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

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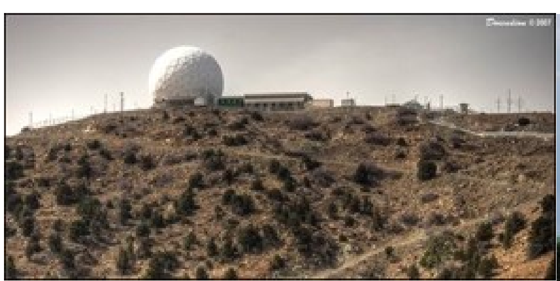



Space

China's Tiangong-1 space station 'out of control' and will crash to Earth

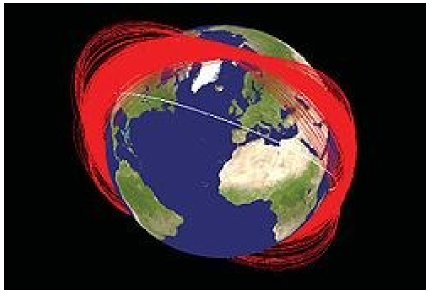
Chinese authorities confirm the eight-tonne ‘Heavenly Palace’ lab will re-enter the atmosphere sometime in 2017 with some parts likely to hit Earth

China's Long March 2-F rocket, which took the Tiangong-1 space module into space. Photograph: STR/AFP/Getty Images

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

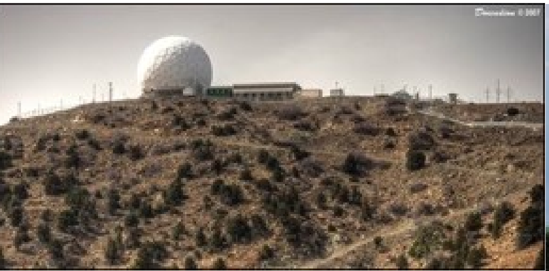
https://en.wikipedia.org/wiki/2009_satellite_collision

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

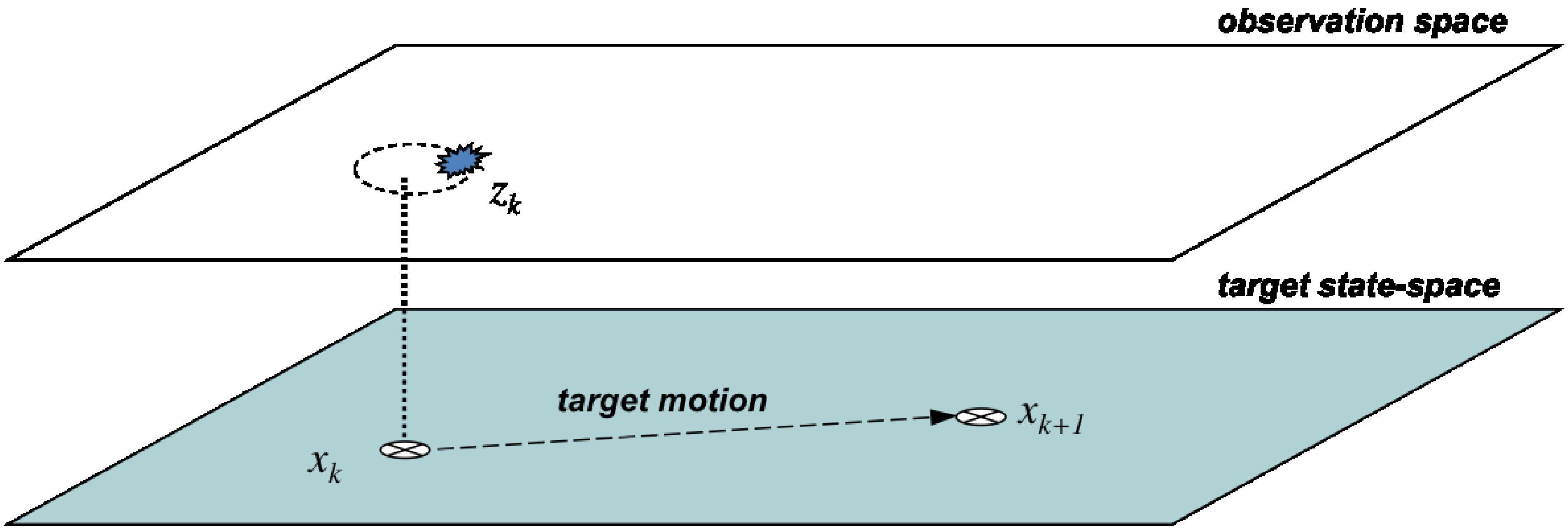
Multi-sensor multi-target tracking techniques for Space Situational Awareness

Topics:

1. **Tracking trajectories of individual objects**
2. **Multi-target tracking**
3. **Joint sensor motion, target tracking, and classification**



