Attitude Estimation of Inactive Resident Space Objects from Photometric Measurements Using Particle Filtering

Clean Space Days 2024

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uc3m PHD

gmv INNOVATING SOLUTIONS

40TH

Excellence and beyond

FOUR DECADES **PUSHING THE LIMITS**

Agenda

- Introduction
- Attitude estimation from photometric measurements
- Particle filtering methods for attitude estimation
- Results
  - ✓ Case 1: unimodal posterior PDF
  - ✓ Case 2: multimodal posterior PDF
- Conclusions and future work

Introduction

Introduction

- **Resident Space Objects (RSOs) characterisation**
  - New Space era ⟶ space traffic ↑ space debris ↑
  - Mitigate the proliferation of space debris
  - Holistic characterisation of RSOs
  - Estimate size, shape, materials, rotation, attitude...
  - Use ground-based sensors (telescopes, radars) for observations

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- **Applications in the context of SST & SEP**
  - Mission analysis and design
    - Active Debris Removal (ADR)
    - In-Orbit Servicing (IOS)
  - Address uncontrolled re-entries
  - Verify contingency attitude modes

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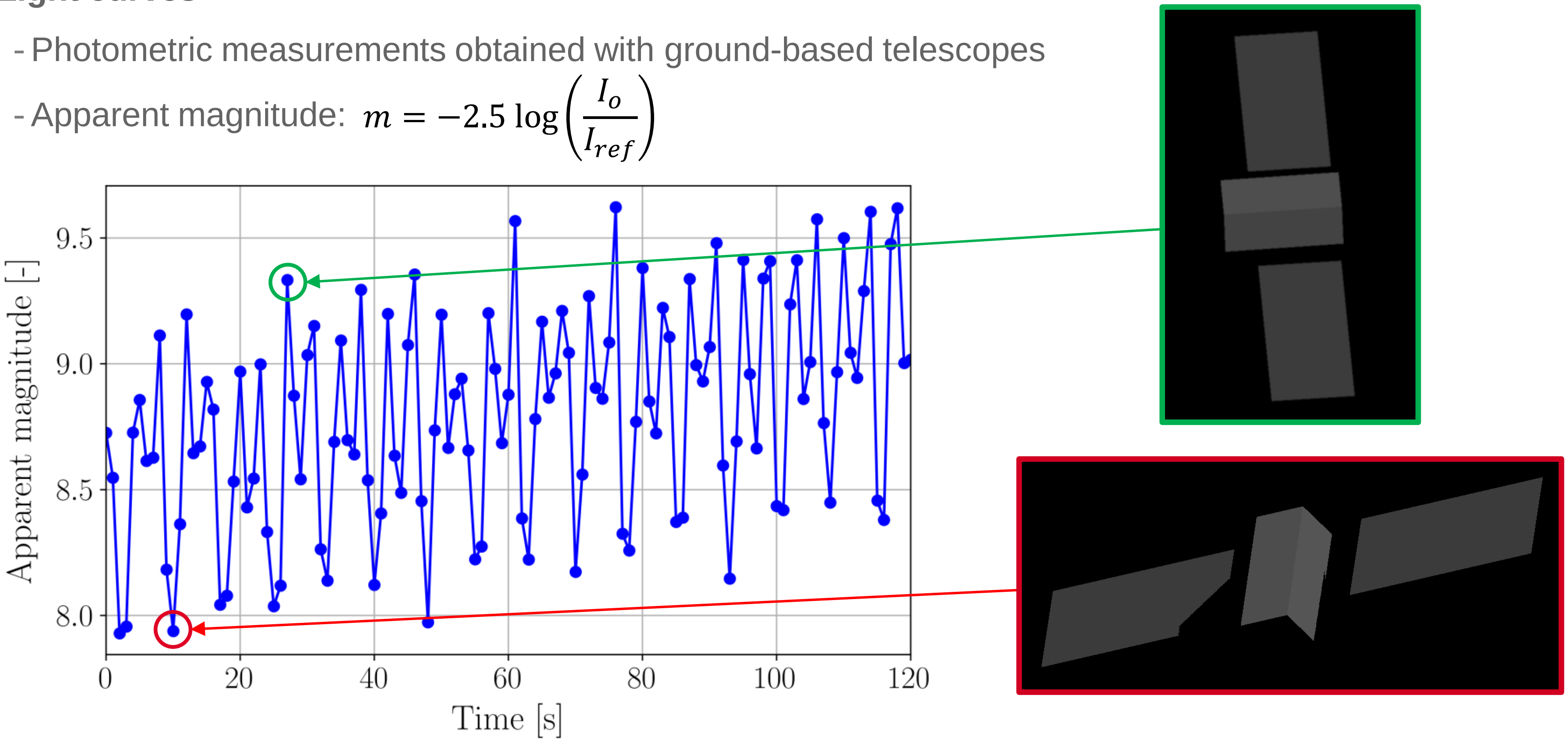
Attitude estimation from photometric measurements

Attitude estimation from photometric measurements

- **Light curves**
  - Photometric measurements obtained with ground-based telescopes
  - Apparent magnitude: $m = -2.5 \log\left(\frac{I_o}{I_{ref}}\right)$



Attitude estimation from photometric measurements

- **Typical assumptions in light curve inversion for attitude estimation**
  - Knowledge of the RSO’s shape, size and surface optical properties
  - Knowledge of the Aerosol Optical Depth (AOD)
- **Challenges of the light curve inversion problem**
  - Ambiguities in measurements
  - Nonlinear measurement model
- **GMV’s previous experience**
  - Least Squared Method (LSM)
  - Unscented Kalman Filter (UKF)
    - Reliance on an initial estimate
    - Tendency to converge to local minima

Particle filtering methods for attitude estimation

Particle filtering methods for attitude estimation

Particle filter

- Approximate Bayesian estimator that represents probability densities using a weighted set of samples
- It effectively handles multimodal probability density functions (PDFs)

Formulation

- The posterior PDF at time k is approximated by:

$$p(\boldsymbol{x}_k|\boldsymbol{z}_{1:k}) \approx \sum_{i=1}^{N_s} w_k^i \delta(\boldsymbol{x}_k - \boldsymbol{x}_k^i)$$

- Principle of importance sampling $\longrightarrow$ weights. Samples are drawn from a proposal density q.

$$w_k^i \propto w_{k-1}^i \frac{p(\boldsymbol{z}_k|\boldsymbol{x}_k^i)p(\boldsymbol{x}_k^i|\boldsymbol{x}_{k-1}^i)}{q(\boldsymbol{x}_k^i|\boldsymbol{x}_{k-1}^i, \boldsymbol{z}_k)}$$

- If the importance density is chosen to be the prior:

$$q(\boldsymbol{x}_k^i|\boldsymbol{x}_{k-1}^i, \boldsymbol{z}_k) = p(\boldsymbol{x}_k^i|\boldsymbol{x}_{k-1}^i) \longrightarrow w_k^i \propto w_{k-1}^i p(\boldsymbol{z}_k|\boldsymbol{x}_k^i)$$

Particle filtering methods for attitude estimation

- **Generic particle filter**
  - Sequential Importance Sampling (SIS) algorithm + Resampling

Draw samples from q

↓

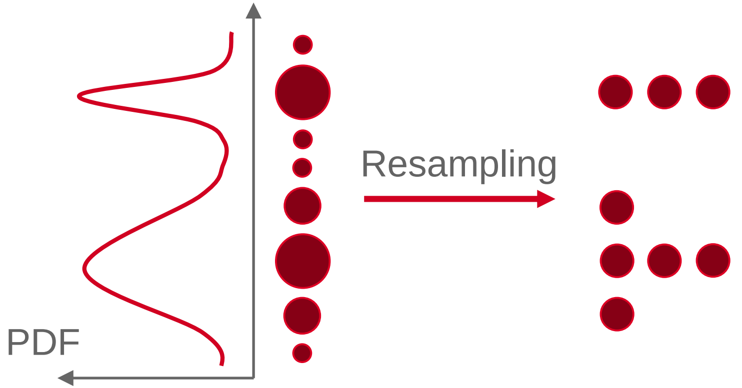
Update particle weights

↓

Resampling

SIS

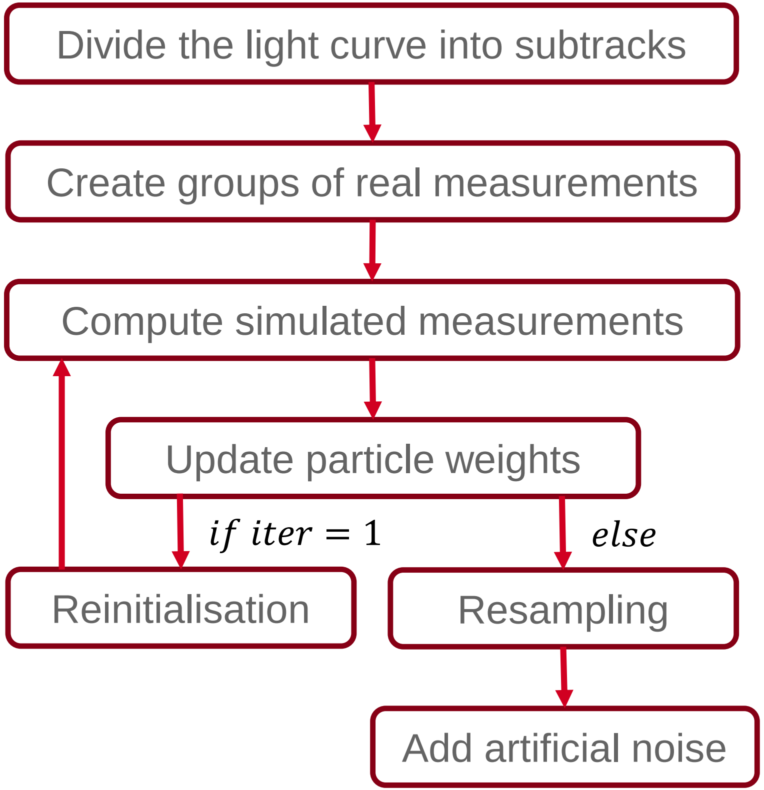
Resampling avoids the **degeneracy problem**…



