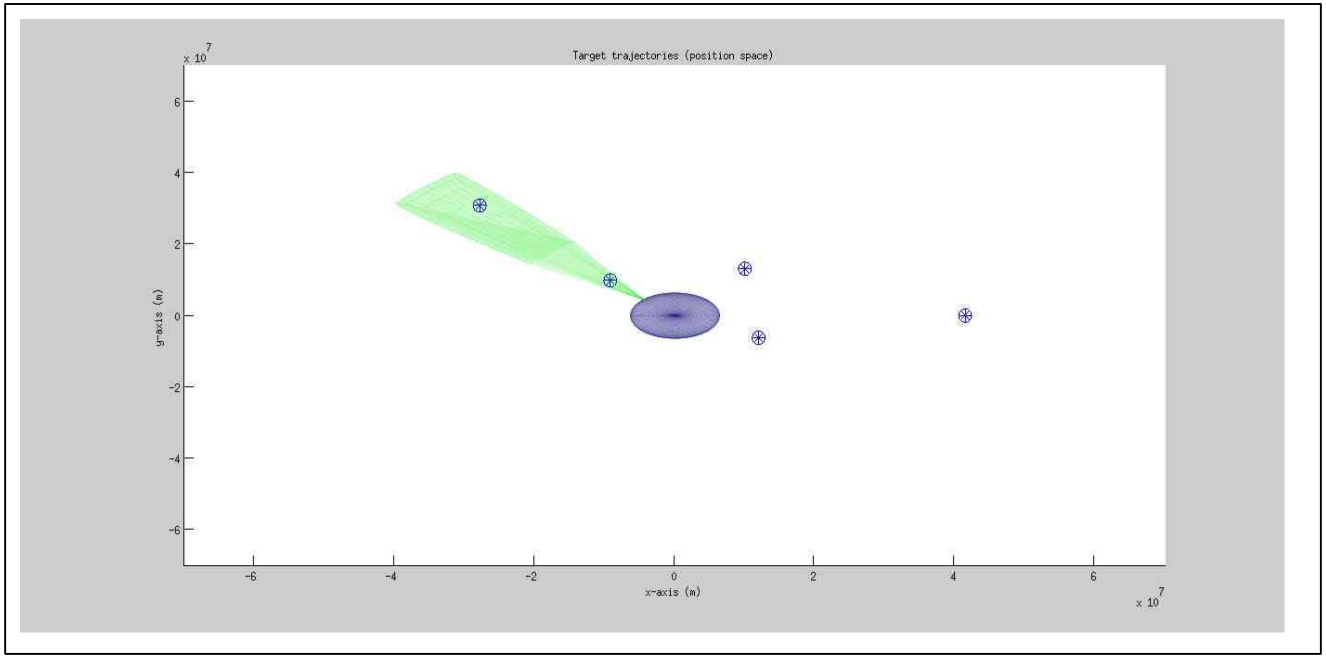
Multi-object likelihood

Multi-object observation model needs to account for:

- Observations from targets.
- Possibility of not observing targets.
- False alarms from the sensor.

Multi-object filtering

SSA challenges: orbit estimation with uncertainty, data association, sensor modelling, long periods of non-observability, sensor integration.



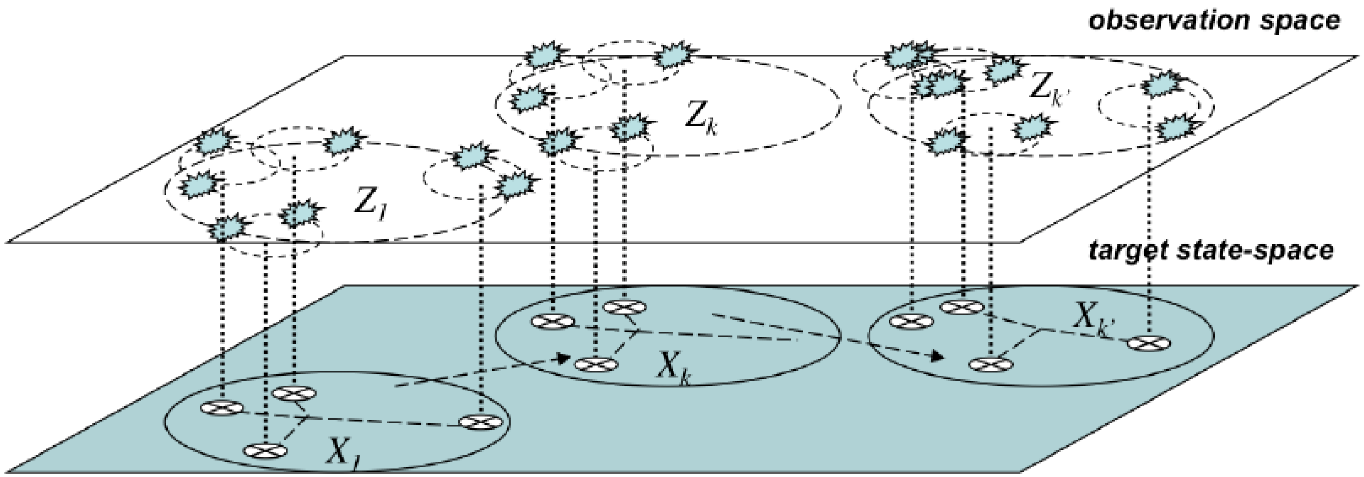
AAS 15-376

MULTI-OBJECT FILTERING FOR SPACE SITUATIONAL AWARENESS

E. D. Delande ; C. Frueh ; J. Houssineau ; D. E. Clark

Multi-object smoothing

SSA context: Refine orbit estimates



$$p_{k'|k}(X) = \int \left\{ \frac{f_{k'+1|k'}(Y \mid X)\, p_{k'|k'}(X)}{p_{k'+1|k'}(Y)} \right\} p_{k'+1|k}(Y)\delta Y, \;\; k' < k.$$

Multi-object smoothing uses the entire sequence of measurement sets $Z_{1:k} = Z_1, \ldots, Z_k$.

A tractable forward-backward CPHD smoother

Sharad Nagappa, Emmanuel D. Delande, Daniel E. Clark and Jérémie Houssineau

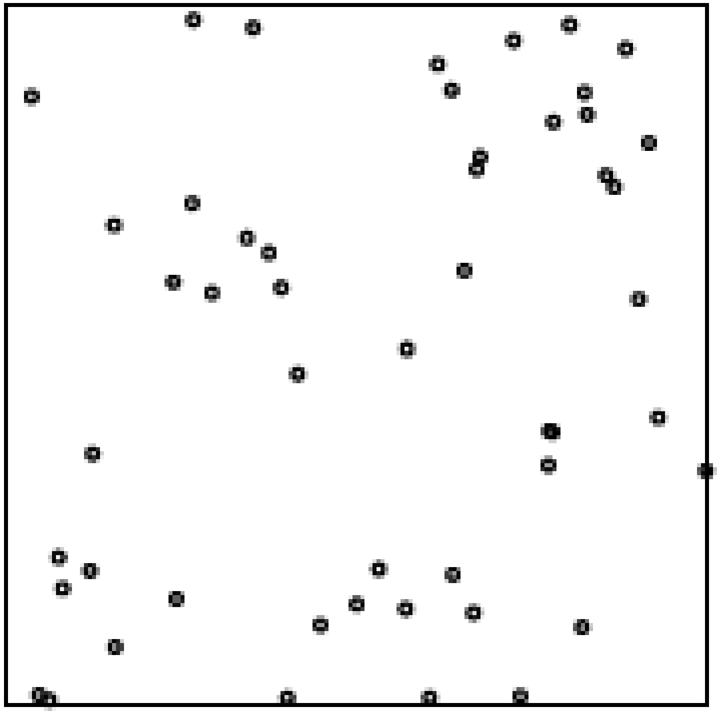
Multi-object modelling

SSA context: eg. debris modelling

A **spatial point process** is a probabilistic representation of a random set of objects
For example:

- 2-dimensional positions of objects in an image from a sensor (i.e. an observation space)

- 3-dimensional positions and velocities of objects in some real-world environment (i.e. a state space).



Point processes

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	$\rho(n)$	$p_n(x_1, x_2, x_3, x_4, \ldots, x_n)$
...	...	...

Representation: The probability generating functional (p.g.fl.)

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

THE GENERAL THEORY OF STOCHASTIC POPULATION PROCESSES

BY

J. E. MOYAL

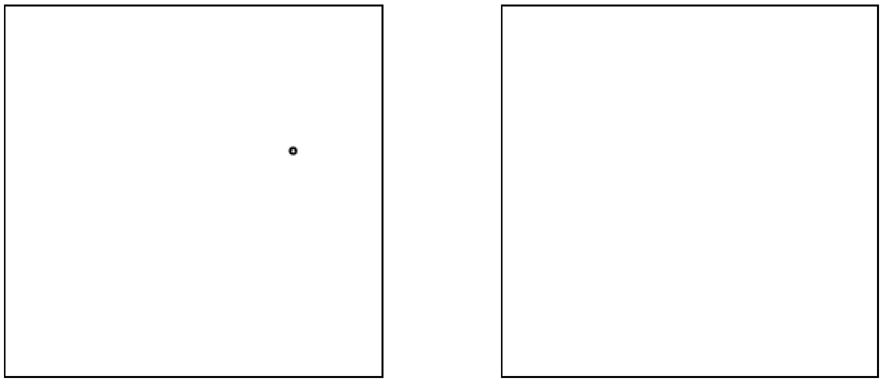
Australian National University, Canberra, Australia (1)

Point process model - Bernoulli

The Bernoulli point process is one of the simplest examples of a point process:

- A point exists with probability p .
- If the point exists, the location of the point is distributed according to some spatial distribution s(x) .

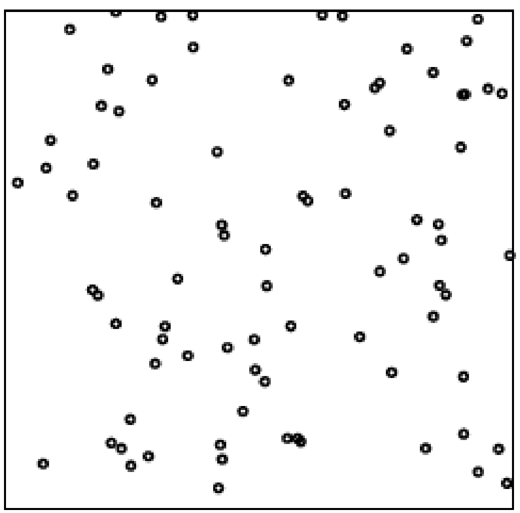
$$G_{\Phi}(h) = 1 - p + p \int h(x) s(\mathrm{d}x).$$



Point process model - Poisson

The Poisson point process with Poisson rate λ > 0 has the following properties

- The expected number of objects in the region is λ .
- The locations of the points are i.i.d. according to some spatial distribution s(x).