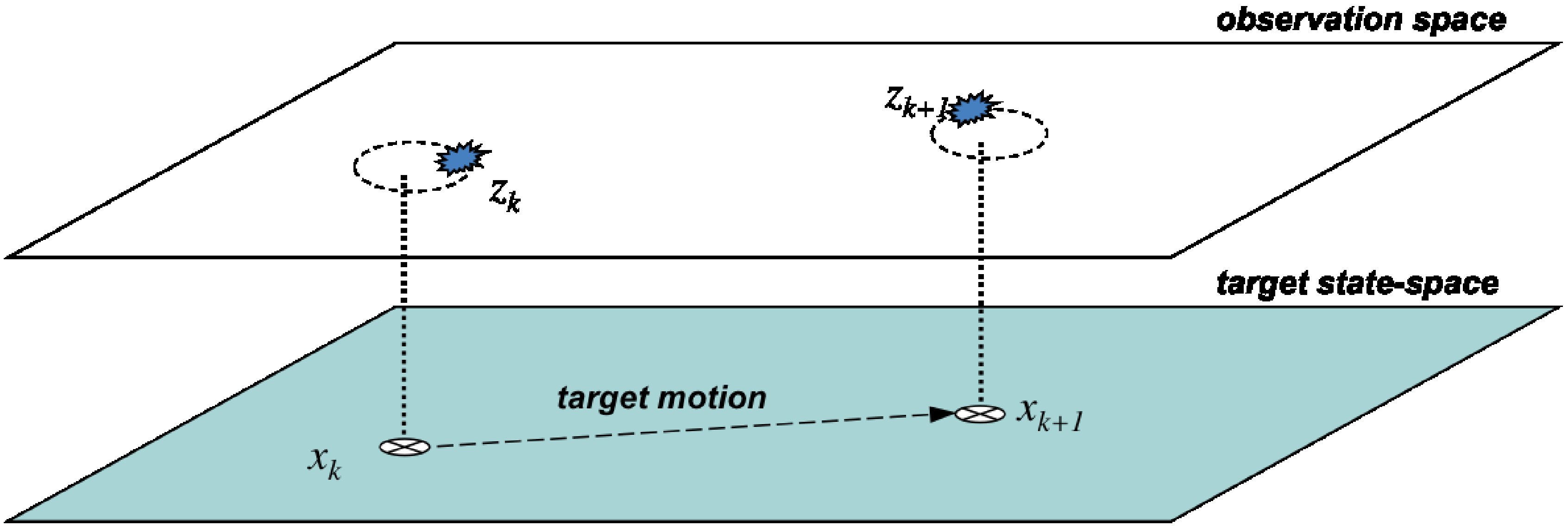

TARGET TRACKING: PREDICTION



Markov transition density

$$p_{k+1|k}(x_{k+1}|z_{1:k}) = \int f_{k+1|k}(x_{k+1}|x)\,p_k(x|z_{1:k})\,dx$$

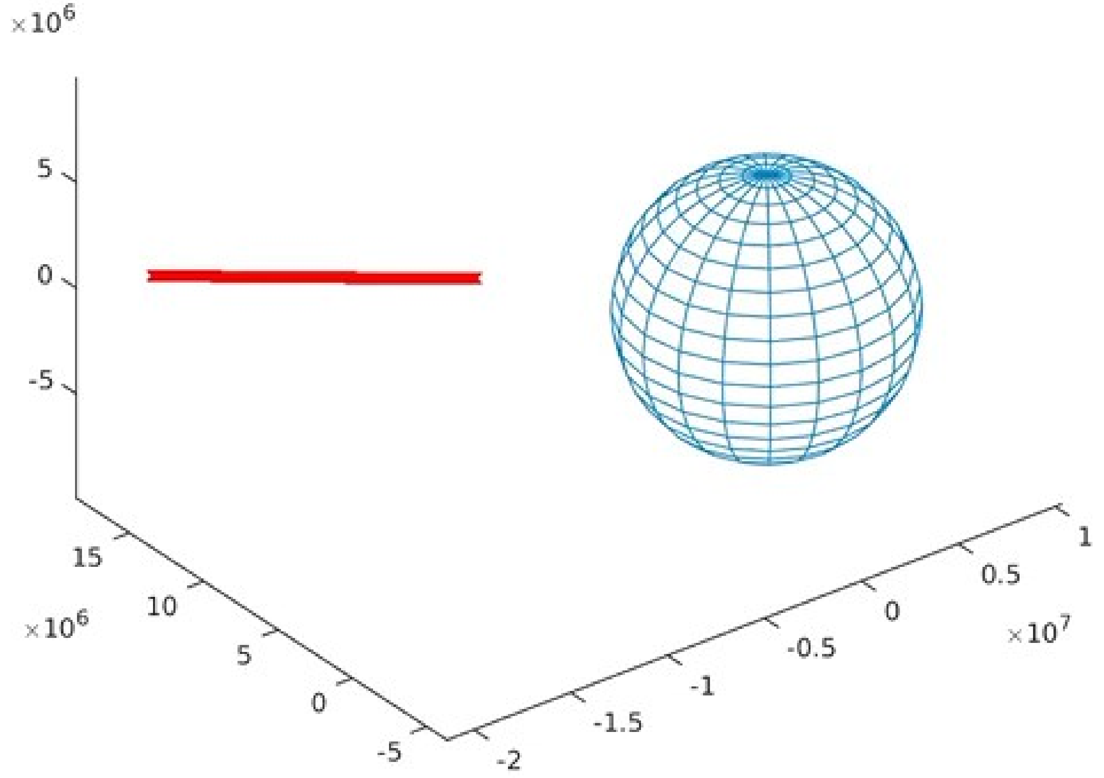
TARGET TRACKING: UPDATE



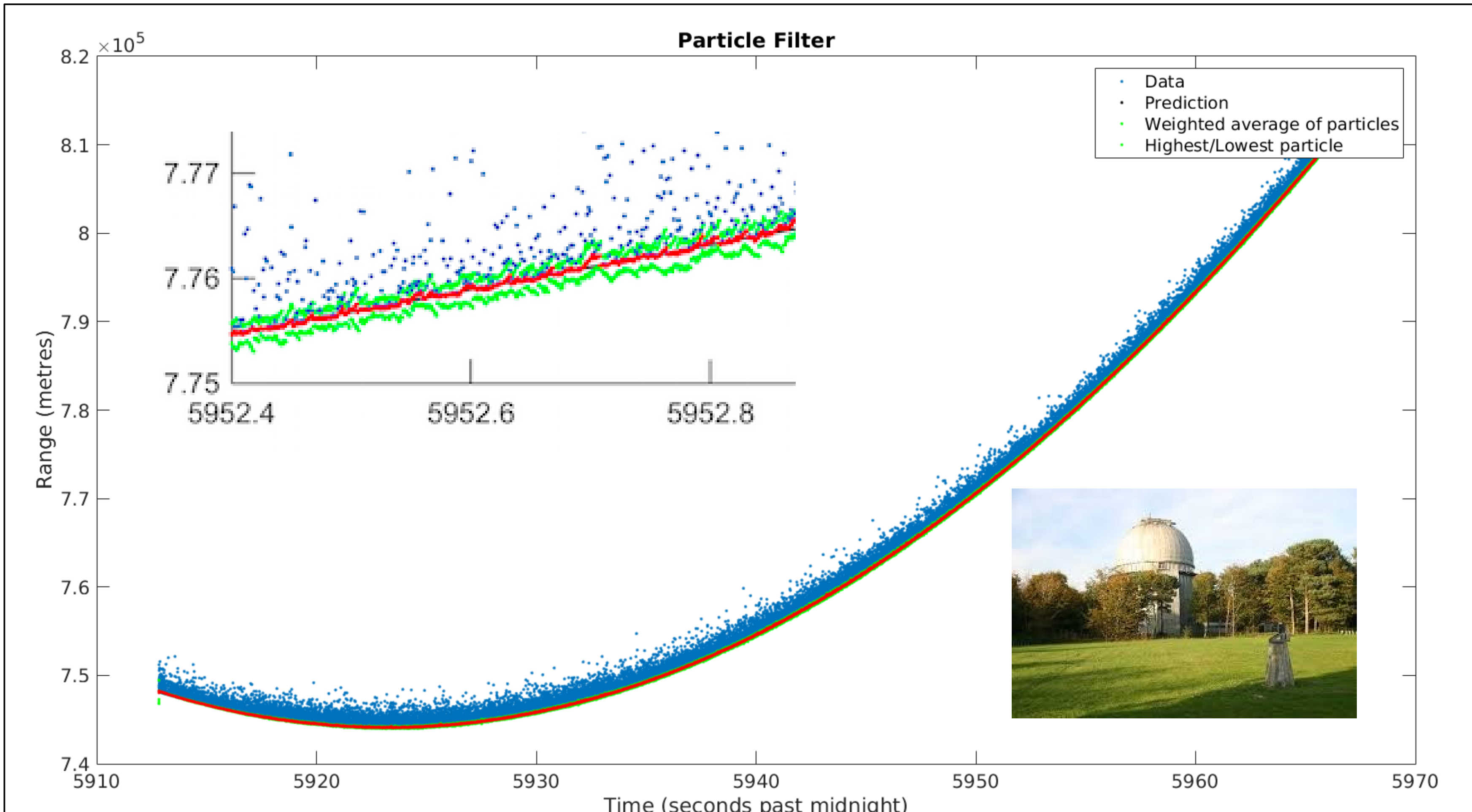
Conditional likelihood

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

TARGET TRACKING: ORBITING OBJECTS



TRACKING A SATELLITE FROM LASER RANGING



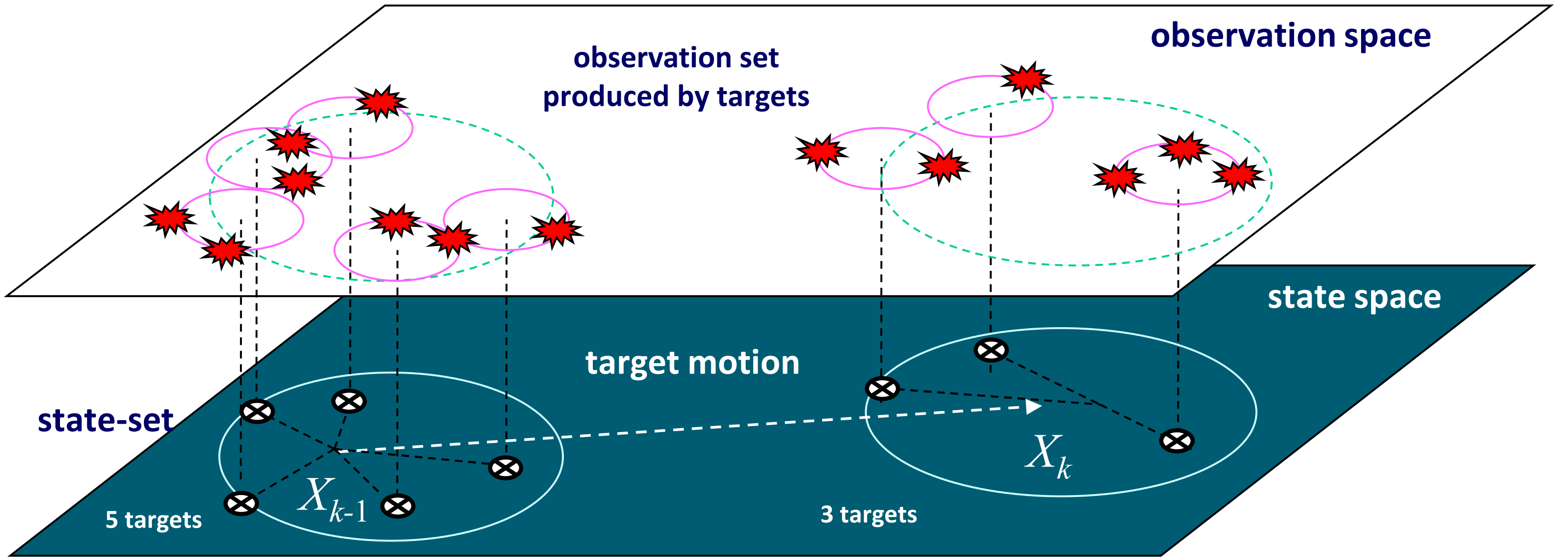
TRACKING FROM WEATHER RADAR

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/

MULTI-OBJECT FILTERING



multi-object Bayes filter

$$\cdots \rightarrow p_{k-1}(\mathbf{X}_{k-1} | \mathbf{Z}_{1:k-1}) \xrightarrow{\text{prediction}} p_{k|k-1}(\mathbf{X}_k | \mathbf{Z}_{1:k-1}) \xrightarrow{\text{data-update}} p_k(\mathbf{X}_k | \mathbf{Z}_{1:k}) \rightarrow \cdots$$

$$\int f_{k|k-1}(\mathbf{X}_k | \mathbf{X}_{k-1})\, p_{k-1}(\mathbf{X}_{k-1} | \mathbf{Z}_{1:k-1})\, \delta\mathbf{X}_{k-1}$$