…but may produce **sample impoverishment**

Particle filtering methods for attitude estimation

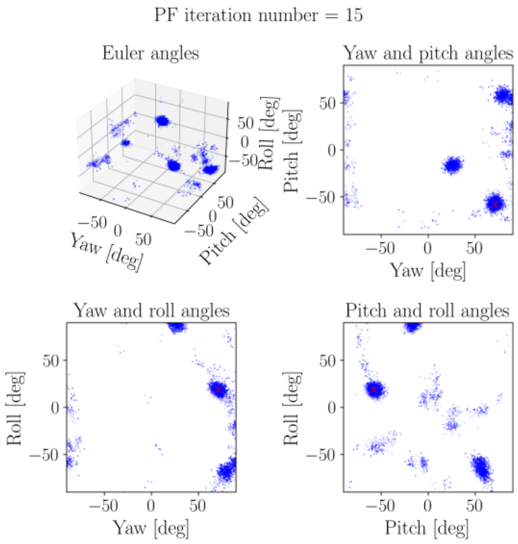
- **Developed particle filter**
  - Estimates the attitude of the RSO at a specific time
  - **Pseudo-batch algorithm**
    - Selects measurements from light curve subtracks
    - Updates particle weights according to the RMSE
    - Advantage: reduces the occurrence of local minima
  - **Reinitialisation** in the first iteration
    - Moves particles with higher RMSE to regions of higher probability
    - Recomputes the weights of the new particles
    - Advantage: refines the initial posterior PDF



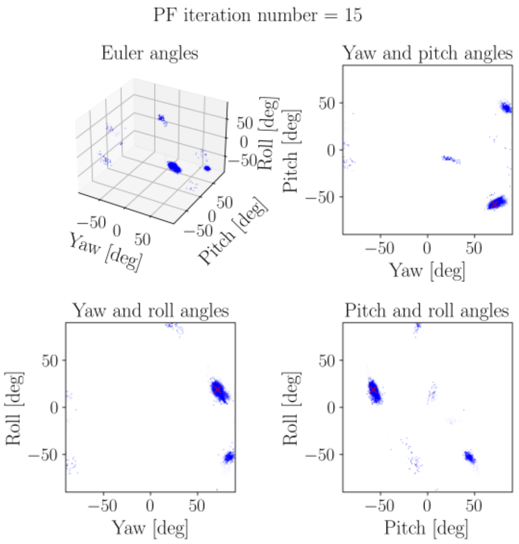
Particle filtering methods for attitude estimation

- **Generic vs. developed particle filters**

Generic (sequential) PF



Pseudo-batch PF



Advantages

Less local minima

Higher accuracy

Better computational performance

Noisy real measurements

Very high flexibility

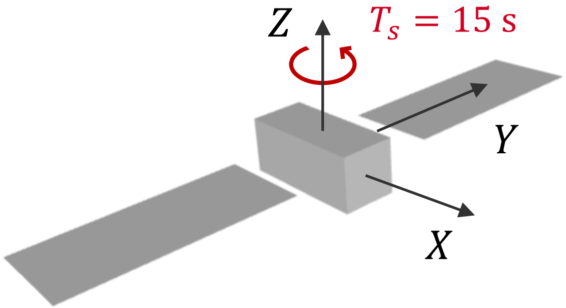
Particle filtering methods for attitude estimation

- **High-fidelity simulator of photometric observations**
  - GMV's ***Grial*** tool, implemented in Java using OpenGL.
  - Calculates contributions to reflected light from each illuminated and visible pixel on a 3D shape and aggregates these contributions
  - Bidirectional Reflectance Distribution Functions (BRDFs)
    - Cook and Torrance (specular reflection)
    - Lommel-Seeliger (diffuse reflection)
- **Post-processing of the posterior PDF**
  - Cluster analysis to identify the modes of the resulting posterior PDF
  - Clustering algorithm: Density-Based Spatial Clustering of Applications with Noise (DBSCAN)
  - Analysis of PDF modes to identify the most probable attitude

Results

Previous considerations

- **General considerations**
  - Estimate the initial attitude of an RSO from simulated observations
  - Assume that the RSO's shape, size and surface optical properties, as well as the AOD, are known
  - Assume that the uncontrolled RSO follows a spinning attitude law over the tracking duration
  - Spinning attitude law parameters: RSO's orientation, spin rotation axis and spin angular velocity
  - Additional assumptions:
    - Spin angular velocity can be estimated using a period-finding method (e.g. Lomb-Scargle periodogram)
    - In the long-term, the RSO eventually rotates about its principal axis of maximum inertia (flat spin)
- **RSO model properties**
  - Low Earth Orbit (LEO) at an altitude of 2000 km
  - Satellite's platform optical properties: $K_d = 0.15$, $K_s = 0.7$
  - Solar array optical properties: $K_d = 0$, $K_s = 0.1$

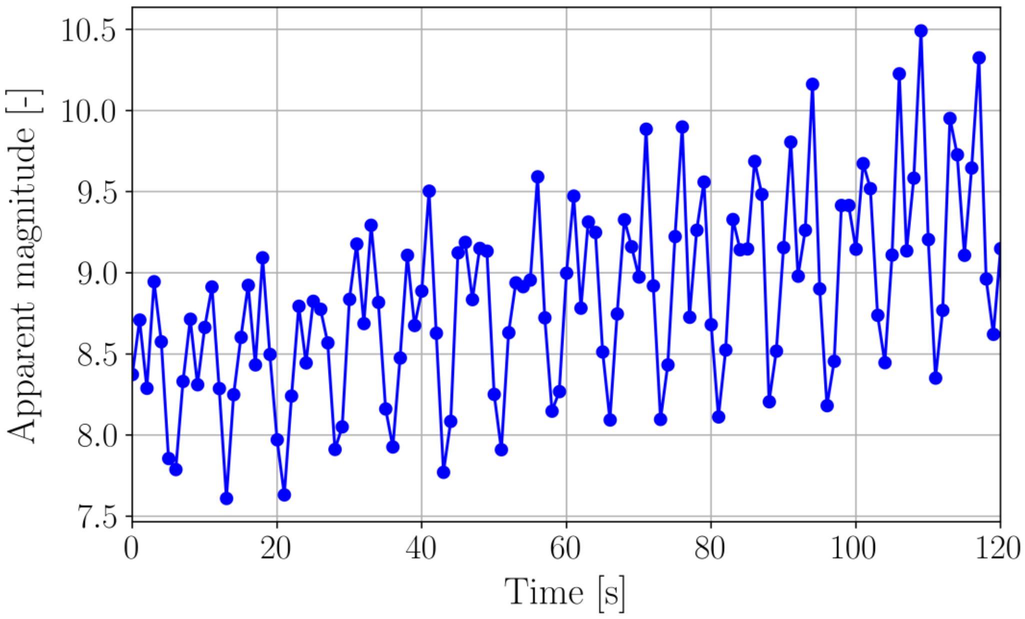


Results

- **Case 1: unimodal posterior PDF**

Results. Case 1: unimodal posterior PDF

- Case 1: light curve

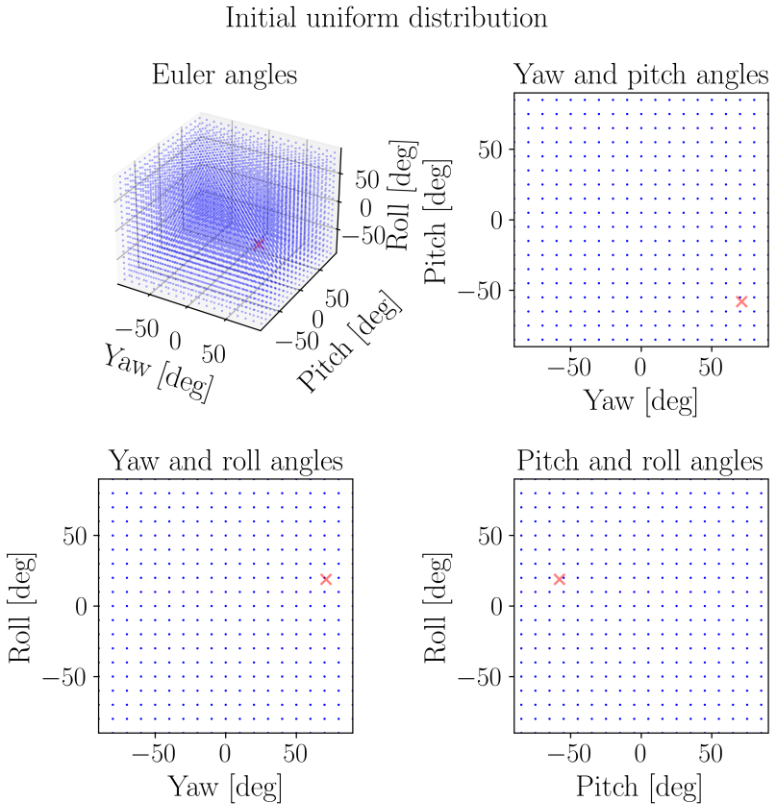


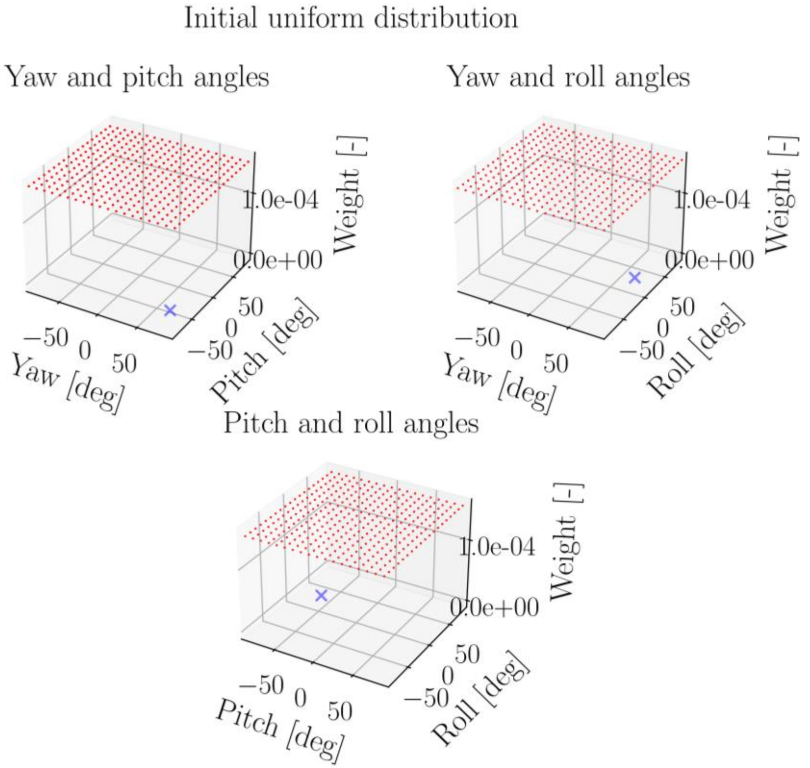
Attitude: $\boldsymbol{x}_0 = [71,\ -58,\ 19]\,\mathrm{deg}$