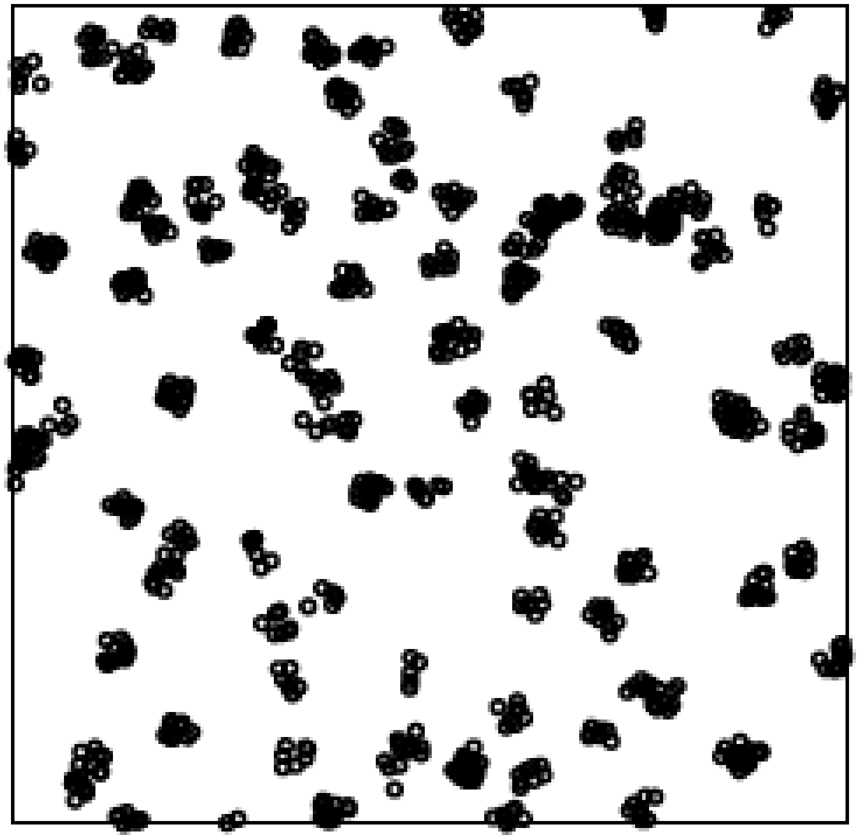


$$G_{\Phi}(h) = \exp\left[\lambda\left(\int h(x)s(\mathrm{d}x) - 1\right)\right]$$

Point process modelling – Poisson clusters

$$G_{\Phi_d}(h) = G_{\Phi_p}(G_{\Phi_e}(h|\cdot))$$

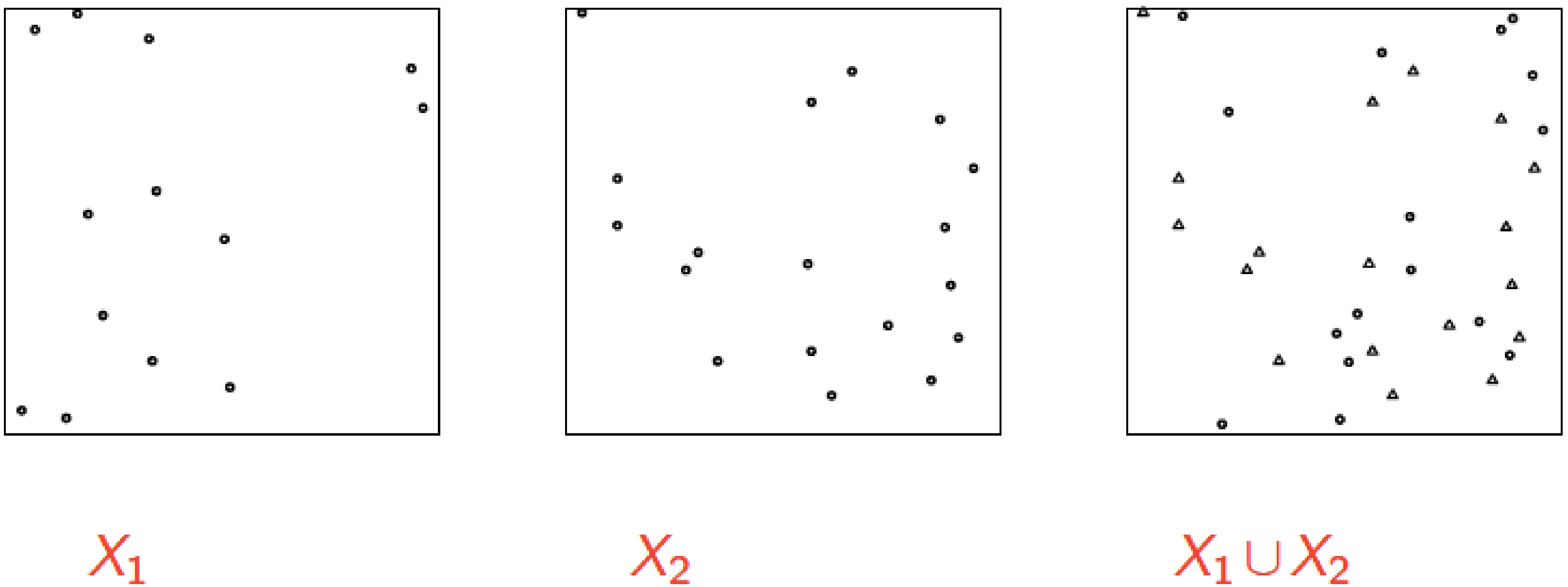
Composition of Poisson processes:



Point process modelling - superposition

Often we observe different (independent) point patterns in the same region originating from different processes (e.g. false and true target detections).

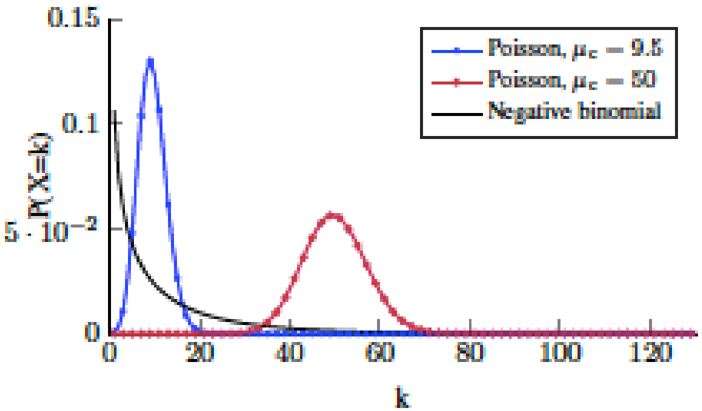
We can model this phenomenon as the superposition of independent point processes:



$$G_{\Phi_1 \cup \Phi_2}(h) = G_{\Phi_1}(h) G_{\Phi_2}(h).$$

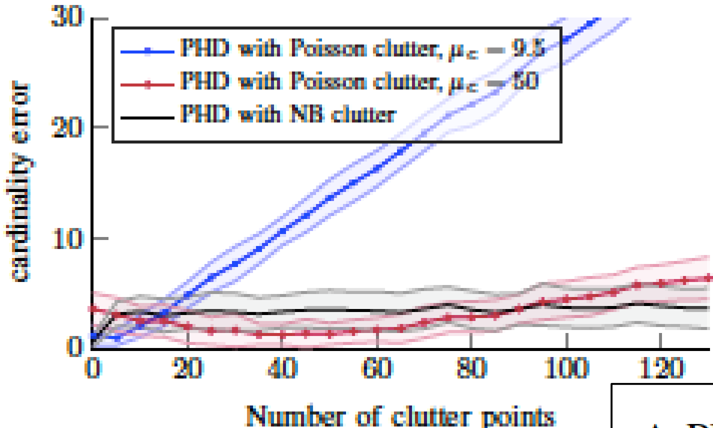
Application - clutter modelling

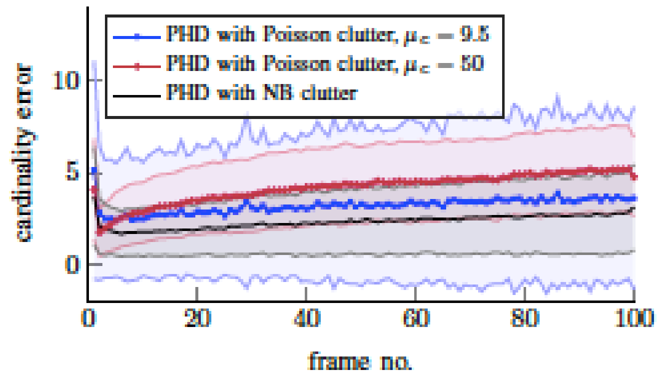
SSA context: applicable to different sensors - radar, optical, telescope.



$$G_{\text{Poisson}}(h) = \exp\left(\int [h(x) - 1]\mu(x)\mathrm{d}x\right)$$

$$G_{\text{NB}}(h) = \left(1 + \frac{1}{\beta}\int_{\mathcal{X}} [1 - h(x)]s(x)\mathrm{d}x\right)^{-\alpha}$$





A PHD Filter With Negative Binomial Clutter

Isabel Schlangen*, Emmanuel Delande*, Jérémie Houssineau* and Daniel E. Clark*
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Heriot-Watt University, Edinburgh EH14 4AS, UK
Email: {is117, E.D.Delande, J.Houssineau, D.E.Clark}@hw.ac.uk

EPSRC Engineering and Physical Sciences Research Council
MRC Medical Research Council
dstl