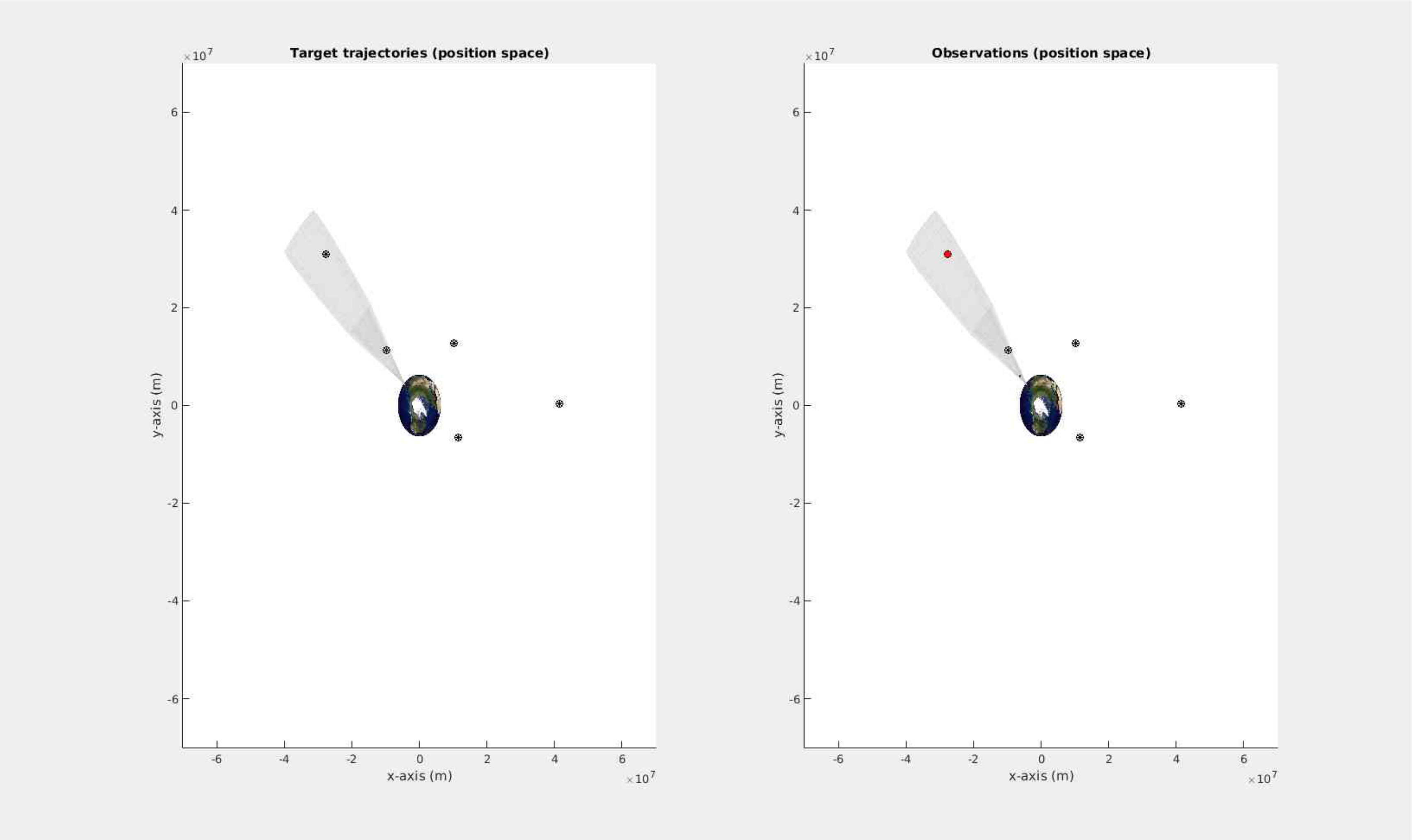
Markov Transition

new observation

$$K^{-1}\, p_{k|k-1}(\mathbf{X}_k | \mathbf{Z}_{1:k-1})\, g_k(\mathbf{Z}_k | \mathbf{X}_k)$$

Likelihood

TRACKING MULTIPLE ORBITING OBJECTS



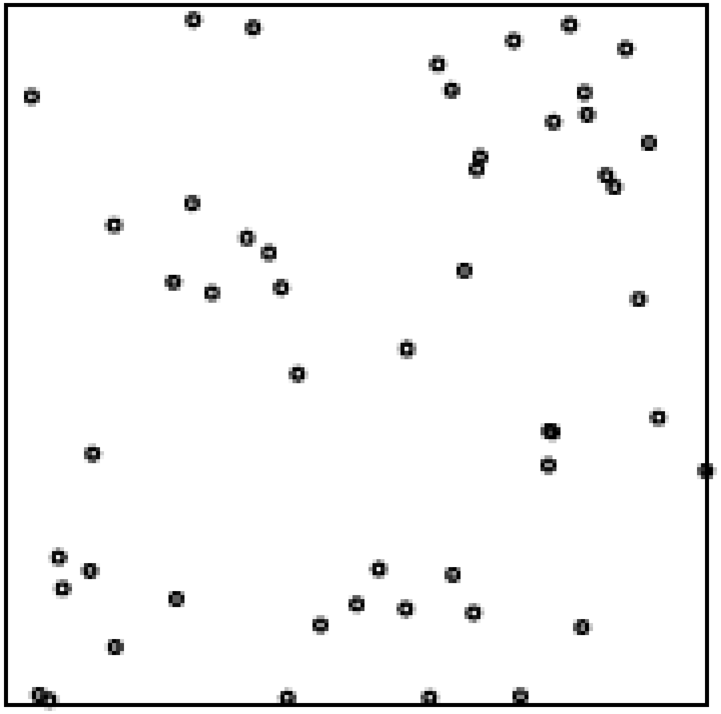
Multi-object modelling

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.)

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

THE GENERAL THEORY OF STOCHASTIC POPULATION PROCESSES

BY

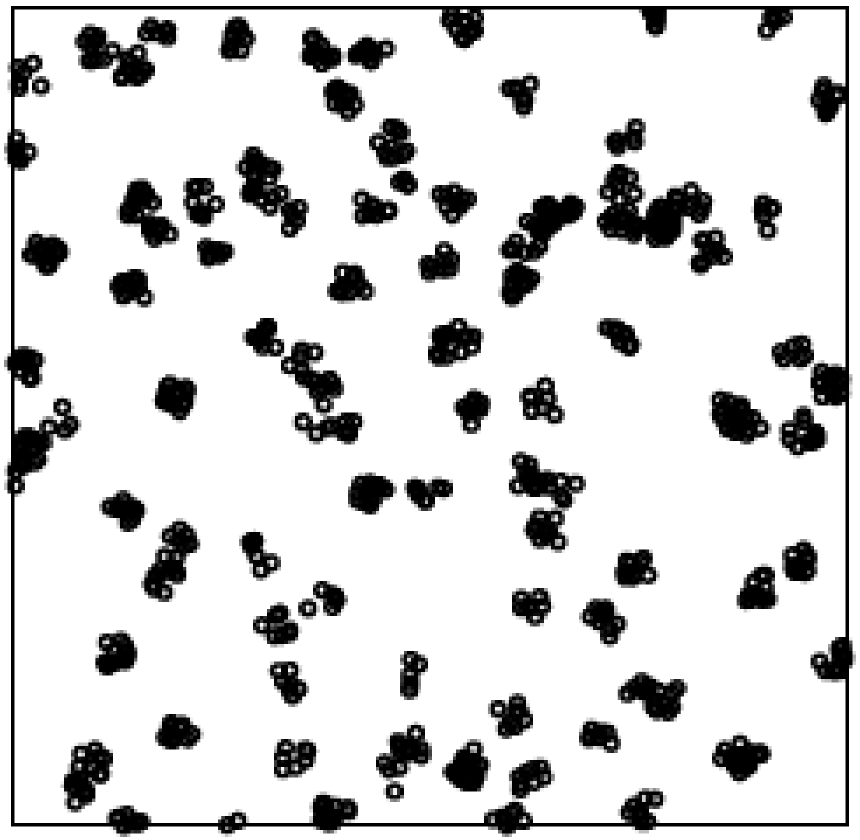
J. E. MOYAL

Australian National University, Canberra, Australia (1)