Sensor noise: $\sigma = 0.1$

Results. Case 1: unimodal posterior PDF

- **Case 1: particle filter execution**





Results. Case 1: unimodal posterior PDF

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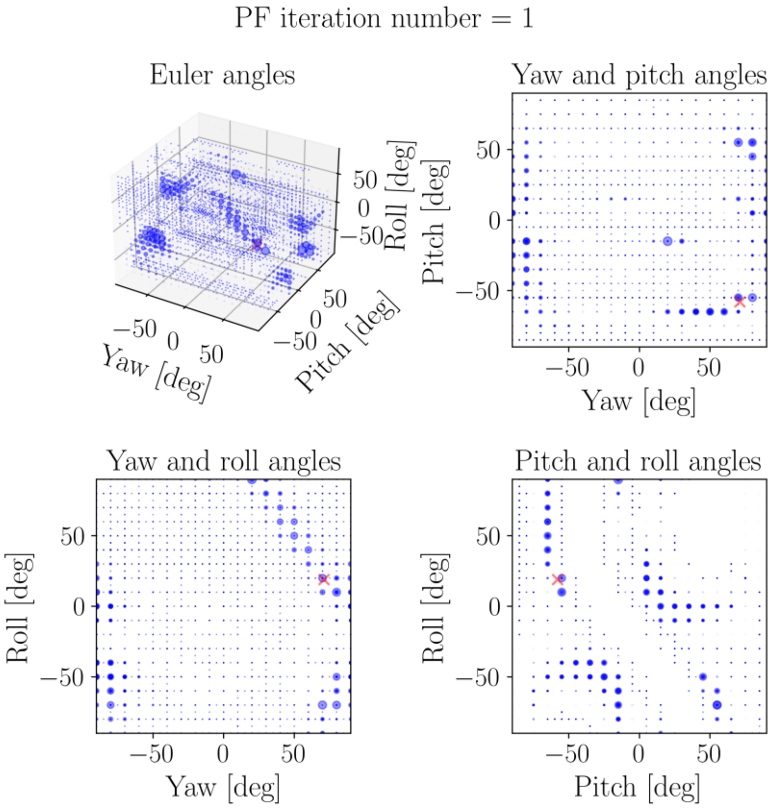

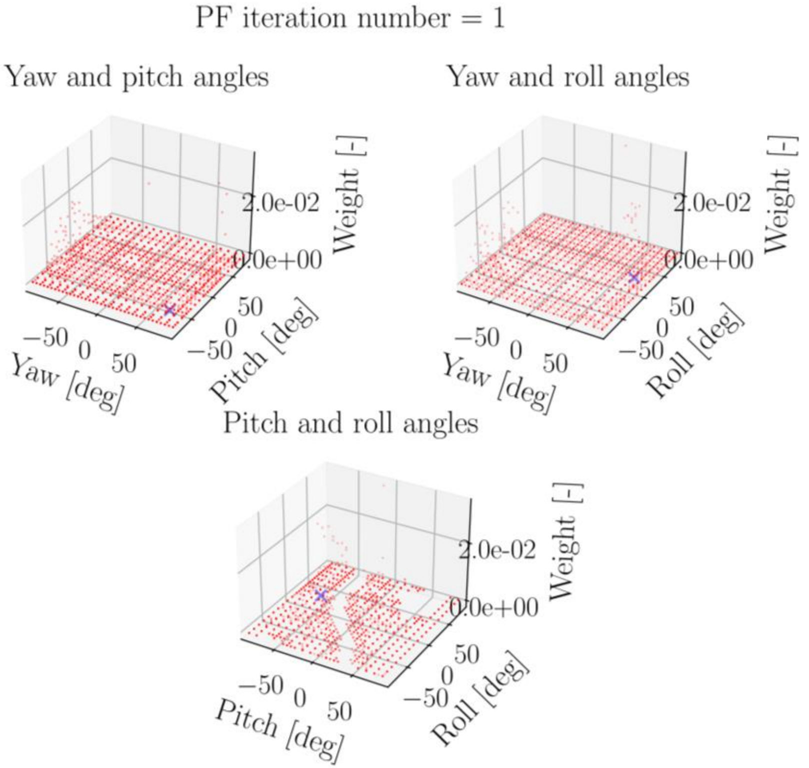

Results. Case 1: unimodal posterior PDF

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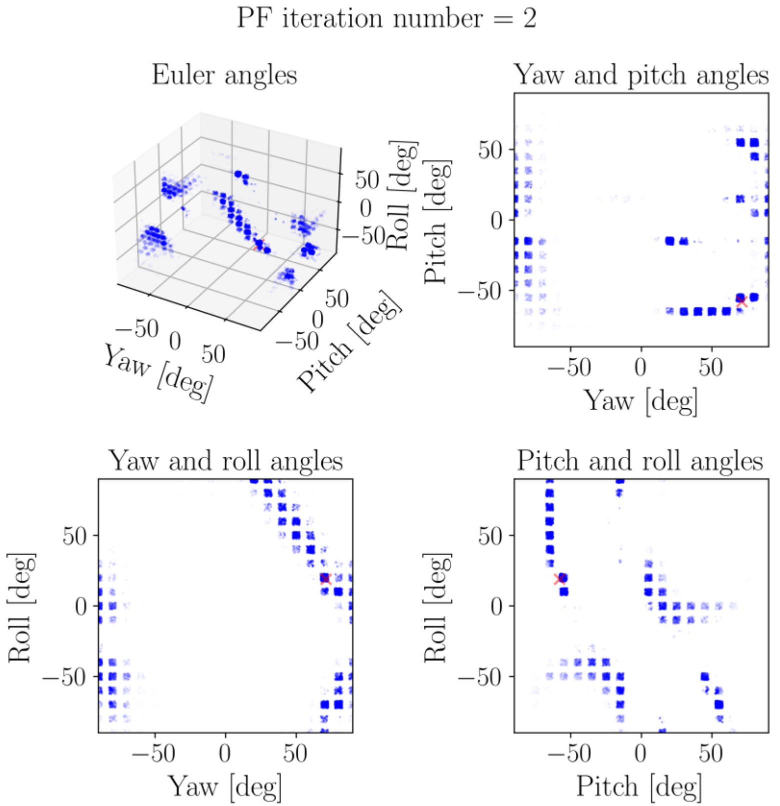