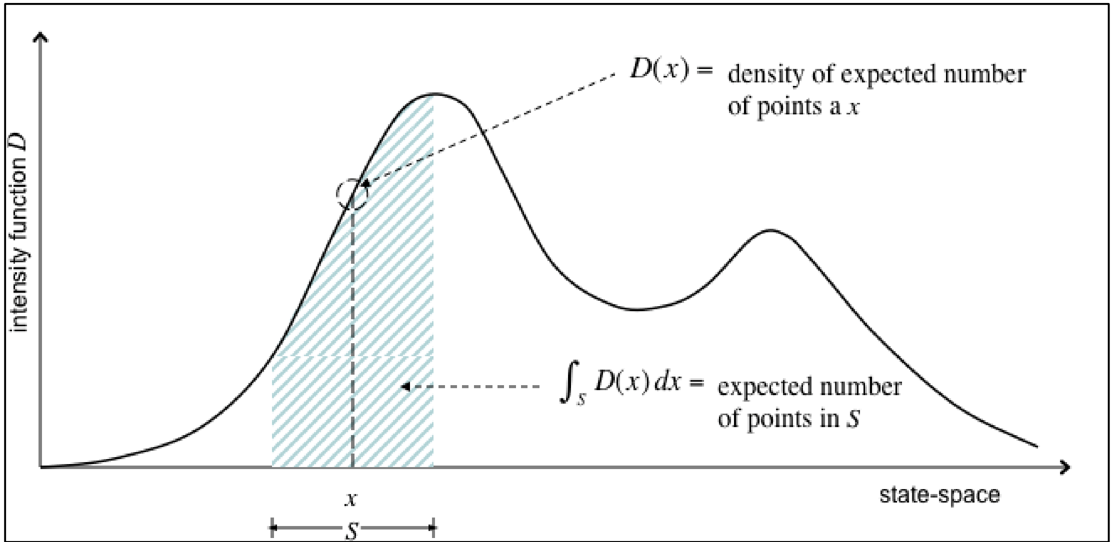
Functional derivatives and the population mean

Important statistical quantities are determined from the p.g.fl. with functional derivatives:

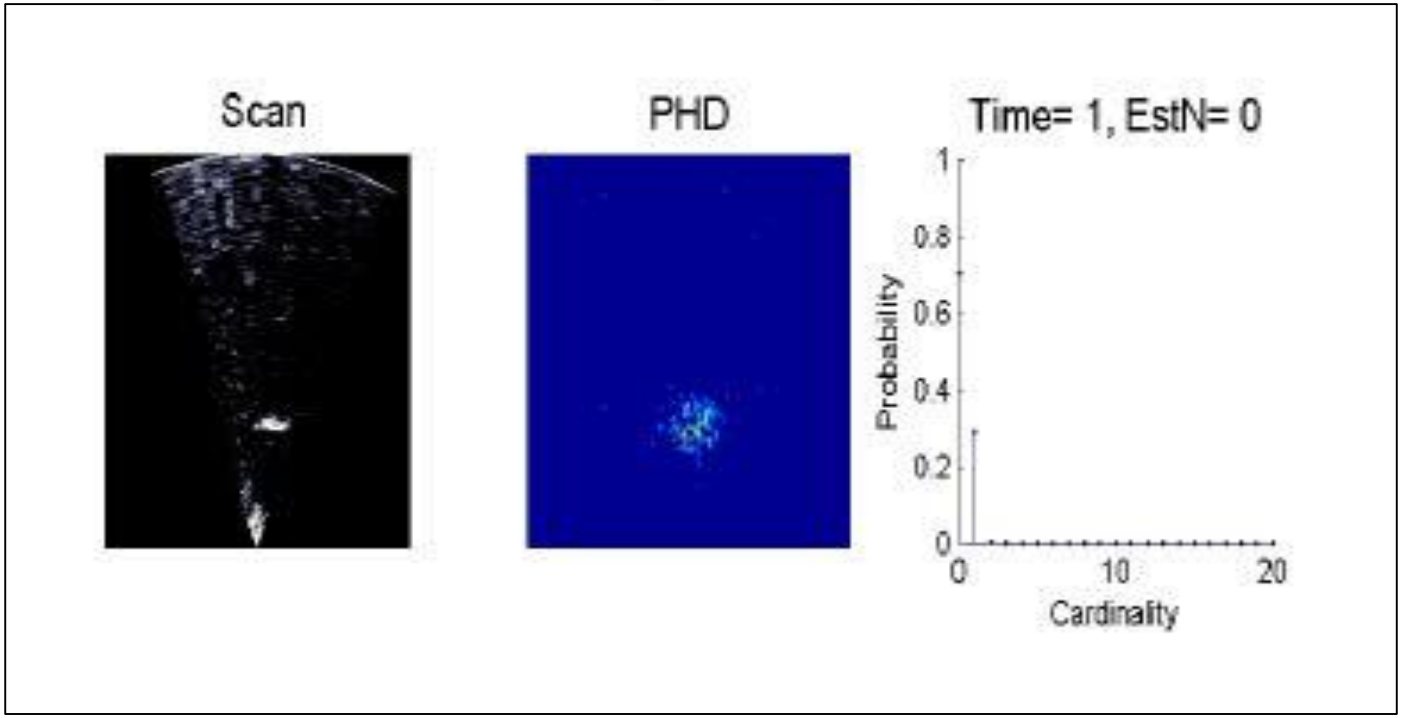
$$\delta f(x;\eta) = \lim_{n\to\infty} \frac{1}{\theta_n}\left(f(x+\theta_n\eta_n) - f(x)\right)$$

For example, the mean, or intensity, measure is found with

$$\mu_{\Phi}^{(1)}(B) = \delta(\mathcal{G}_{\Phi}[h]; 1_B)|_{h=1},$$



Application – estimating the population mean



First industrial application of the multi-object filtering framework was for oil pipeline tracking for BP (2006) in SeeByte Ltd (Clark).

IEEE TRANS AEROSPACE AND ELECTRONIC SYSTEMS, VOL. X, NO. X, MONTH 20XX 1

Adaptive target birth intensity for PHD and CPHD filters

B. Ristic[a], D. Clark[b], Ba-Ngu Vo[c], Ba-Tuong Vo[d]

Bayesian multiple target tracking in forward scan sonar images using the PHD filter

D.E. Clark and J. Bell

IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 54, NO. 7, JULY 2006

Convergence Results for the Particle PHD Filter

Daniel Edward Clark, *Student Member, IEEE,* and Judith Bell

Data Association and Track Management for the Gaussian Mixture Probability Hypothesis Density Filter

KUSHA PANTA, Student Member, IEEE
The University of Melbourne
DANIEL E. CLARK
Heriot-Watt University
BA-NGU VO
The University of Melbourne

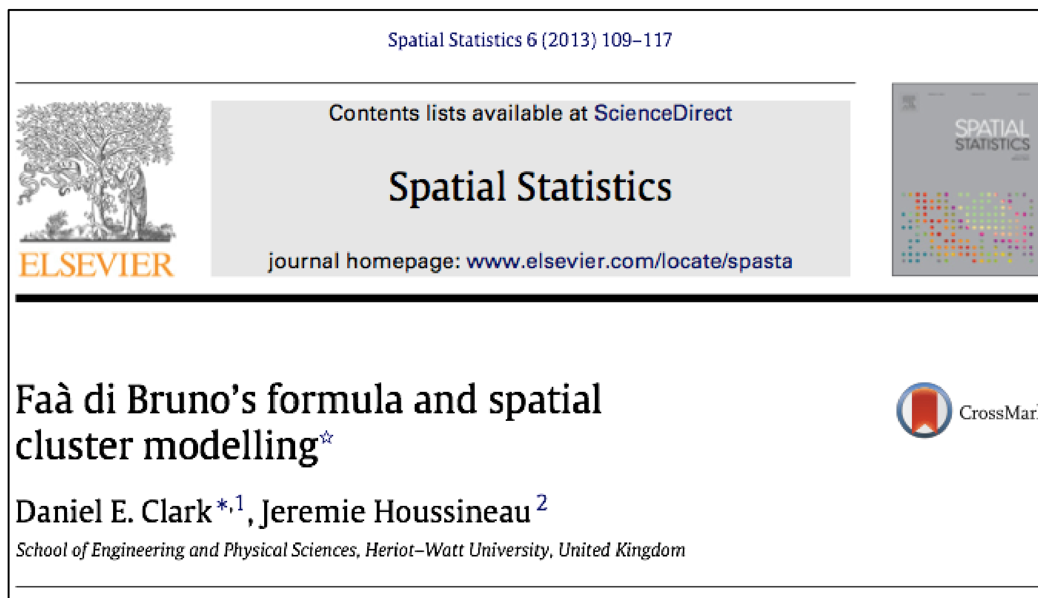
Functional derivatives of composite functionals

Models are often constructed with composite functionals, and properties found with functional derivatives.

It is therefore useful to have a higher-order chain rule (Clark and Houssineau),

$$\delta^{n}(f \circ g)(x; \eta_1, \ldots, \eta_n) = \sum_{\pi \in \Pi(\eta_1, \ldots, \eta_n)} \delta^{|\pi|} f\left(g(x); \delta^{|\omega|} g\left(x; \xi : \xi \in \omega\right) : \omega \in \pi\right)$$

$$G_{\Phi_d}(h) = G_{\Phi_p}\left(G_{\Phi_e}(h|\cdot)\right)$$


Spatial Statistics 6 (2013) 109–117

Contents lists available at ScienceDirect

Spatial Statistics

journal homepage: www.elsevier.com/locate/spasta

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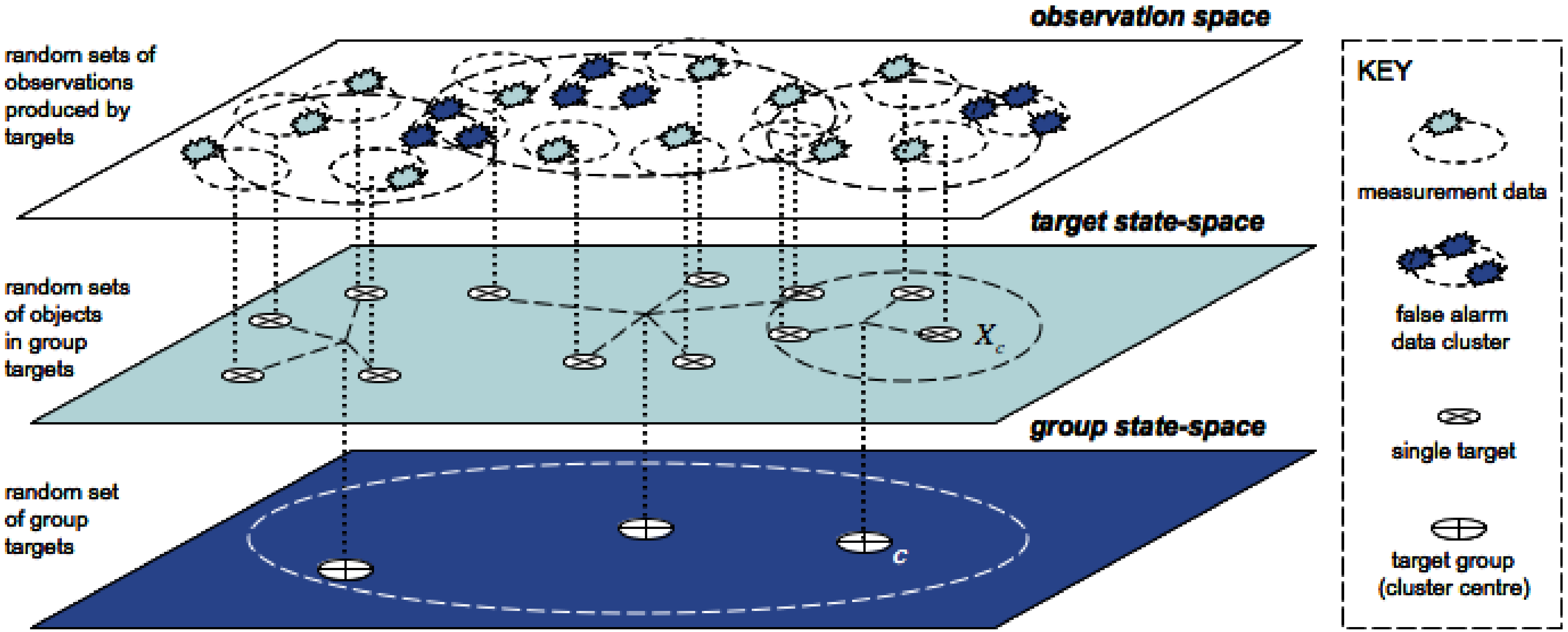
Faà di Bruno's formula and spatial cluster modelling☆