Point process modelling – Poisson clusters

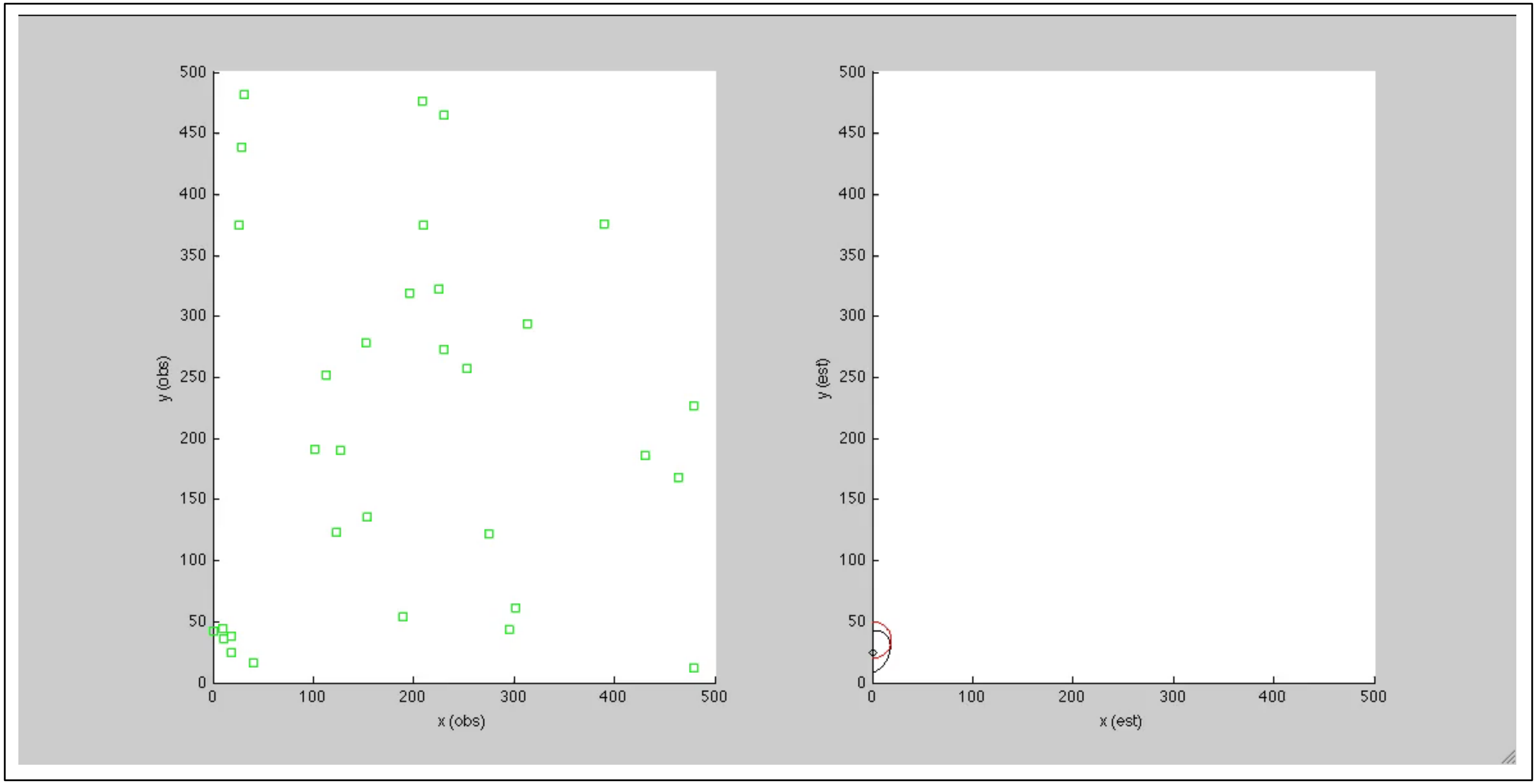
$$G_{\Phi_d}(h) = G_{\Phi_p}\left(G_{\Phi_e}(h|\cdot)\right)$$

Composition of Poisson processes:



Application - tracking groups

SSA context: eg. tracking debris clouds



ROYAL ACADEMY OF ENGINEERING

EPSRC Engineering and Physical Sciences Research Council

Selex ES A Finmeccanica Company

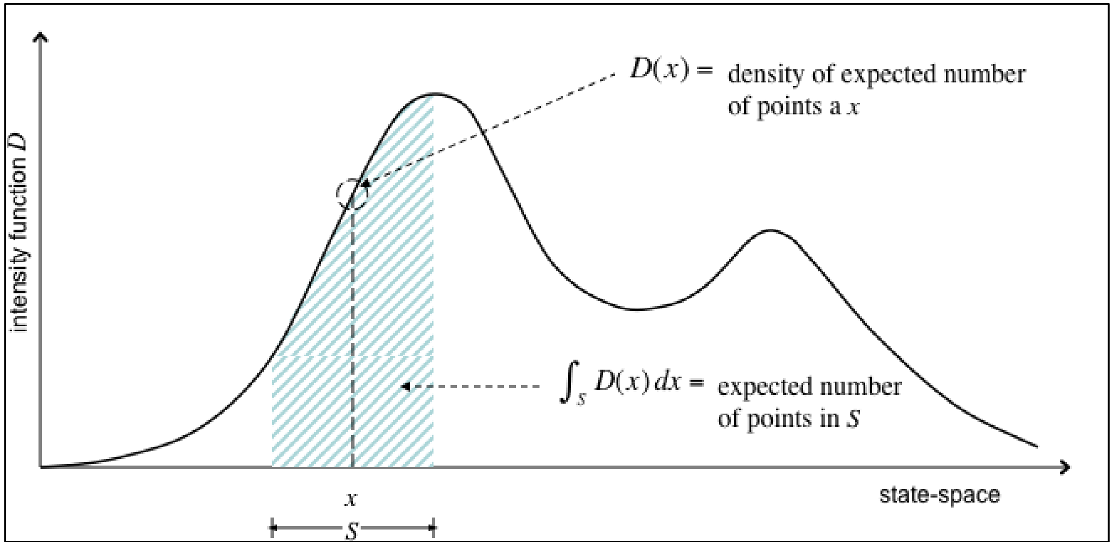
Functional derivatives and the population mean

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

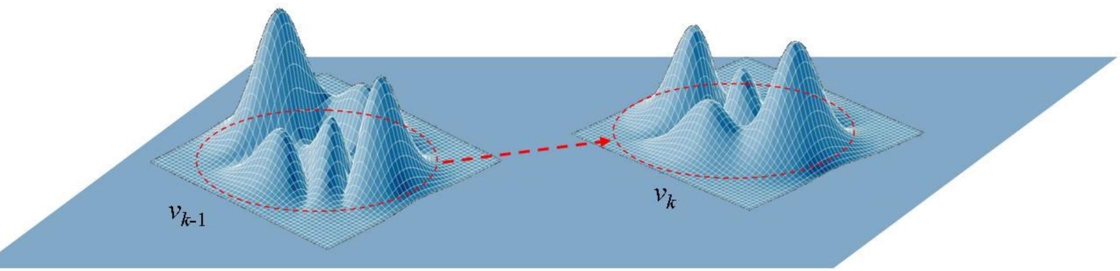
$$\delta f(x;\eta) = \lim_{n\to\infty} \frac{1}{\theta_n}\left(f(x+\theta_n\eta_n) - f(x)\right)$$