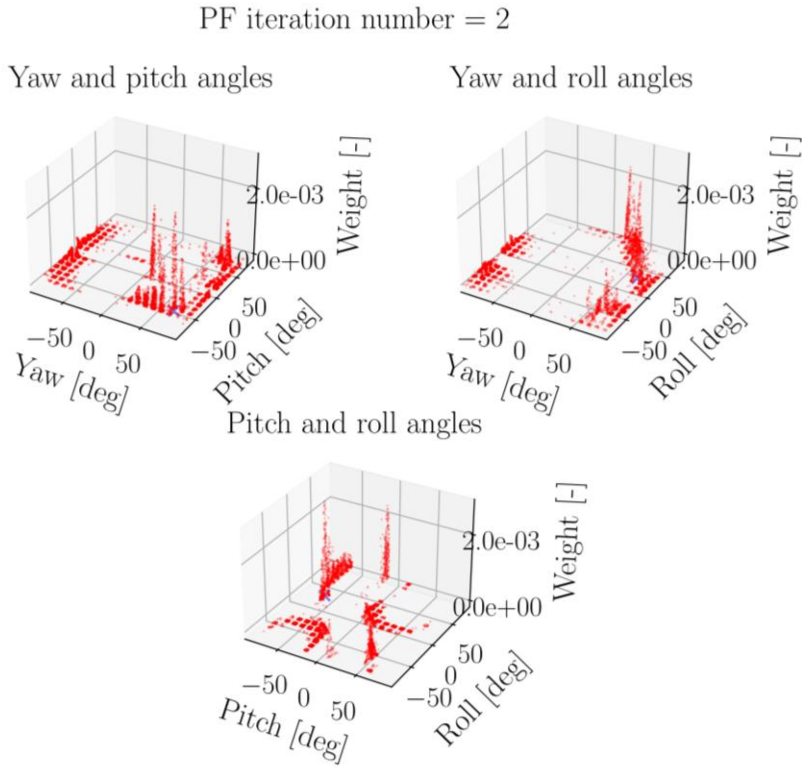

Results. Case 1: unimodal posterior PDF

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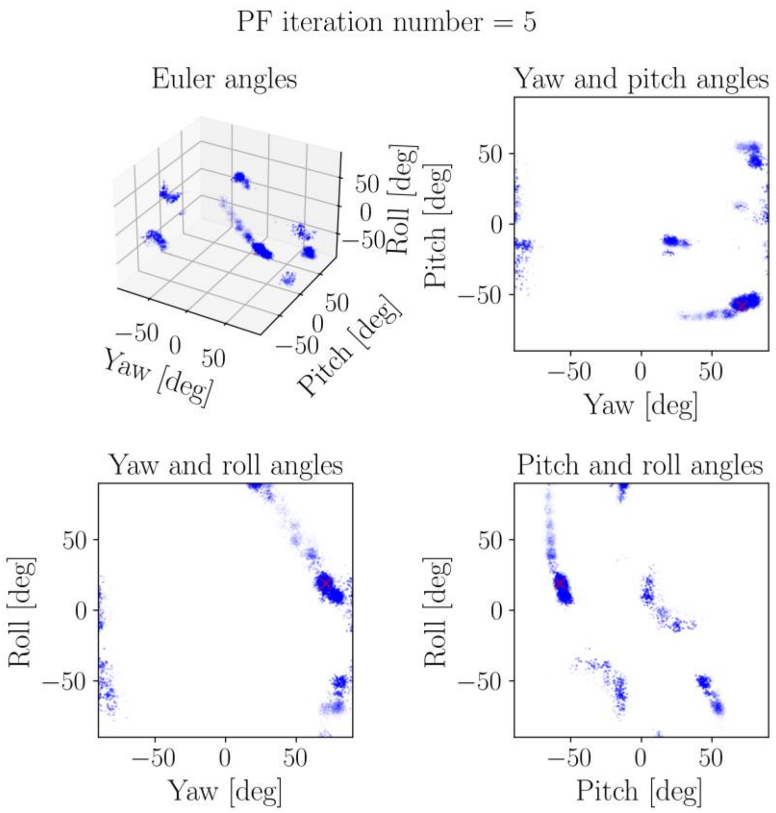

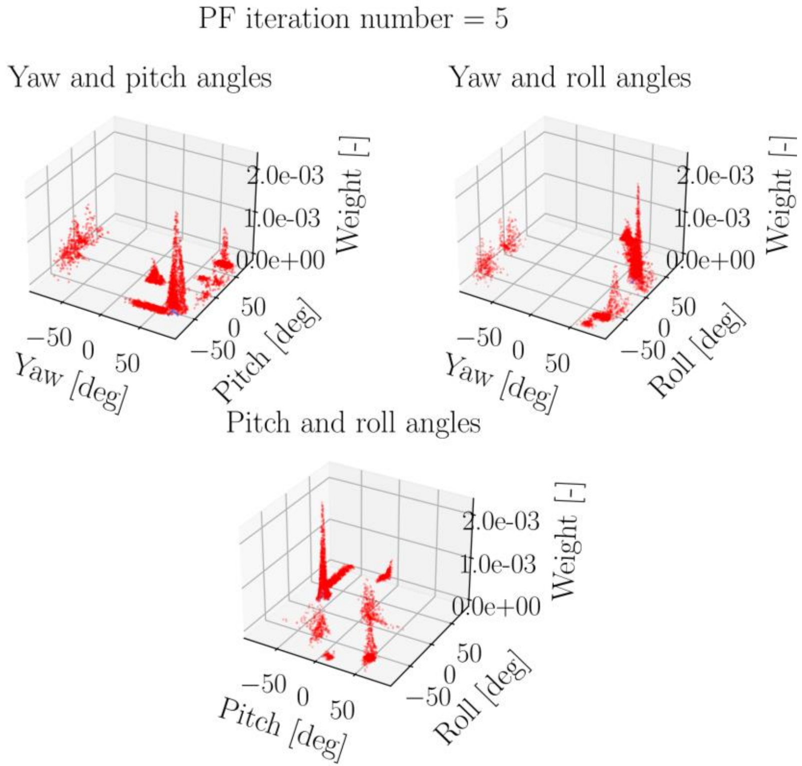

Results. Case 1: unimodal posterior PDF

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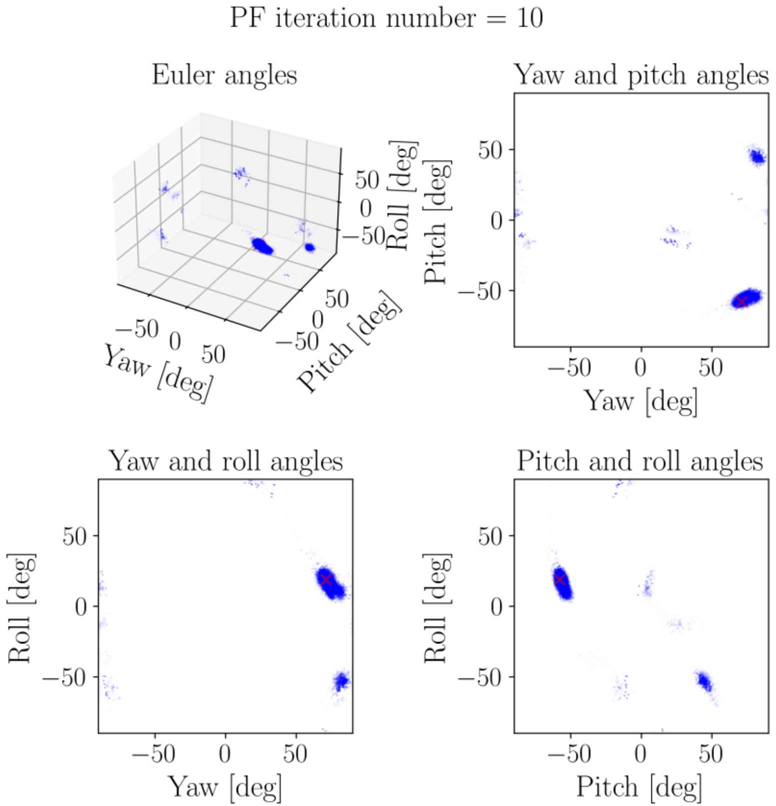