Daniel E. Clark*,1, Jeremie Houssineau 2

School of Engineering and Physical Sciences, Heriot–Watt University, United Kingdom

Application - tracking groups



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

Available online at www.sciencedirect.com
SciVerse ScienceDirect
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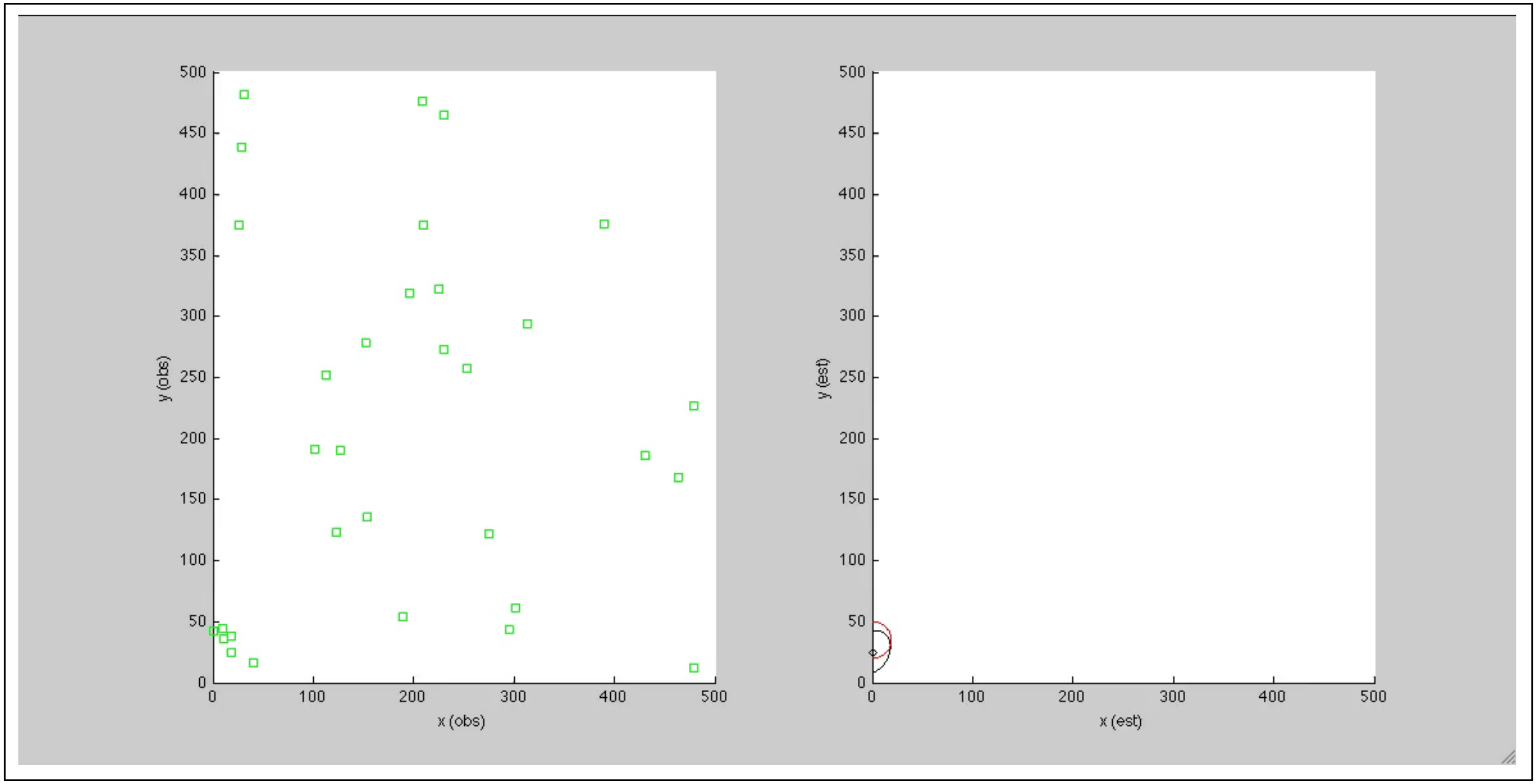
Procedia Environmental Sciences 4 (2011) 56–61
Procedia Environmental Sciences
1st Conference on Spatial Statistics 2011

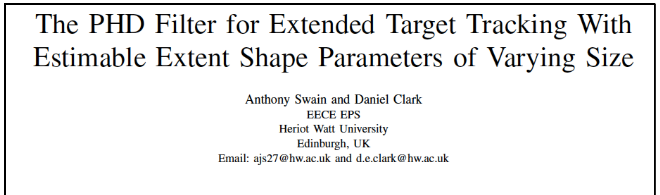
Bayesian Estimation of the Intensity for Independent Cluster Point Processes: An analytic solution

Anthony Swain[a], Dr Daniel Clark[a] *
[a]Heriot Watt University, Edinburgh, EH14 4AS, UK

Application - tracking groups

SSA context: eg. tracking debris clouds




The PHD Filter for Extended Target Tracking With Estimable Extent Shape Parameters of Varying Size

Anthony Swain and Daniel Clark
EECE EPS
Heriot Watt University
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Email: ajs27@hw.ac.uk and d.e.clark@hw.ac.uk

ROYAL ACADEMY OF ENGINEERING

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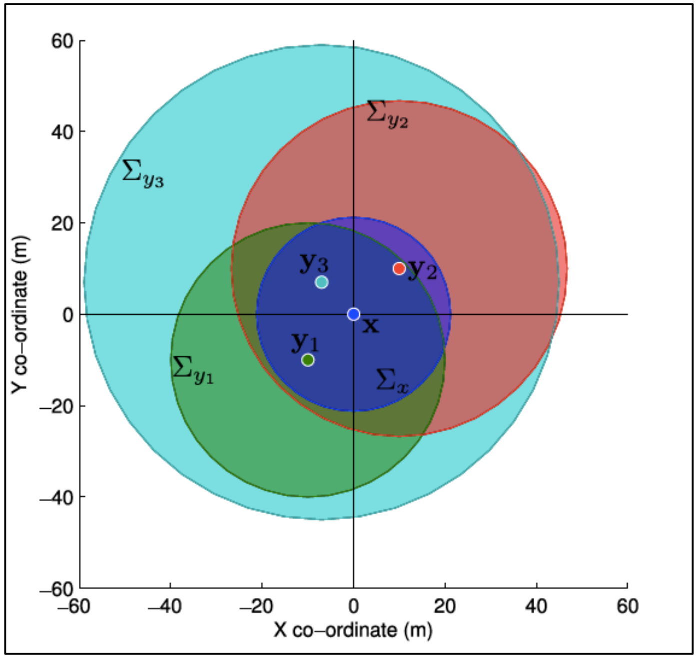
Performance assessment

-Methods for performance assessment crucial for understanding reliability.

-SSA context: Important to account for uncertainty in orbital estimates



Metric: $d(\cdot,\cdot)$

(identity) $d(x, y) = 0$ iff $x = y$;

(symmetry) $d(x, y) = d(y, x)$ for all x, y

(triangle inequality) $d(x, y) \leq d(x, z) + d(z; y)$ for all x, y, z.

Incorporating Track Uncertainty into the OSPA Metric

Sharad Nagappa, Daniel Clark and Ronald Mahler

ROYAL ACADEMY OF ENGINEERING

EPSRC Engineering and Physical Sciences Research Council

Functional derivatives and the population variance

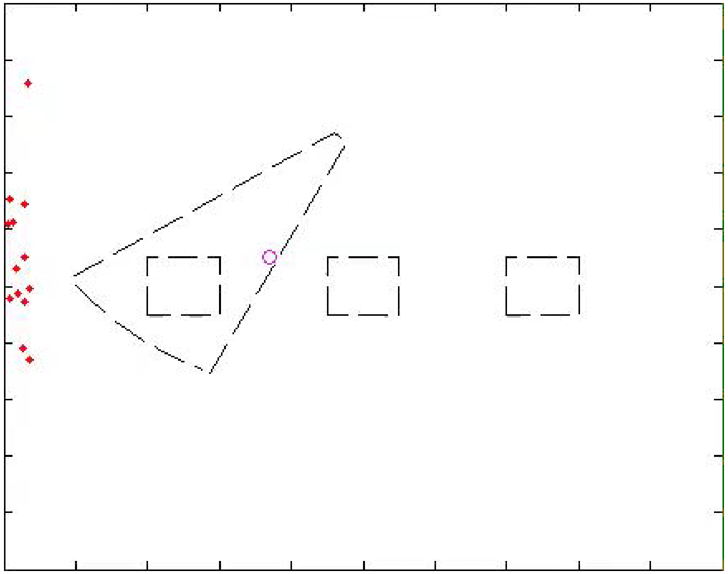
Modelling global populations allows us to determine population statistics: variance of the number of targets in a region.