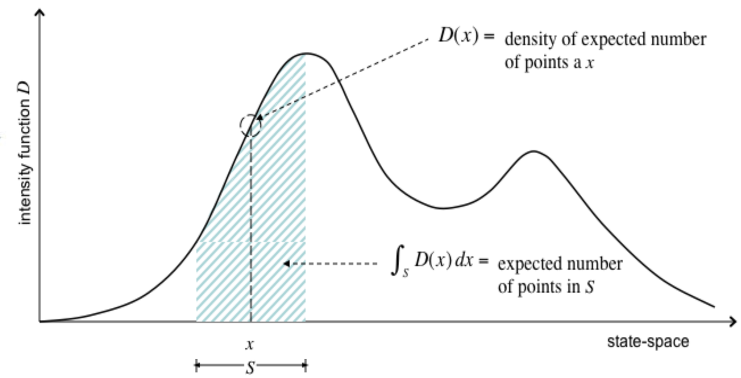
For example, the mean, or intensity, measure is found with

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



THE PHD FILTER





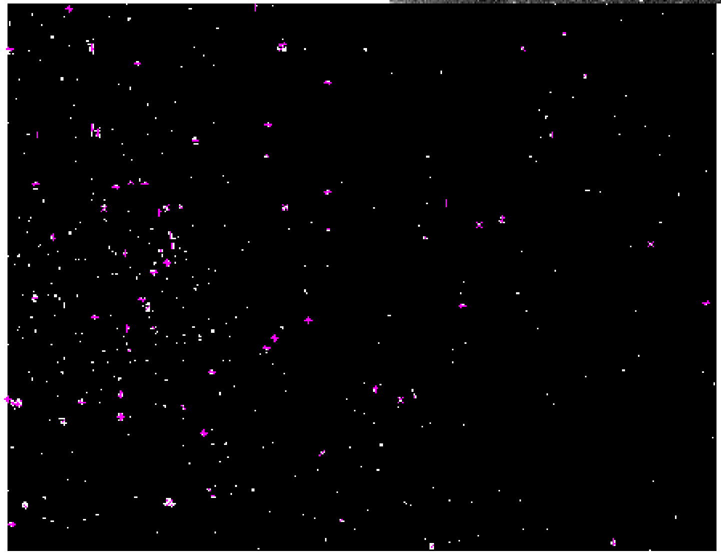
PHD filter [Mahler 03]

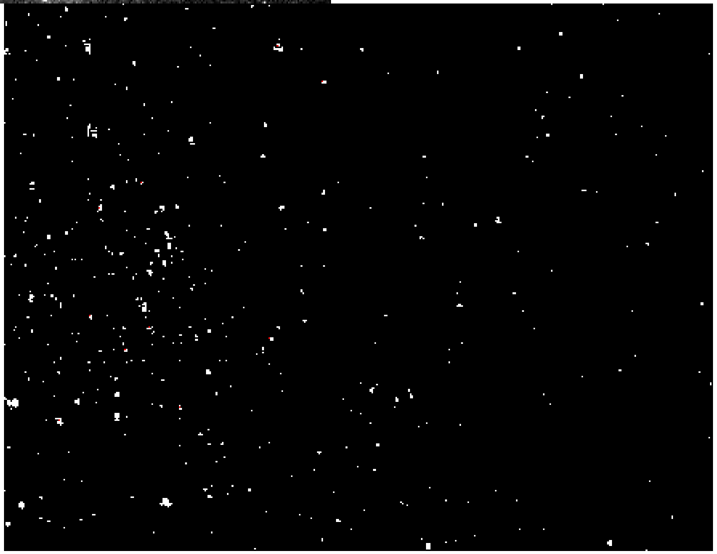
$$\cdots \rightarrow v_{k-1|k-1}(x_{k-1}|Z_{1:k-1}) \xrightarrow[\text{prediction}]{\text{PHD}} v_{k|k-1}(x_k|Z_{1:k-1}) \xrightarrow[\text{update}]{\text{PHD}} v_{k|k}(x_k|Z_{1:k}) \rightarrow \cdots$$

$$\cdots \rightarrow p_{k-1|k-1}(X_{k-1}|Z_{1:k-1}) \xrightarrow{\text{prediction}} p_{k|k-1}(X_k|Z_{1:k-1}) \xrightarrow{\text{update}} p_{k|k}(X_k|Z_{1:k}) \rightarrow \cdots$$

Multi-target Bayes filter

TRACKING FROM TELESCOPE DATA





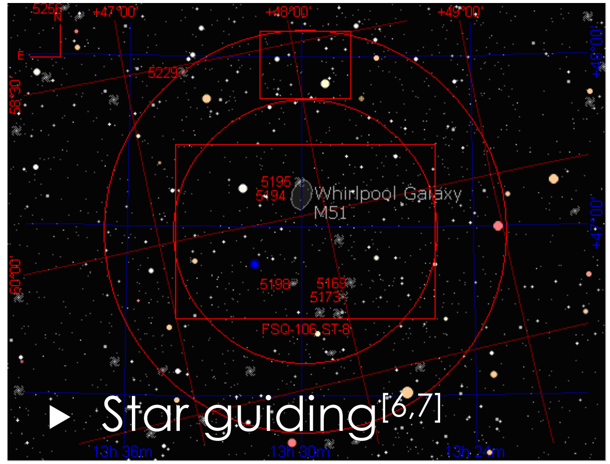
JOINT SENSOR DRIFT AND OBJECT ESTIMATION

- To *detect* and *track* observed objects
- To *classify* objects in the scene (eg. stars vs satellites)
- To *estimate and compensate for telescope drift*