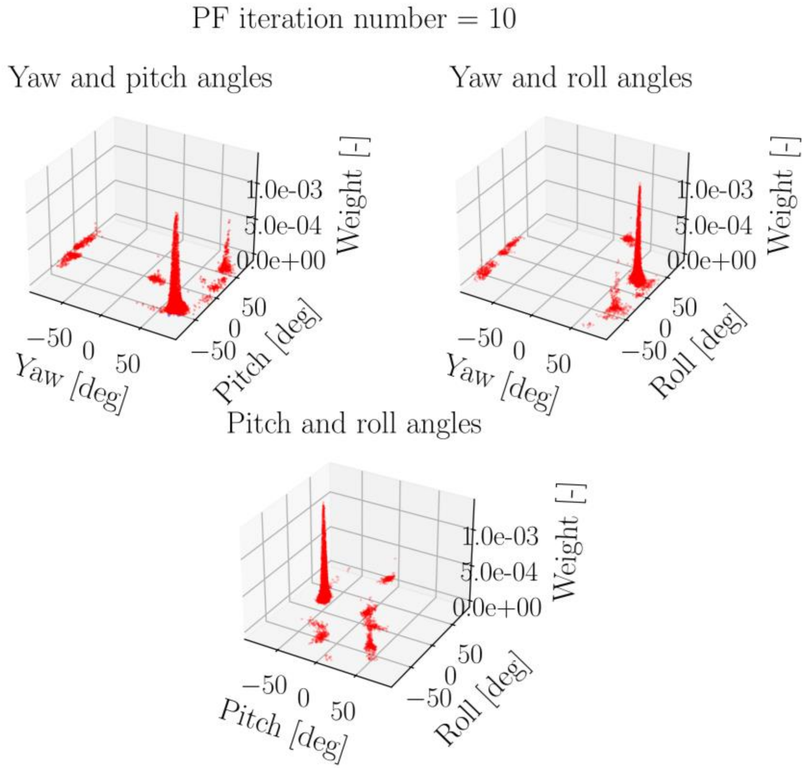

Results. Case 1: unimodal posterior PDF

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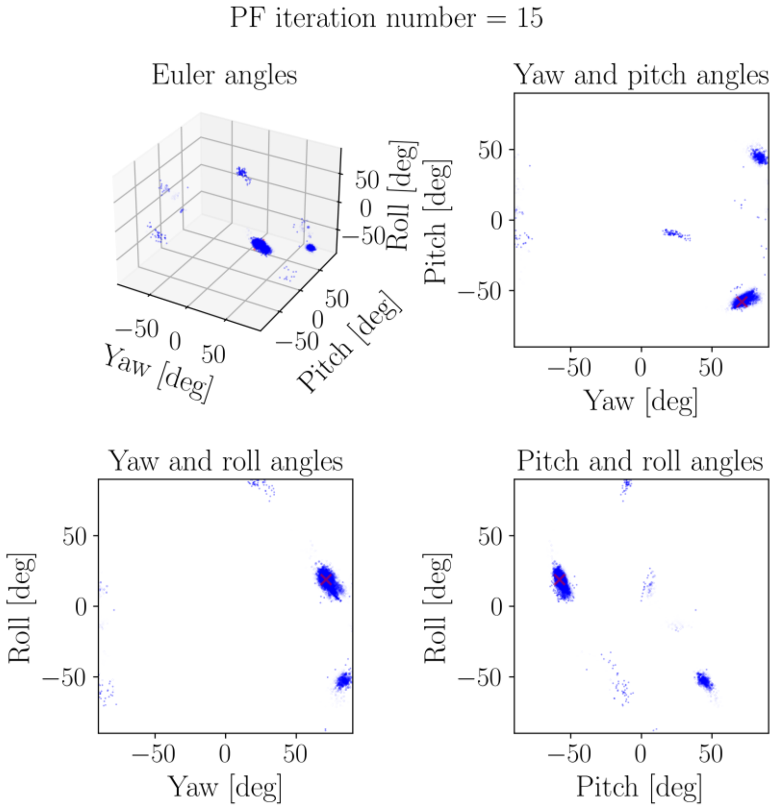
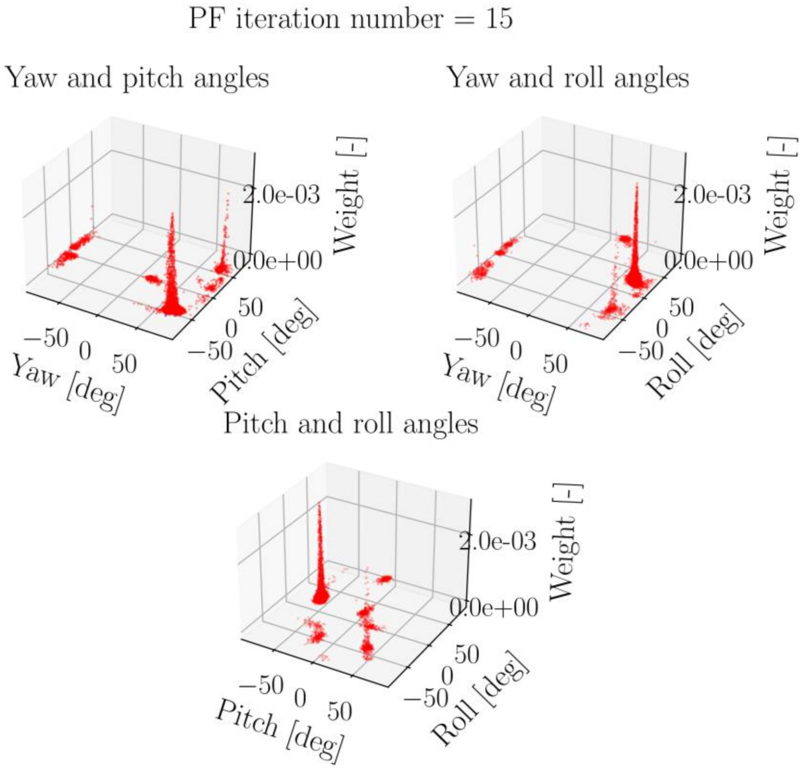
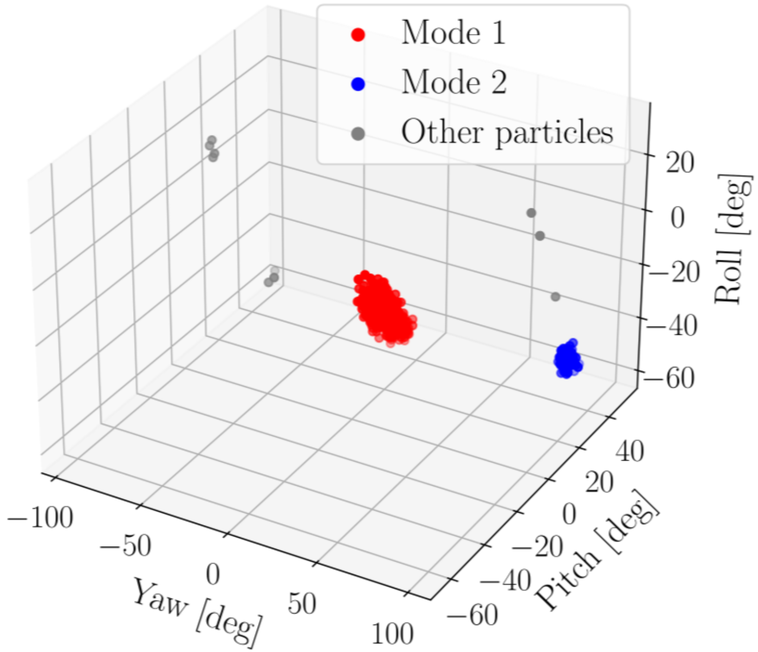




Results. Case 1: unimodal posterior PDF

- **Case 1: cluster and posterior PDF analyses**



True attitude: $\boldsymbol{x}_0 = [71,\ -58,\ 19]$ deg

Mode 1
$W = 0.92 \qquad W_N = 1.5 \times 10^{-4}$
$\boldsymbol{x}_0 = [71.75,\ -57.54,\ 18.74]$ deg
$\boldsymbol{\sigma} = [0.03,\ 0.02,\ 0.04]$ deg

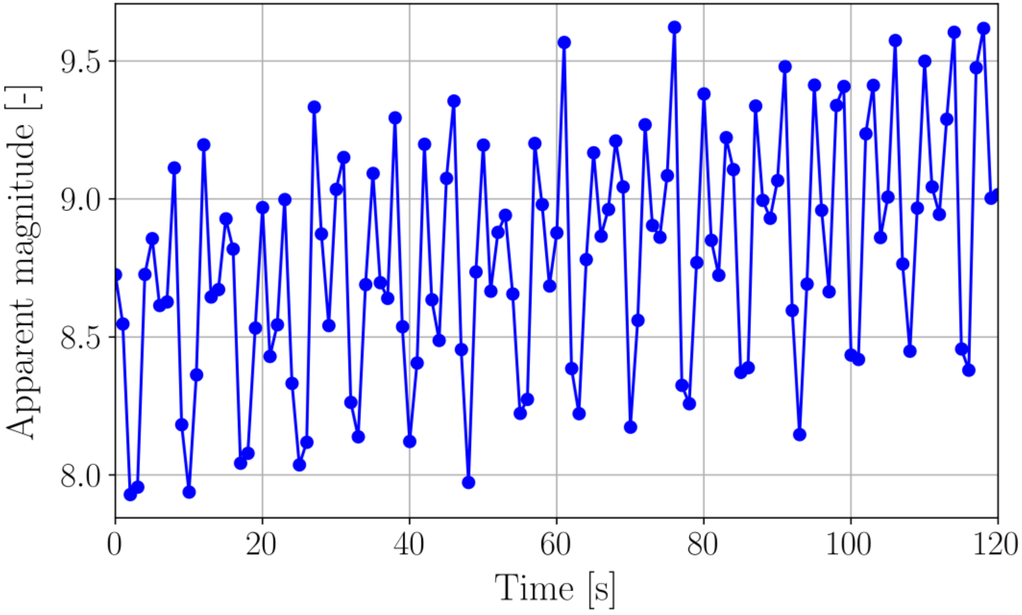
Mode 2
$W = 0.08 \qquad W_N = 1.5 \times 10^{-4}$
$\boldsymbol{x}_0 = [84.43,\ 44.25,\ 52.91]$ deg
$\boldsymbol{\sigma} = [0.09,\ 0.09,\ 0.10]$ deg

Results

- **Case 2: multimodal posterior PDF**

Results. Case 2: multimodal posterior PDF

- **Case 2A: light curve**

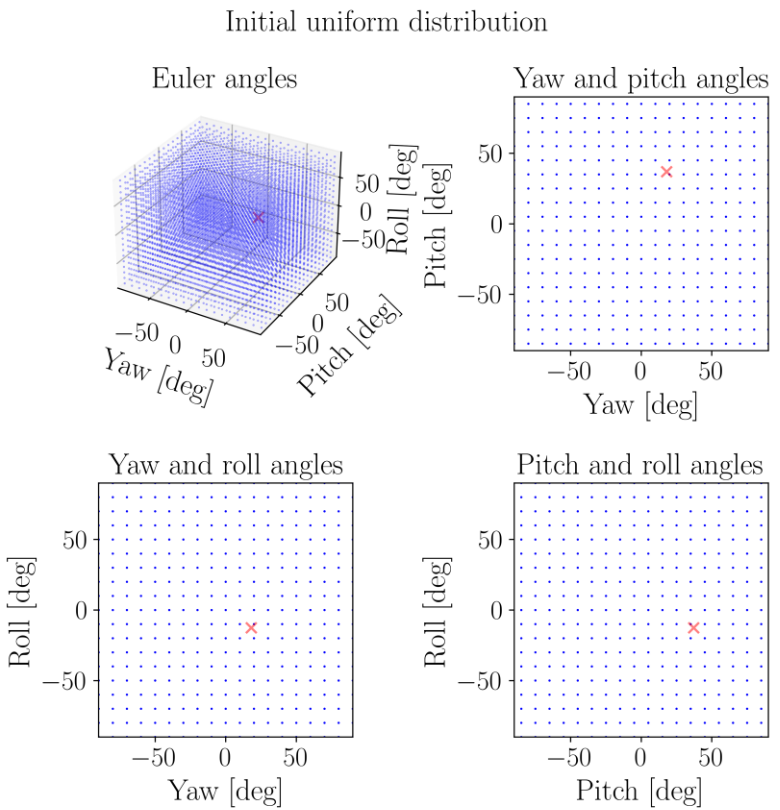


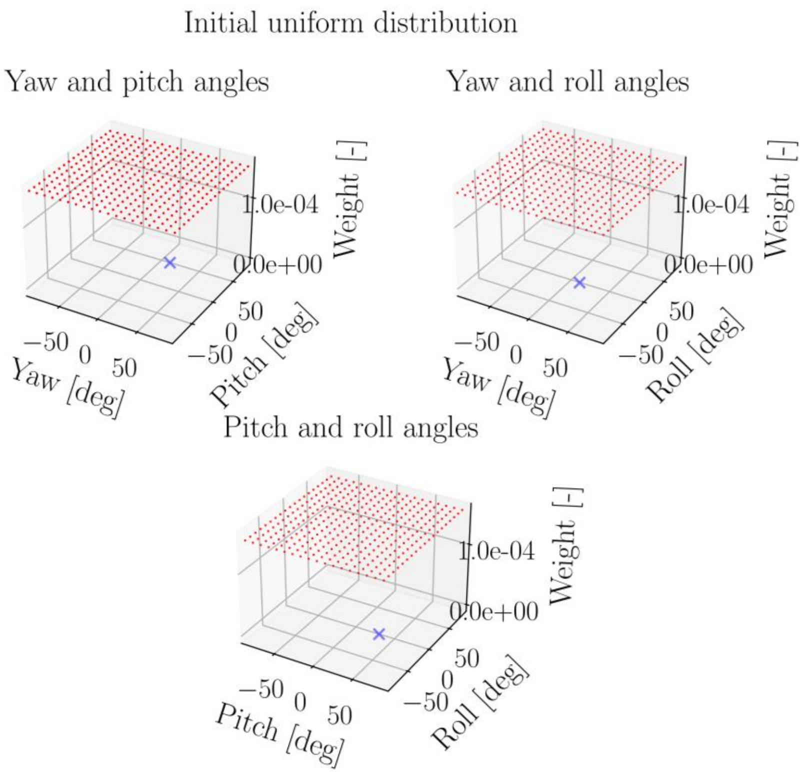
Attitude: $\boldsymbol{x}_0 = [18,\ 37,\ -12.5]\,\mathrm{deg}$