"There are roughly μ(B) targets, give or take ~var(B), within B".

$$\mathrm{var}_\Phi(B) = \mu_\Phi^{(2)}(B,B) - \left[\mu_\Phi^{(1)}(B)\right]^2$$

$$\mu_\Phi^{(1)}(B) = \delta(\mathcal{G}_\Phi[h]; 1_B)|_{h=1},$$
$$\mu_\Phi^{(2)}(B,B') = \delta^2(\mathcal{L}_\Phi[f]; 1_B, 1_{B'})|_{f=0},$$

$$\mathcal{L}_\Phi[f] = \mathbb{E}\left[\prod_{x\in\Phi} e^{-f(x)}\right]$$



IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 62, NO. 13, JULY 1, 2014 3415

Regional Variance for Multi-Object Filtering

Emmanuel Delande, Murat Üney, *Member, IEEE*, Jérémie Houssineau, and Daniel E. Clark, *Member, IEEE*

Sensor management with regional statistics for the PHD filter

Marian Andrecki, Emmanuel D. Delande, Jérémie Houssineau, and Daniel E. Clark
School of Engineering & Physical Sciences, Heriot-Watt University, Edinburgh, UK

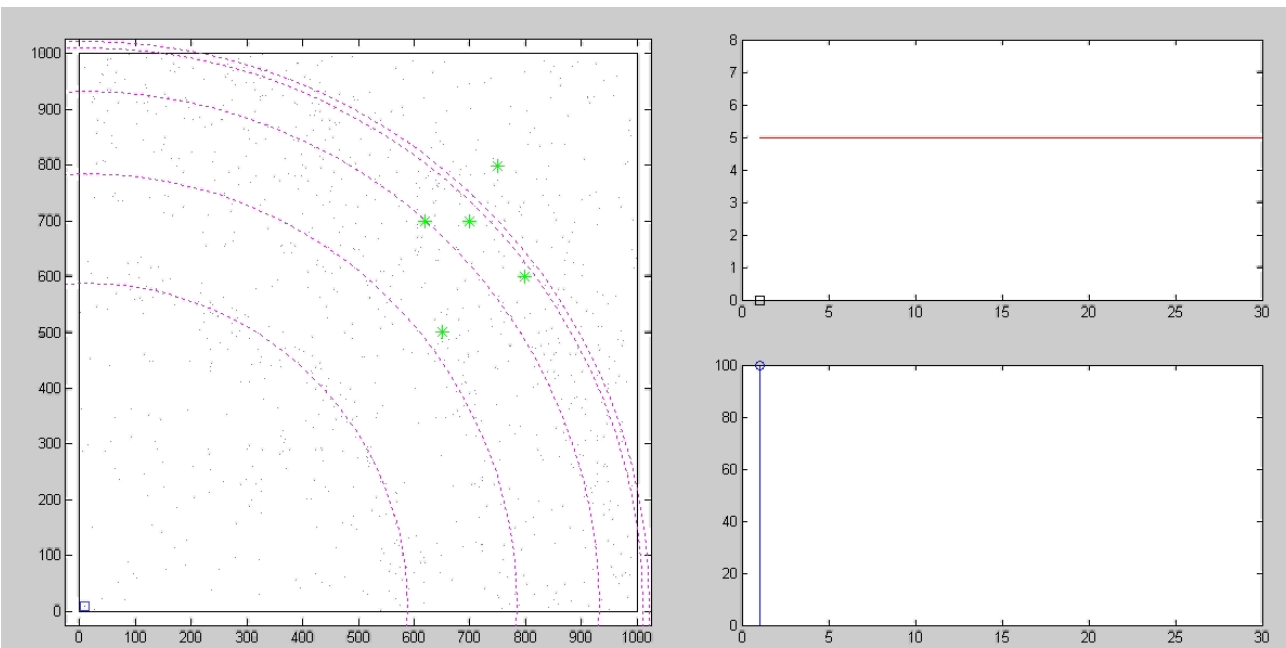
Engineering and Physical Sciences

Information-theoretic sensor control

Information-theoretic properties, such as Renyi divergence, can be used with multi-object filters for sensor control

$$\mathbf{u}_k = \arg\max_{\mathbf{v}\in\mathbb{U}_k} \mathbb{E}[\mathcal{R}(\mathbf{v}, f_{k|k-1}(\mathbf{X}_k|\mathbf{Z}_{1:k-1}), \mathbf{Z}_k(\mathbf{v}))]$$

$$\mathcal{R}(\mathbf{u}_k) = \frac{1}{\alpha-1}\log\int [f_{k|k}(\mathbf{X}_k|\mathbf{Z}_{1:k-1}, \mathbf{Z}_k(\mathbf{u}_{k-1}))]^{\alpha}\,[f_{k|k-1}(\mathbf{X}_k|\mathbf{Z}_{1:k-1})]^{1-\alpha}\delta\mathbf{X}_k.$$



A Note on the Reward Function for PHD Filters with Sensor Control

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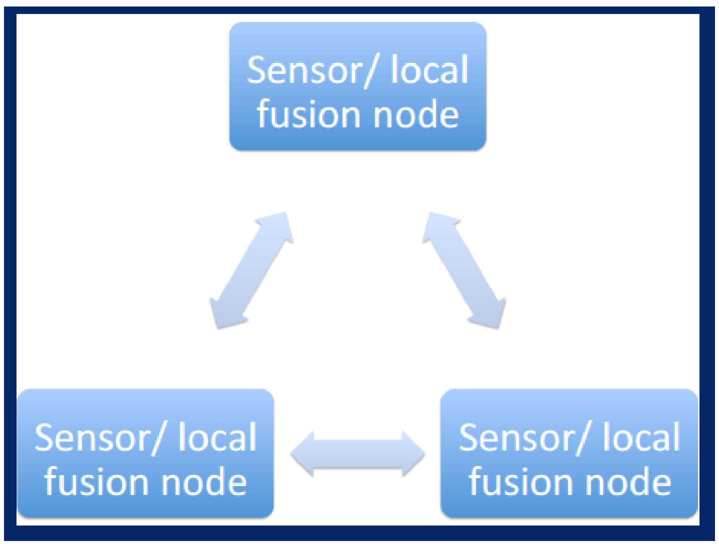
Multi-sensor fusion and calibration

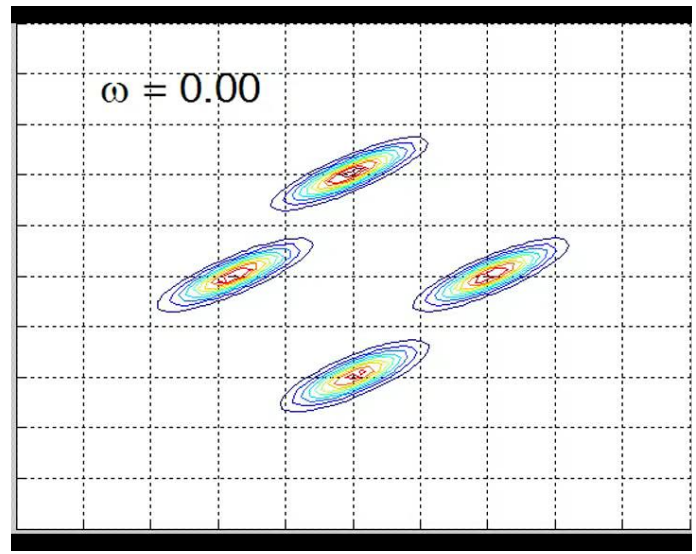
[dstl] THALES

Distributed multi-sensor fusion

Multi-object posteriors can be fused robustly in distributed sensor networks

$$f_\omega(X|Z_0^k, Z_1^k) = \frac{f_0(X|Z_0^k)^{(1-\omega)} f_1(X|Z_1^k)^\omega}{\int f_0(Y|Z_0^k)^{(1-\omega)} f_1(Y|Z_1^k)^\omega \delta Y},$$





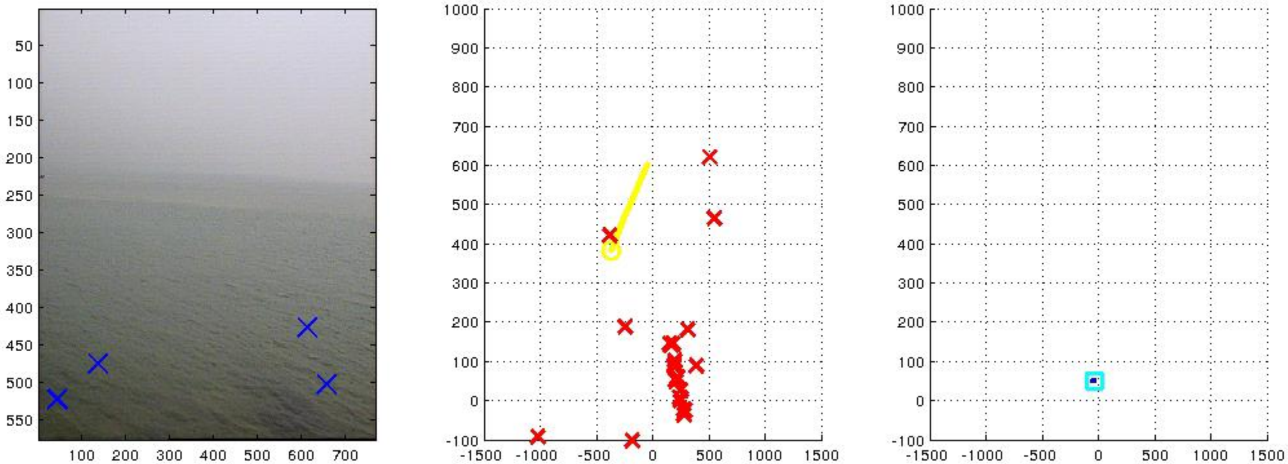
IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING 1

Distributed Fusion of PHD Filters via Exponential Mixture Densities

Murat Üney, *Member, IEEE,* Daniel E. Clark, *Member, IEEE,* Simon J. Julier, *Member, IEEE,*