TELESCOPE DRIFT

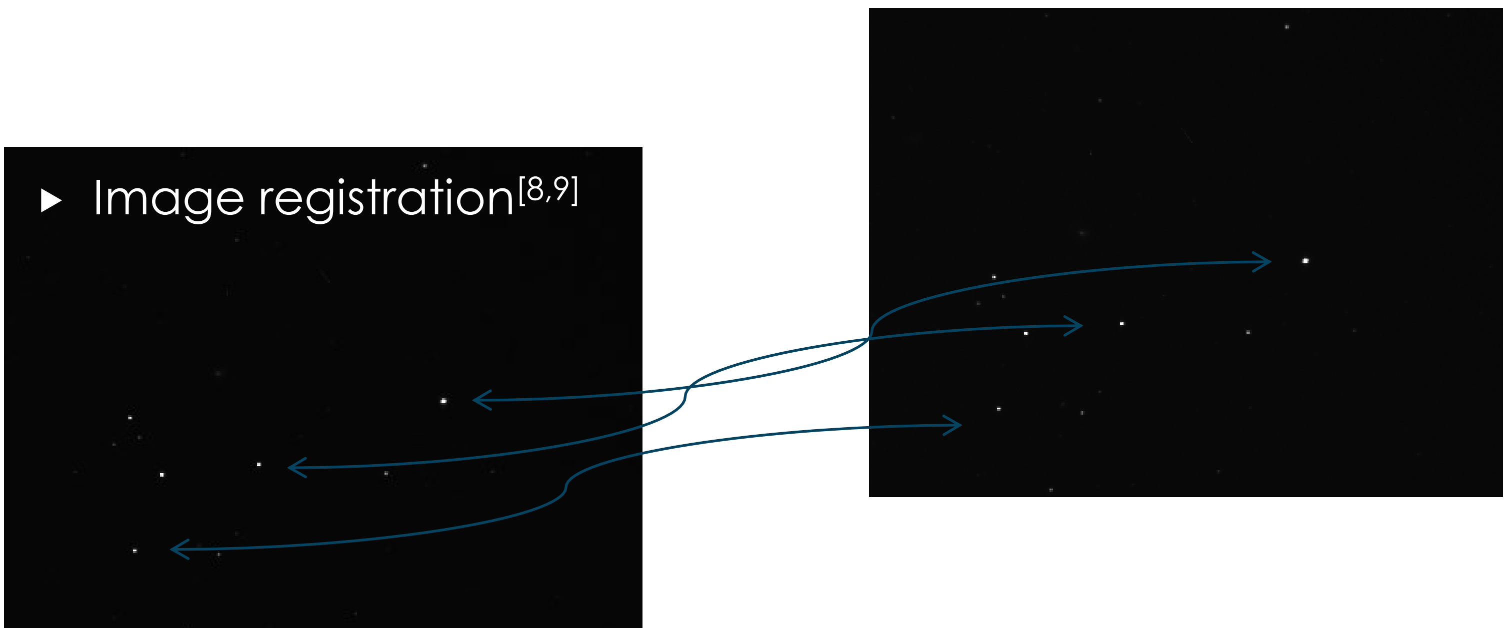
- Mechanical imperfections of the mount
- Diurnal motion of the stars (in case of the static mount)
- Basic jitter due to the wind or unstable earth

CURRENT SOLUTIONS



- Star guiding[6,7]

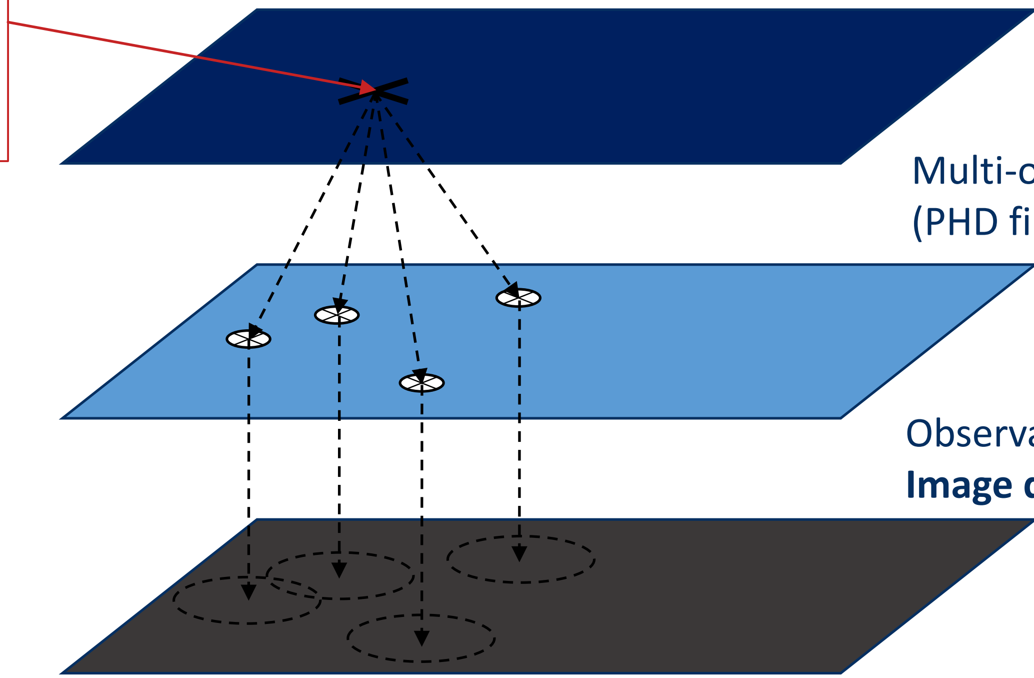
- Image registration[8,9]



SENSOR STATE ESTIMATION

- Joint sensor estimation and multi-target tracking[18]:
  - *Parent process* – telescope motion
  - *Daughter process* – objects motion
- Particle filter for sequential estimation of telescope position

Every particle is a **hypothesis of a telescope position** with linked **multi-target estimation** and **weight**