Sensor noise: $\sigma = 0.1$

Results. Case 2: multimodal posterior PDF

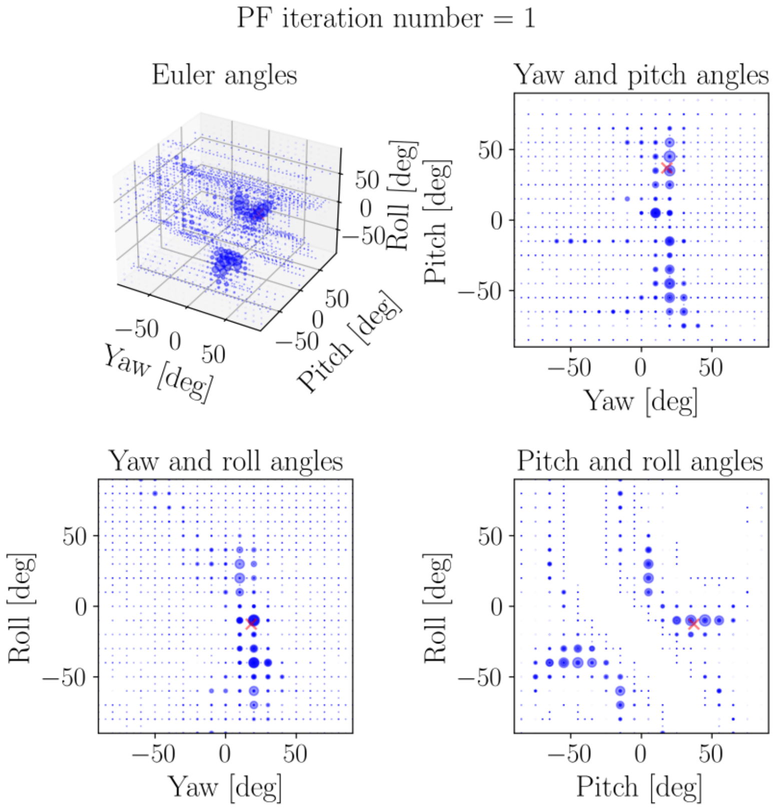
- **Case 2A: particle filter execution**

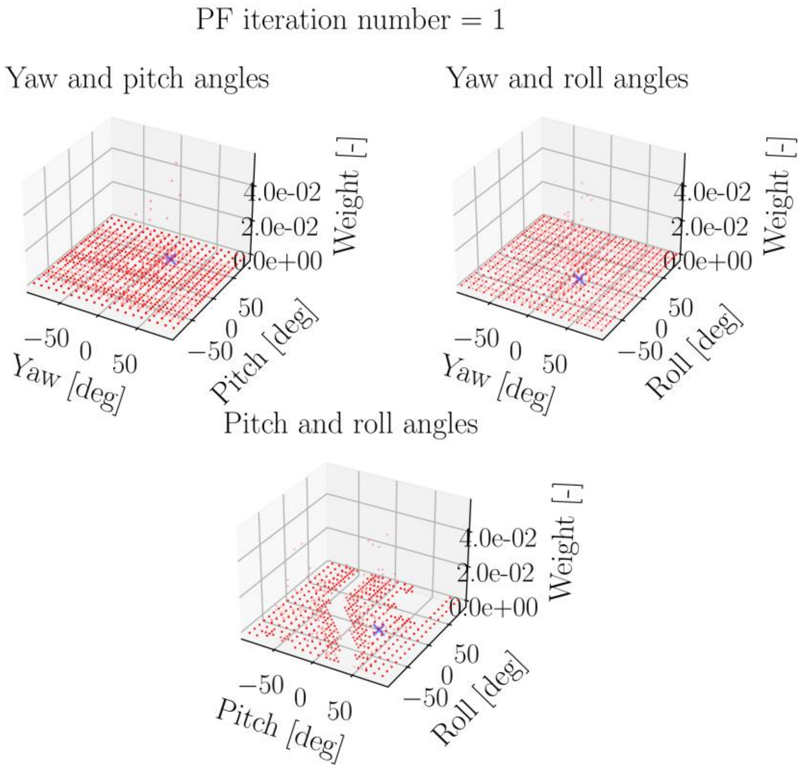




Results. Case 2: multimodal posterior PDF

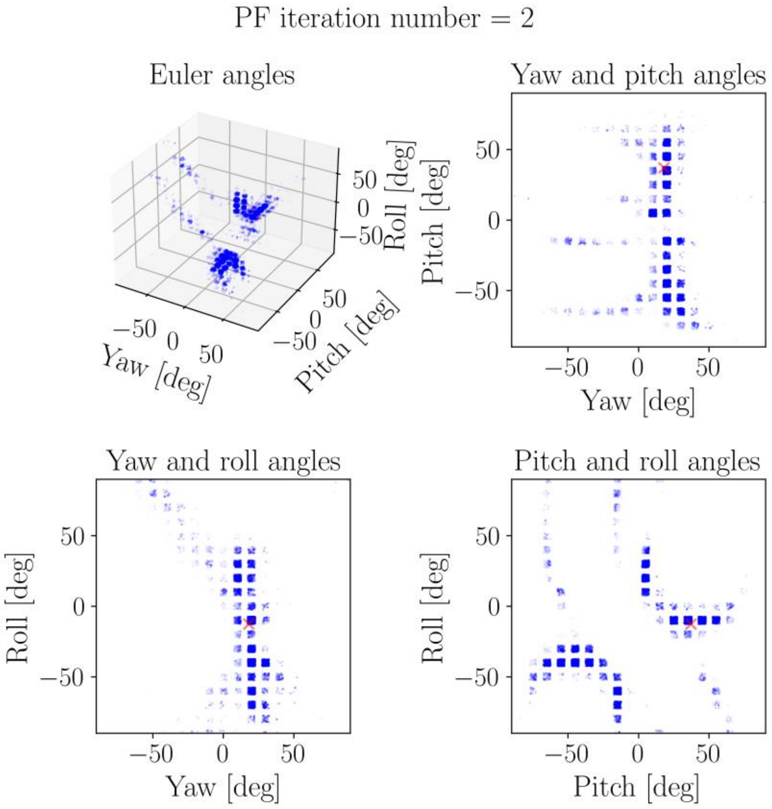
- Case 2A: particle filter execution

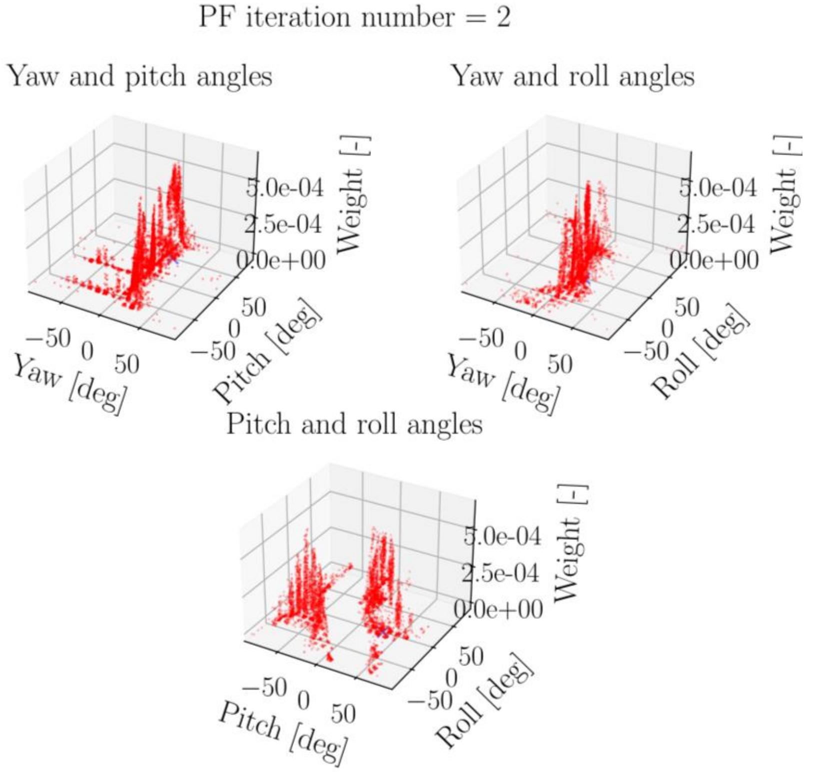




Results. Case 2: multimodal posterior PDF

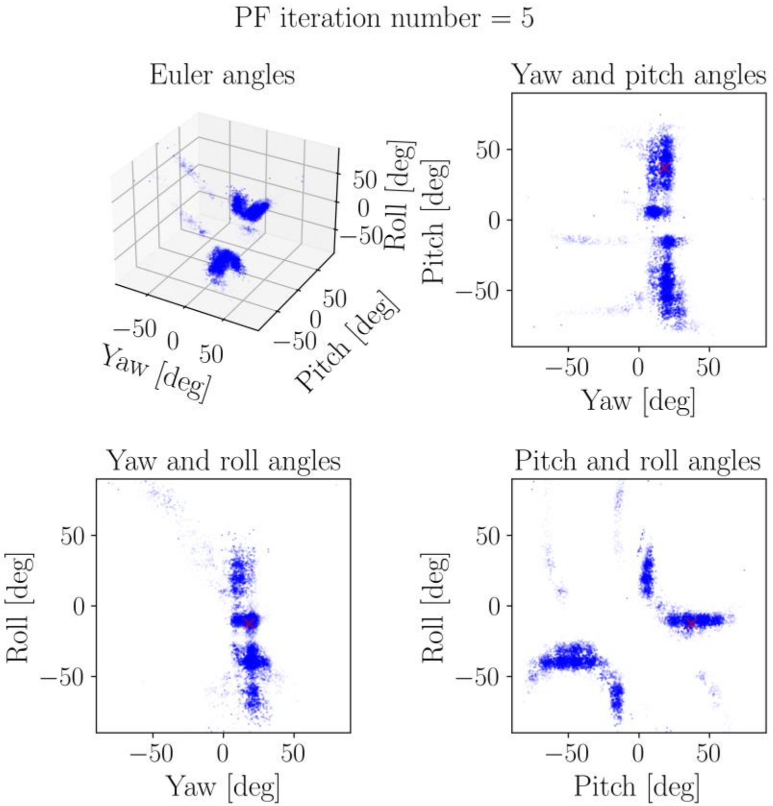
- **Case 2A: particle filter execution**