[dstl] EPSRC Engineering and Physical Sciences Research Council UCL

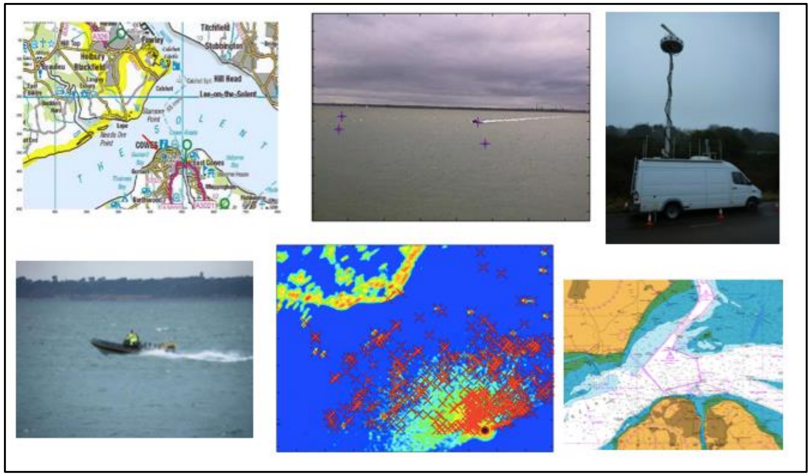
Application: maritime surveillance



A multi-sensor inference and data fusion method for tracking small, manoeuvrable maritime craft in cluttered regions†

By Jordi Barr‡[1], Murat Üney[2], Daniel Clark[2], Dave Miller[3], Matthew Porter[1], E. H. Amadou Gning[4], & Simon J. Julier[4]

[1]BAE Systems Advanced Technology Centre, [2]Heriot-Watt University, School of Engineering and Physical Sciences, [3]BAE Systems Maritime Services, [4]Department of Computer Science, University College London

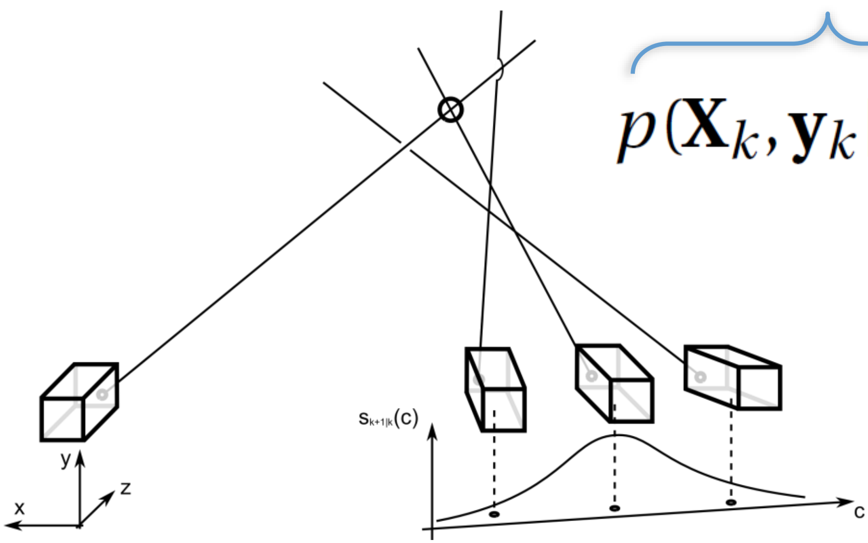


Joint sensor calibration and multi-target tracking

$$\overbrace{p(\mathbf{X}_k,\mathbf{y}_k|\mathbf{Z}_{1:k})}^{\text{Joint sensor-population distribution}} = \overbrace{p(\mathbf{X}_k|\mathbf{Z}_{1:k},\mathbf{y}_k)}^{\text{Conditional population distribution}}\,\overbrace{p(\mathbf{y}_k|\mathbf{Z}_{1:k})}^{\text{Sensor distribution}}$$

Multi-target filter

Particle filter



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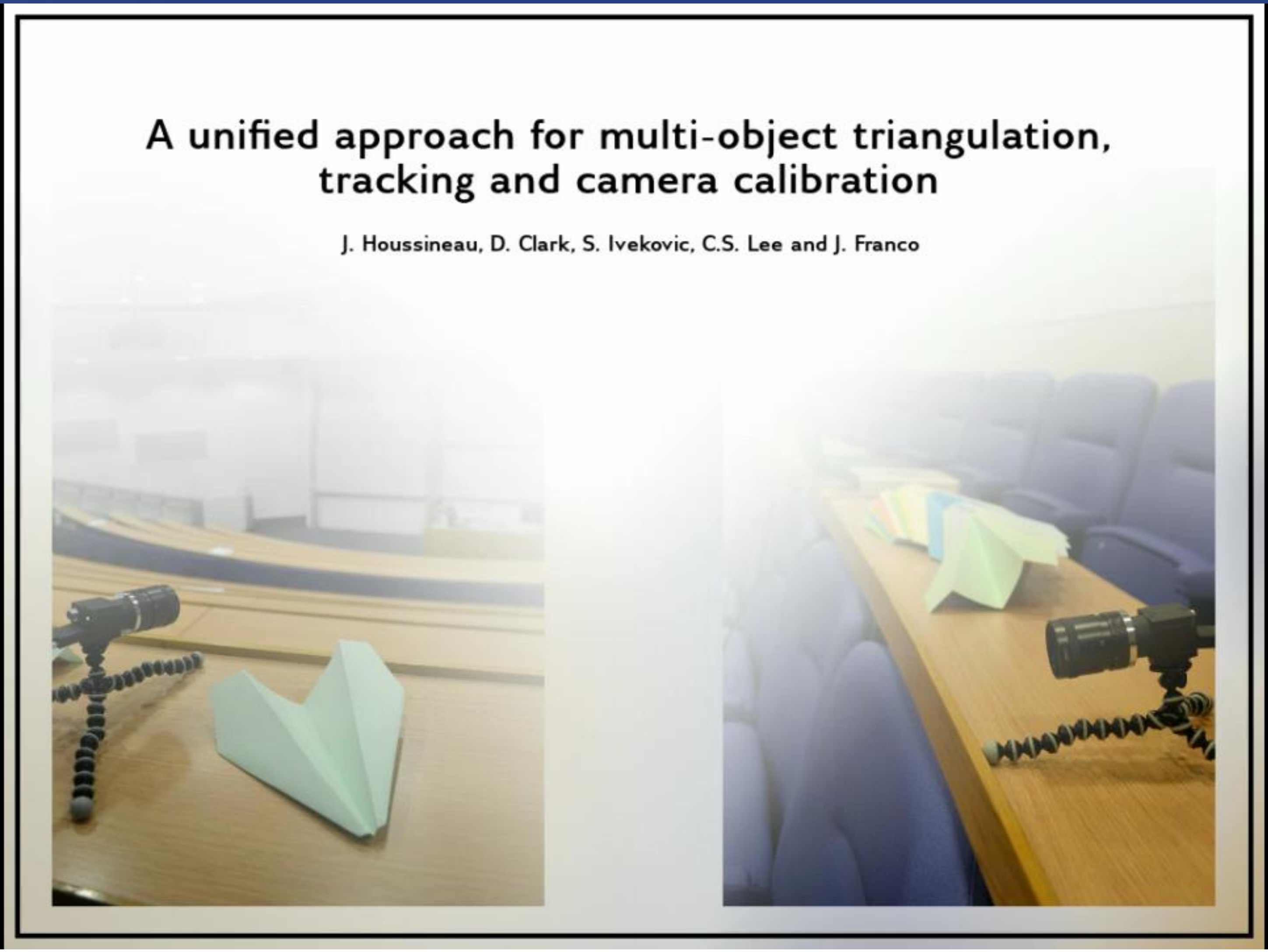
Calibration of Multi-Target Tracking Algorithms Using Non-Cooperative Targets

Branko Ristic, Daniel E. Clark, and Neil Gordon

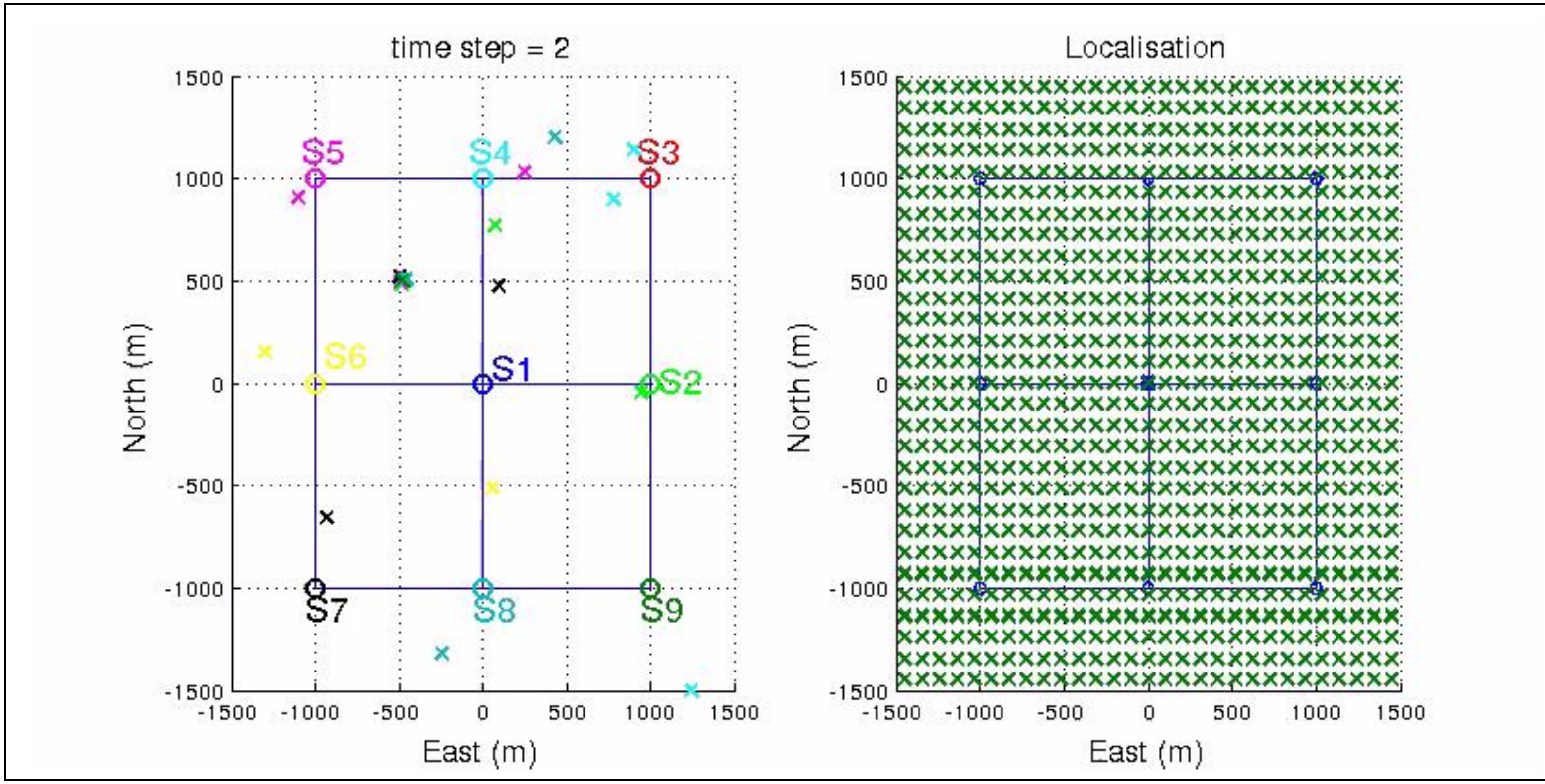


IEEE TRANSACTIONS ON SIGNAL PROCESSING 1

A Unified Approach for Multi-Object Triangulation, Tracking and Camera Calibration