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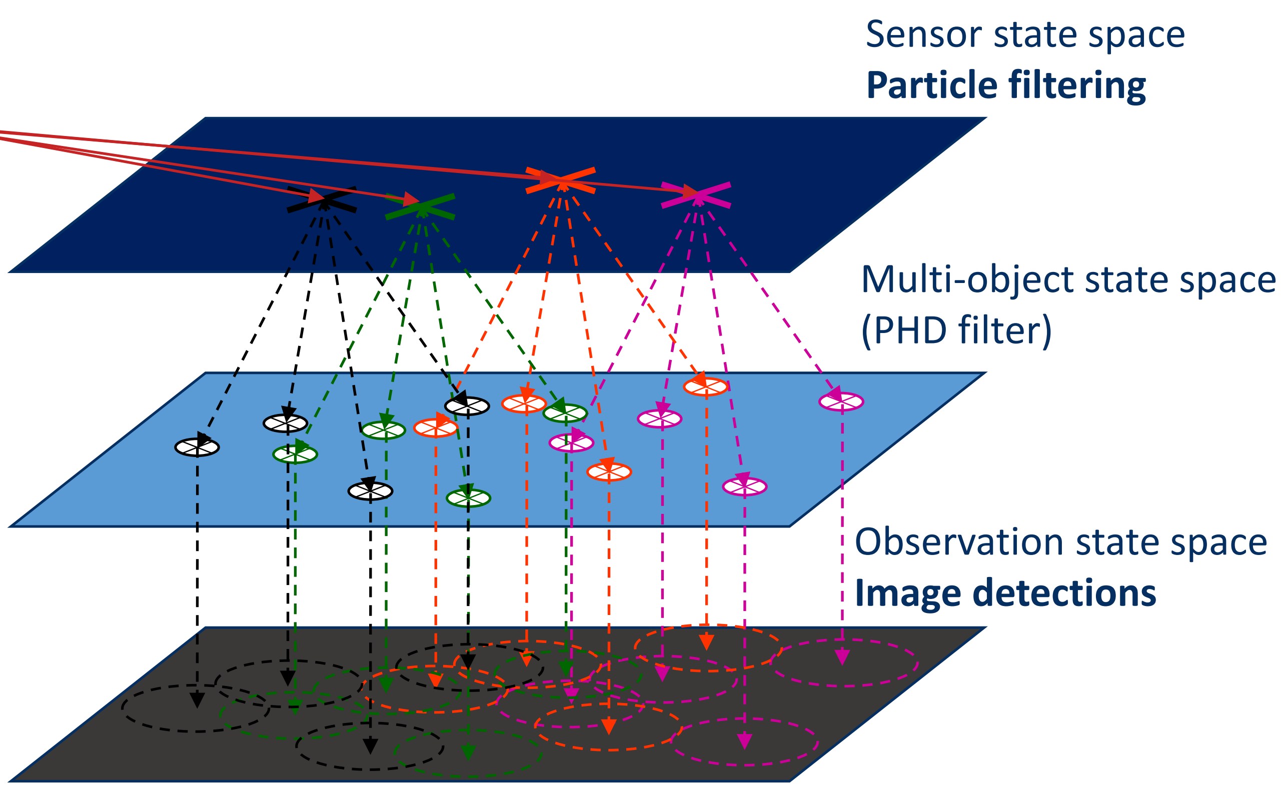


- Weight is assigned to the particles according *to the likelihood of the observations*, given sensor state estimate.

SENSOR STATE ESTIMATION

- Every particle corresponds to:
  - Sensor state estimate *(relative position of the telescope)*
  - Multi-target state for objects (linear motion model)
  - Multi-target state for stars (static)

$$p(\mathbf{X}_k, \mathbf{y}_k | \mathbf{Z}_{1:k}) = p(\mathbf{X}_k | \mathbf{Z}_{1:k}, \mathbf{y}_k)\, p(\mathbf{y}_k | \mathbf{Z}_{1:k})$$

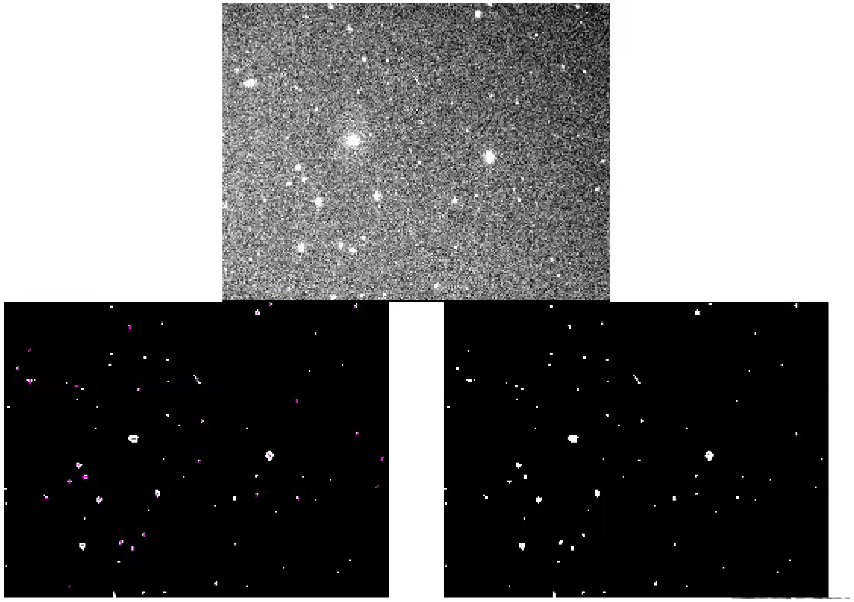
Multi-target filter ↑ (under $p(\mathbf{X}_k | \mathbf{Z}_{1:k}, \mathbf{y}_k)$)

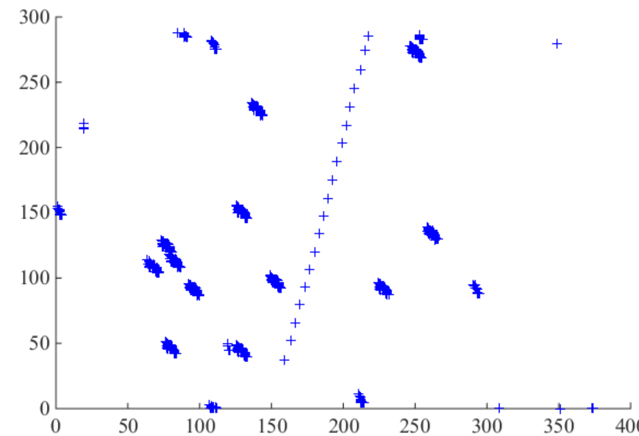
Particle filter ↑ (under $p(\mathbf{y}_k | \mathbf{Z}_{1:k})$)

REAL DATA RESULTS

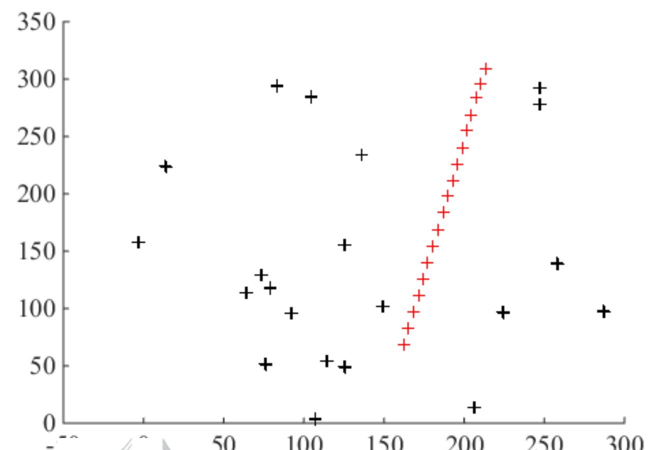
(NEO 2007HA during its close passage to the Earth).

Joint estimation of telescope drift and object tracking





NEO 2007HA during its close passage



Joint Estimation of Telescope Drift and Space Object Tracking

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

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