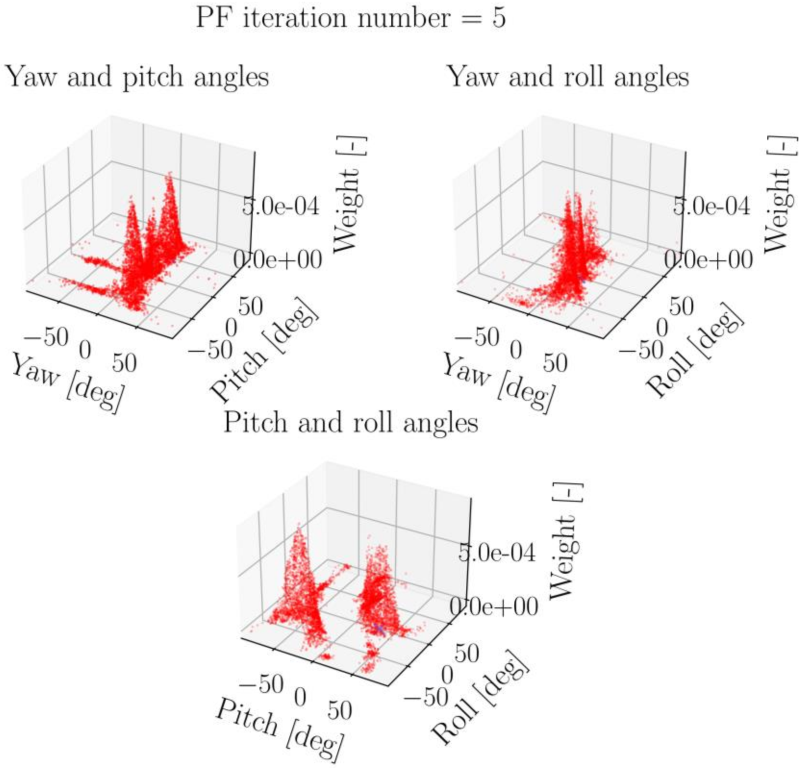




Results. Case 2: multimodal posterior PDF

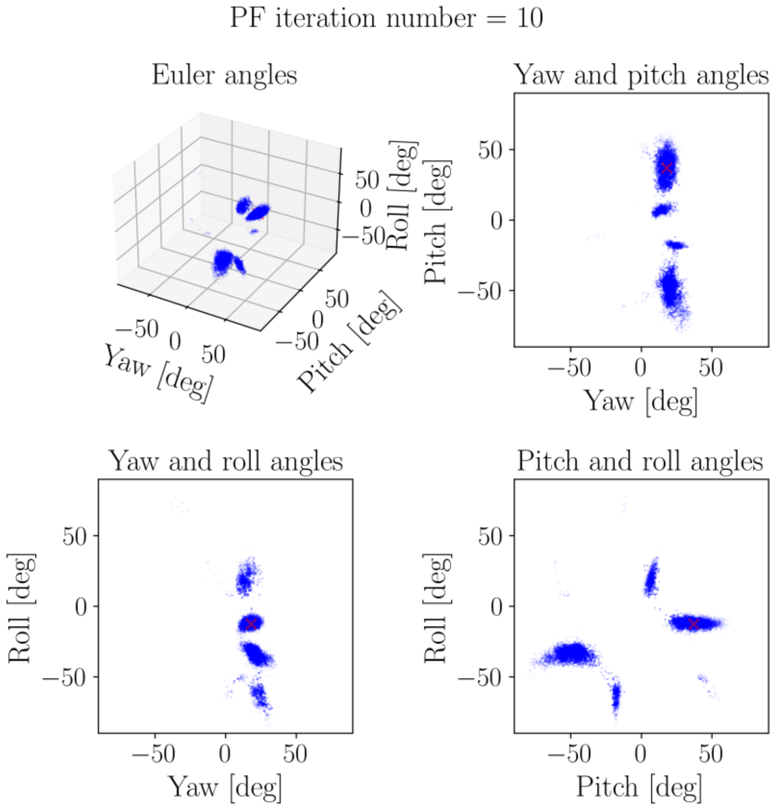
- **Case 2A: particle filter execution**

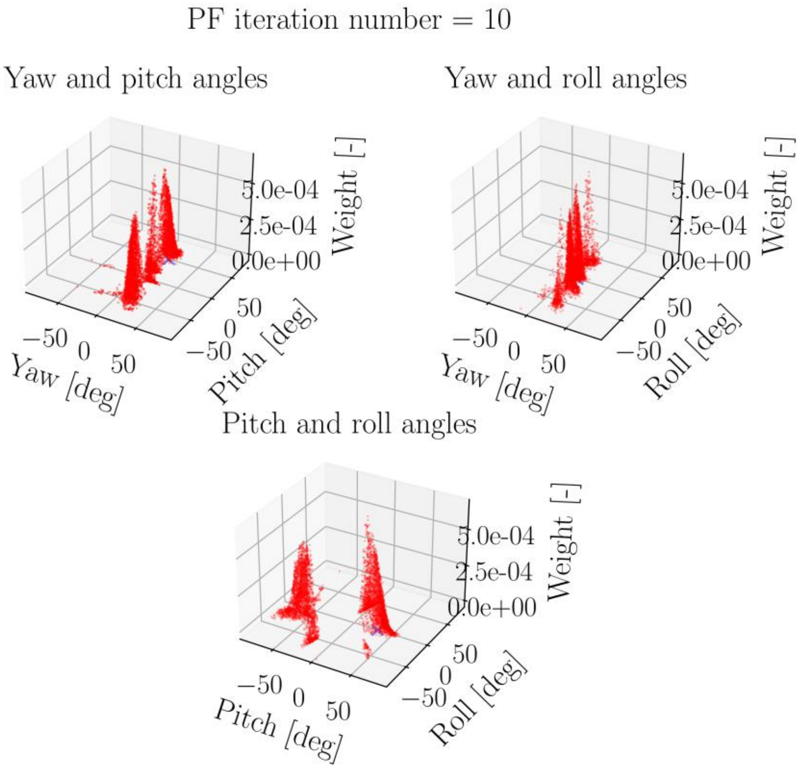




Results. Case 2: multimodal posterior PDF

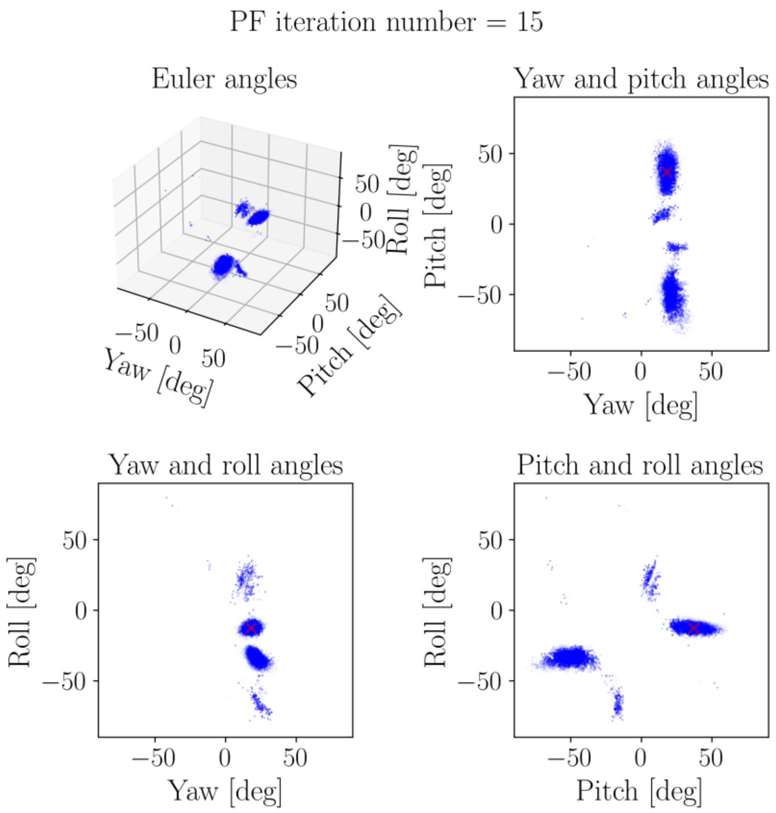
- **Case 2A: particle filter execution**