Jeremie Houssineau, Daniel E. Clark, Spela Ivekovic, Chee Sing Lee, and Jose Franco

Distributed multi-sensor registration and target tracking



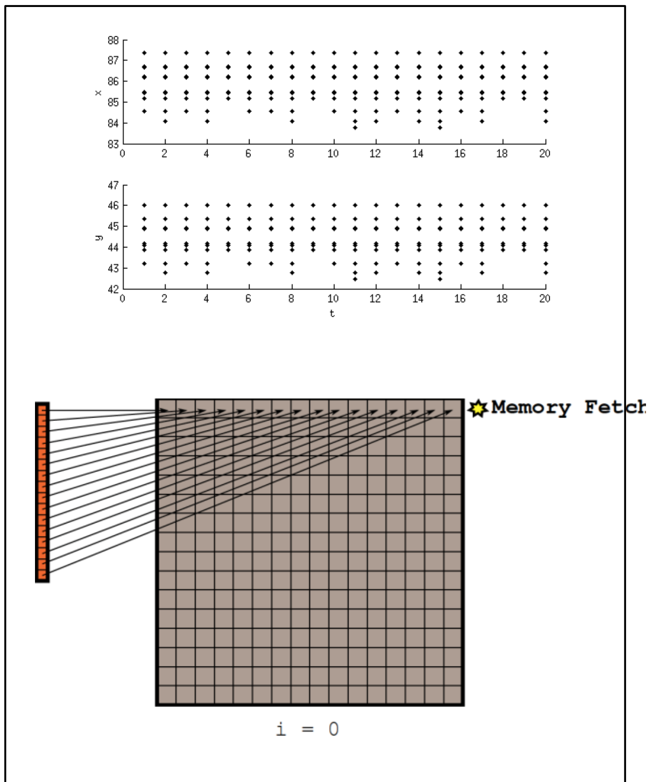
IEEE TRANSACTIONS ON SIGNAL PROCESSING 1

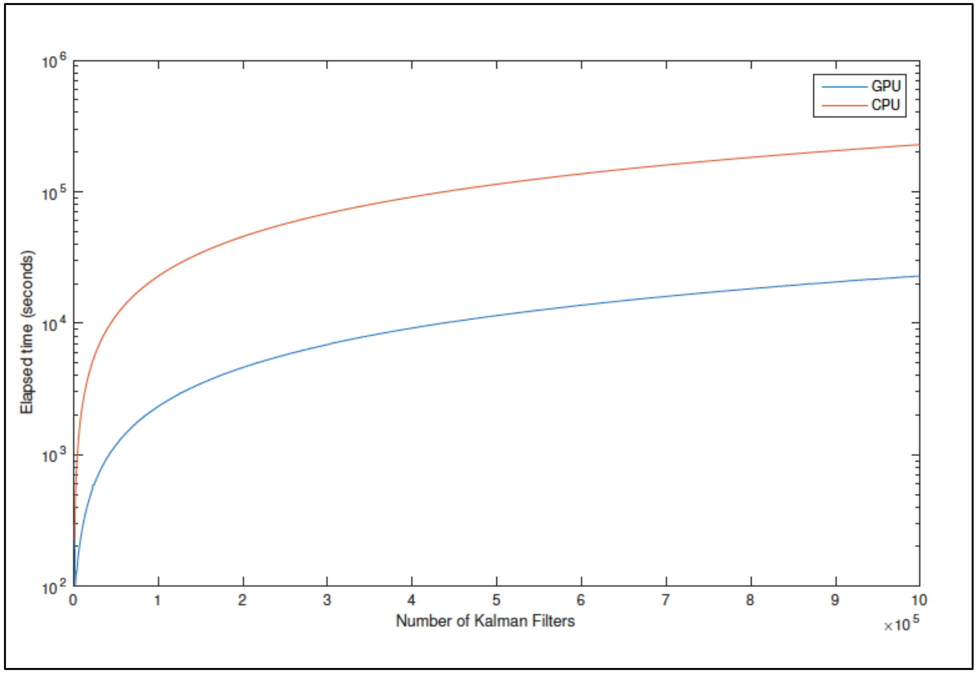
A Cooperative Approach to Sensor Localisation in Distributed Fusion Networks

Murat Üney, *Member, IEEE,* Bernard Mulgrew, *Fellow, IEEE,* Daniel E. Clark, *Member, IEEE*

High-performance computing for tracking many objects

SSA context: tracking space catalogue





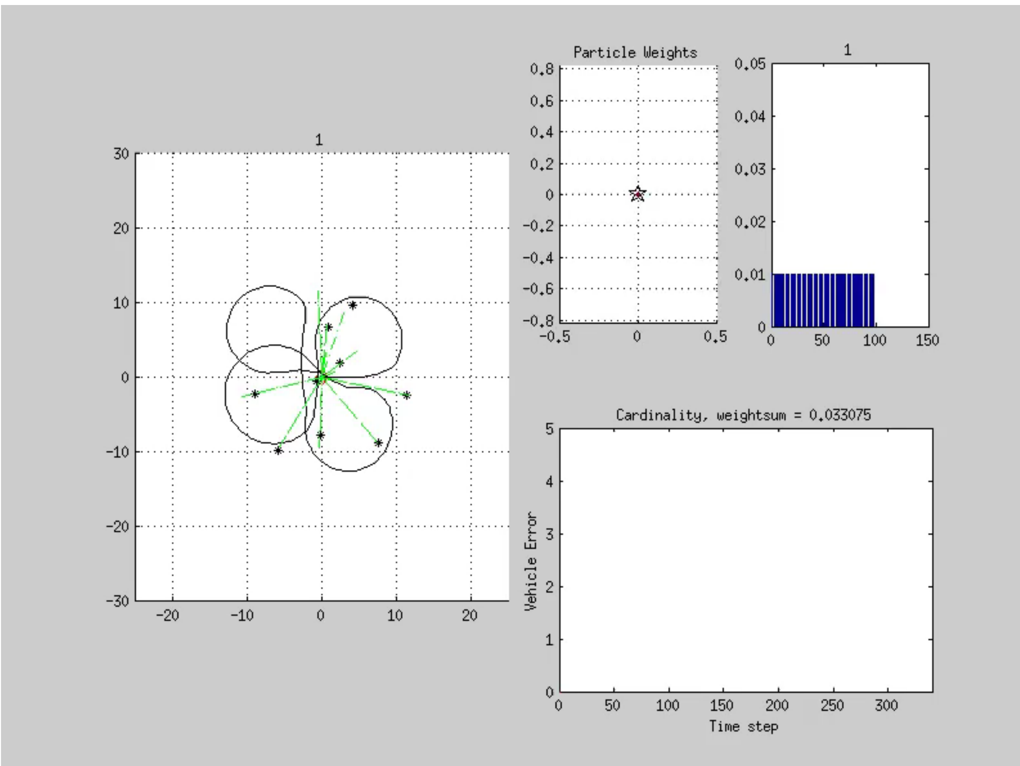
Accelerating the Single Cluster PHD Filter with a GPU Implementation

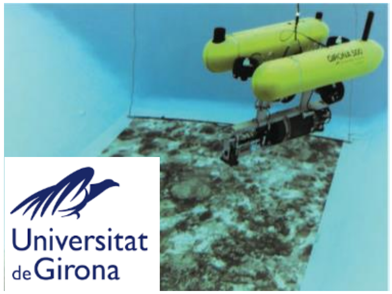
Chee Sing Lee, José Franco, Jérémie Houssineau, Daniel Clark

[dstl] EPSRC Engineering and Physical Sciences Research Council

Dynamic sensor localisation

Tracking and self-localisation in GPS-denied environments





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SLAM With Dynamic Targets via Single-Cluster PHD Filtering

Chee Sing Lee, Daniel E. Clark, and Joaquim Salvi

SLAM with SC-PHD Filters

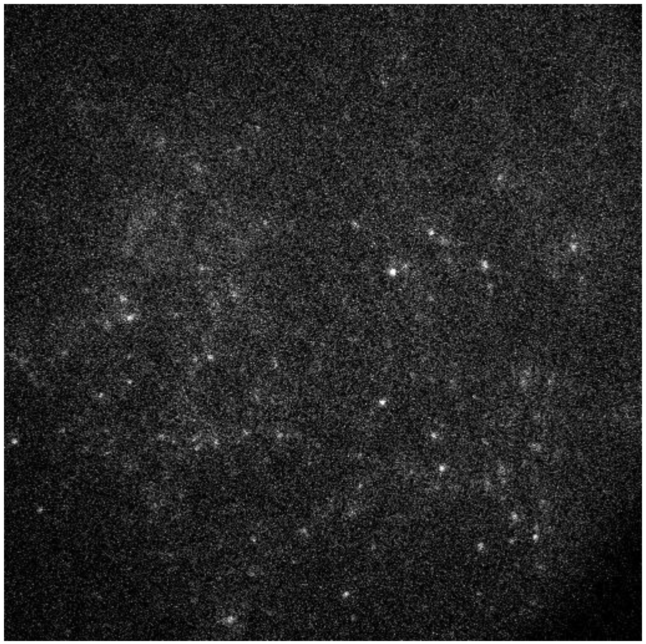
An Underwater Vehicle Application

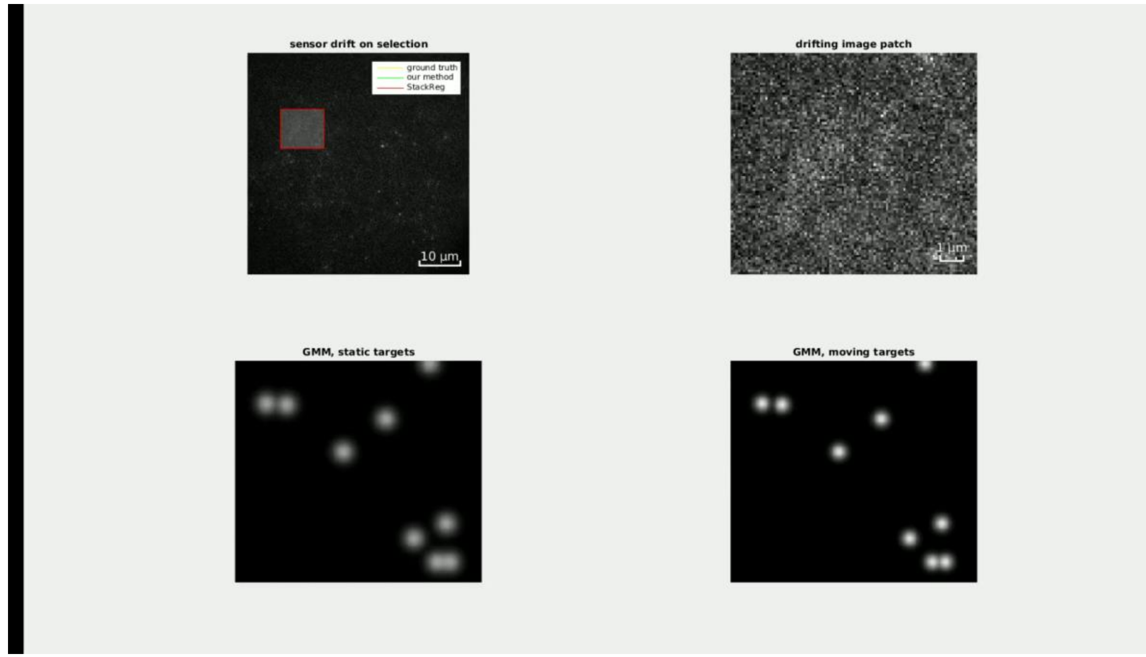
By Chee Sing Lee, Sharad Nagappa, Narcis Palomeras, Daniel E. Clark, and Joaquim Salvi

EPSRC Engineering and Physical Sciences Research Council

Generalitat de Catalunya

Joint estimation of microscope drift and tracking



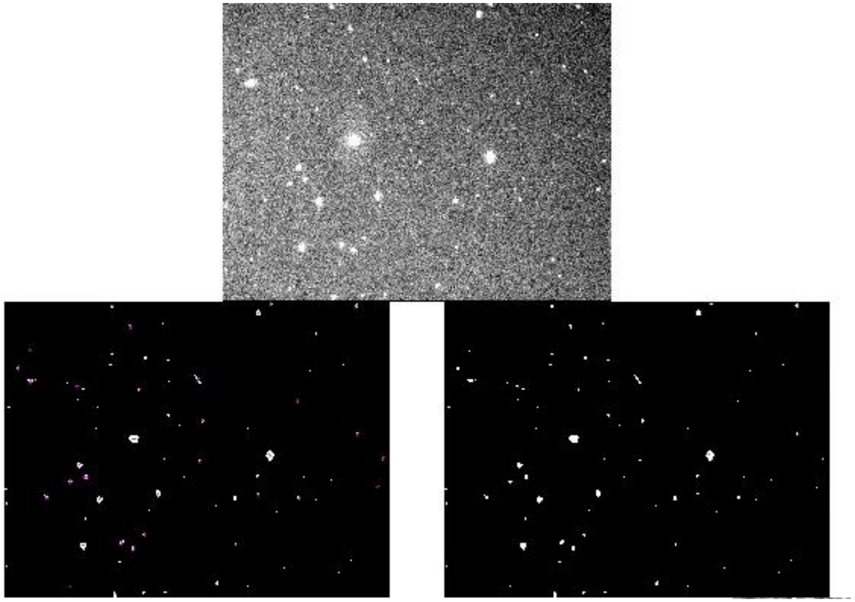


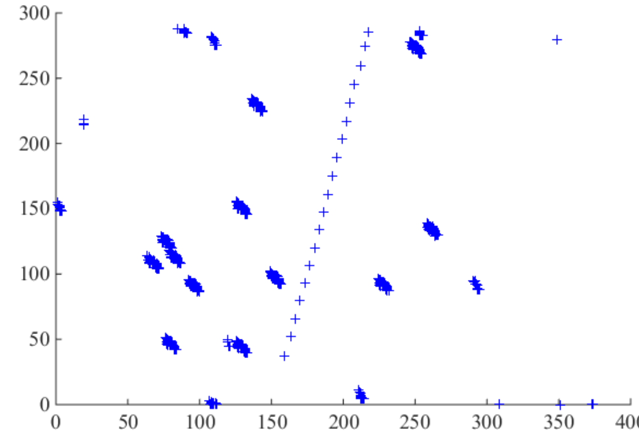
IEEE JOURNAL OF SELECTED TOPICS IN SIGNAL PROCESSING, VOL. 10, NO. 1, FEBRUARY 2016 193

Marker-Less Stage Drift Correction in Super-Resolution Microscopy Using the Single-Cluster PHD Filter

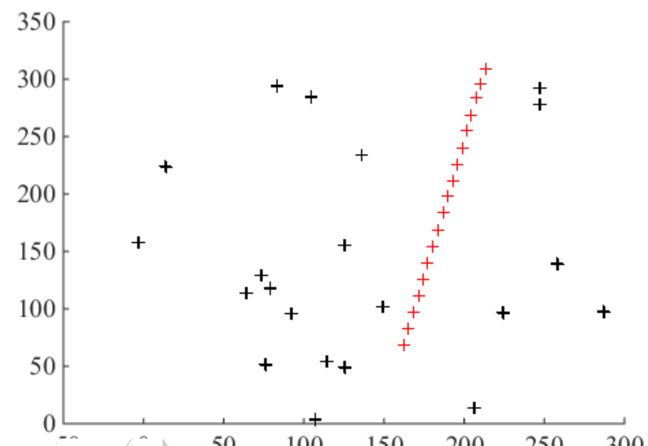
Isabel Schlangen, José Franco, Jérémie Houssineau, William T. E. Pitkeathly, Daniel Clark, Ihor Smal, and Colin Rickman

Joint estimation of telescope drift and object tracking





NEO 2007HA during its close passage



Joint Estimation of Telescope Drift and Low-Earth Object Estimation

O. Hagen, J. Houssineau, I.Schlangen , E. Delande, J. Franco, D. Clark
School of Engineering and Physical Sciences
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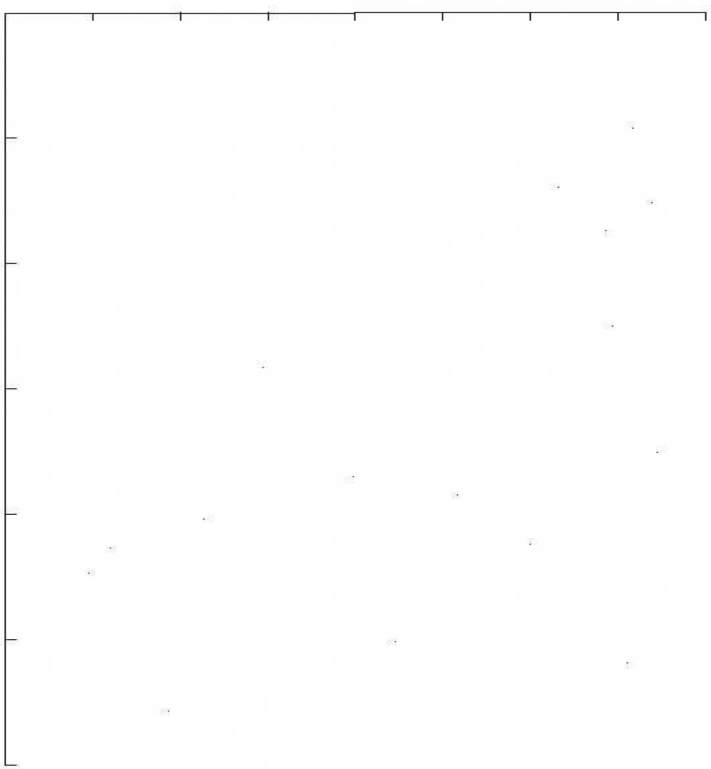
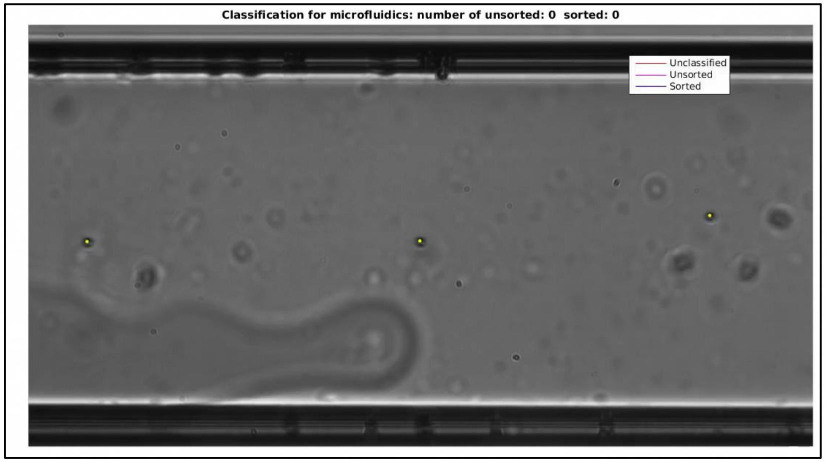
Object classification

If objects from different classes have different statistical models then classification can naturally be performed.
SSA context: eg. orbit classification.





Observing the dynamics of waterborne pathogens for assessing the level of contamination

Isabella McKenna, Francesco Tonolini, Rachael Tobin, Jeremie Houssineau, Helen Bridle
Craig McDougall, Isabel Schlangen, Daniel E. Clark, John McGrath and Melanie Jimenez

TRACKING UNDERWATER OBJECTS USING LARGE MIMO SONAR SYSTEMS

Yan Pailhas[a], Jeremie Houssineau[a], Emmanuel Delande[a], Yvan Petillot[a] & Daniel Clark[a]

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Multi-sensor multi-target tracking techniques

Summary:

1. **Tracking trajectories of individual objects**
2. **Multi-object estimation**
3. **Multi-sensor systems**
4. **Object classification**

Thanks to my team:
Postdocs: Emmanuel Delande, Jeremie Houssineau, Murat Uney, Sharad Nagappa, Yan Pailhas
PhD students: Anthony Swain, Chee Sing Lee, Isabel Schlangen, Jose Franco
MSc interns: Vibhav Bharti, Andrey Pak, Oksana Hagen

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