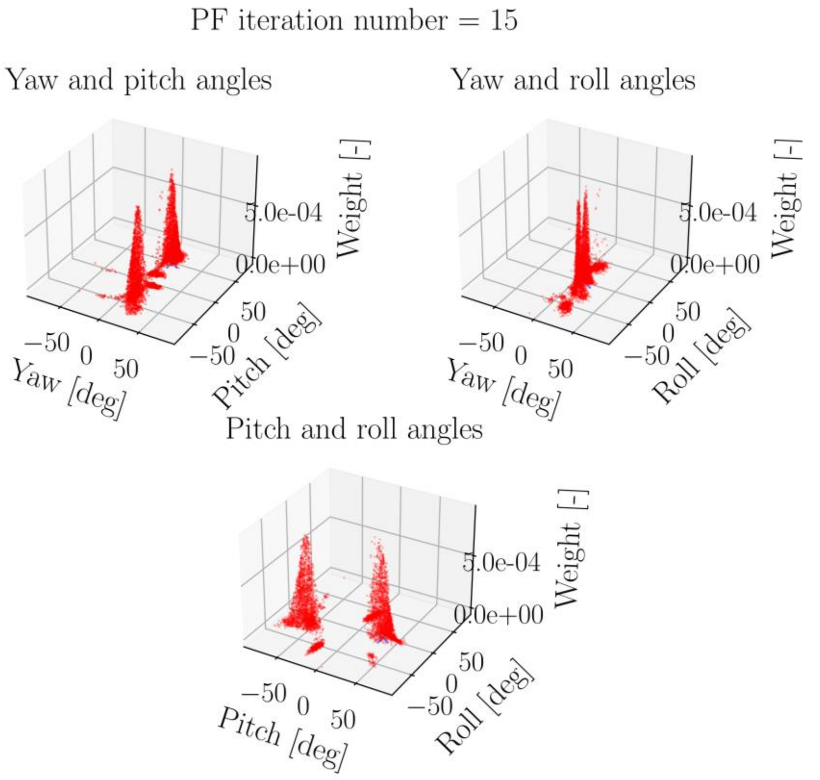




Results. Case 2: multimodal posterior PDF

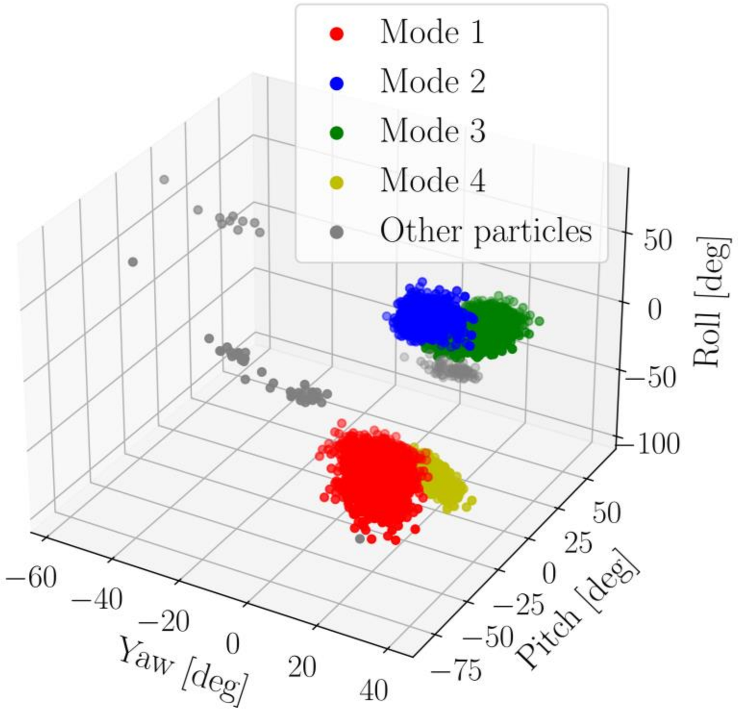
- **Case 2A: particle filter execution**





Results. Case 2: multimodal posterior PDF

- **Case 2A: cluster and posterior PDF analyses**



True attitude: $\boldsymbol{x}_0 = [18,\ 37,\ -12.5]$ deg

Mode 1
$W = 0.52 \quad W_N = 2.1 \times 10^{-4}$
$\boldsymbol{x}_0 = [21.58,\ -49.85,\ -33.42]$ deg
$\boldsymbol{\sigma} = [0.05,\ 0.13,\ 0.06]$ deg

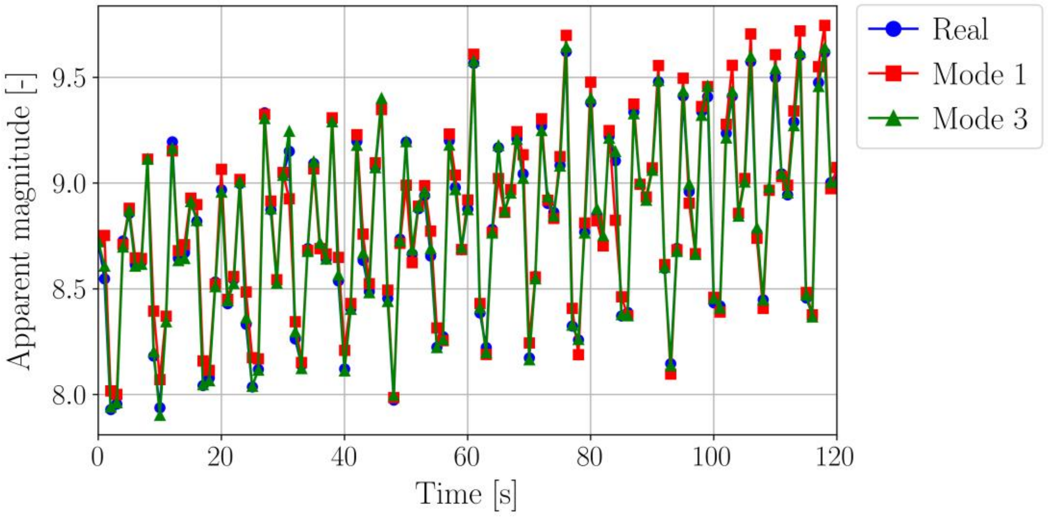
Mode 2
$W = 10^{-4} \quad W_N = 1.2 \times 10^{-5}$
$\boldsymbol{x}_0 = [18.02,\ 9.03,\ 14.78]$ deg
$\boldsymbol{\sigma} = [0.09,\ 0.07,\ 0.17]$ deg

Mode 3
$W = 0.47 \quad W_N = 1.9 \times 10^{-4}$
$\boldsymbol{x}_0 = [18.38,\ 36.41, -12.74]$ deg
$\boldsymbol{\sigma} = [0.05,\ 0.13,\ 0.04]$ deg

Mode 4
$W = 7 \times 10^{-4} \quad W_N = 1.2 \times 10^{-6}$
$\boldsymbol{x}_0 = [25.44,\ -20.91,\ -56.28]$ deg
$\boldsymbol{\sigma} = [0.05,\ 0.04,\ 0.07]$ deg

Results. Case 2: multimodal posterior PDF

- **Case 2A: simulated light curves for the relevant modes**



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$\boldsymbol{x}_0 = [18.38,\ 36.41, -12.74]$ deg
$\boldsymbol{\sigma} = [0.05,\ 0.13,\ 0.04]$ deg

Possible solution: stereoscopic measurements

Results. Case 2: multimodal posterior PDF

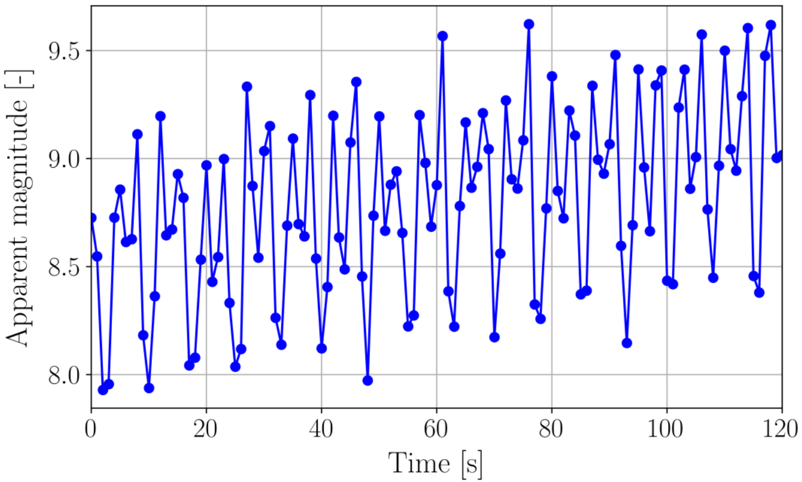
- **Case 2B: light curves from 2 ground stations during the same time interval**

Attitude: $\boldsymbol{x}_0 = [18,\ 37,\ -12.5]\ \mathrm{deg}$

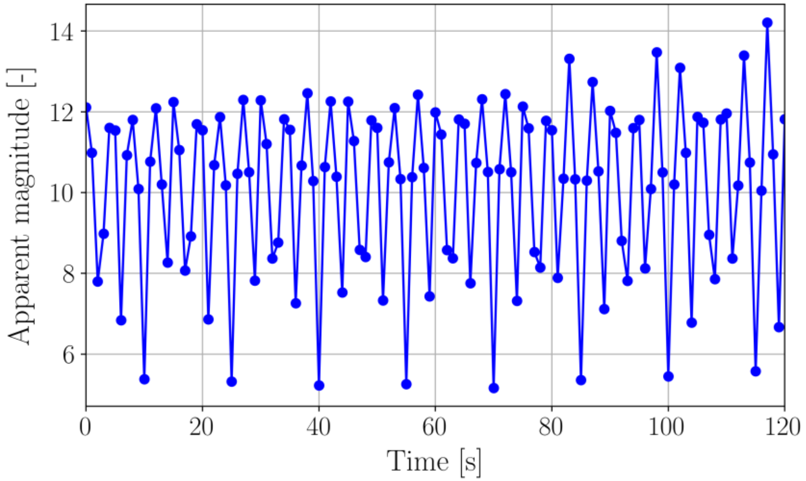
Sensors noise: $\sigma = 0.1$

GS 2: $30°\ \mathrm{N}, 15°\ \mathrm{E}$ w.r.t. GS 1

Ground station 1



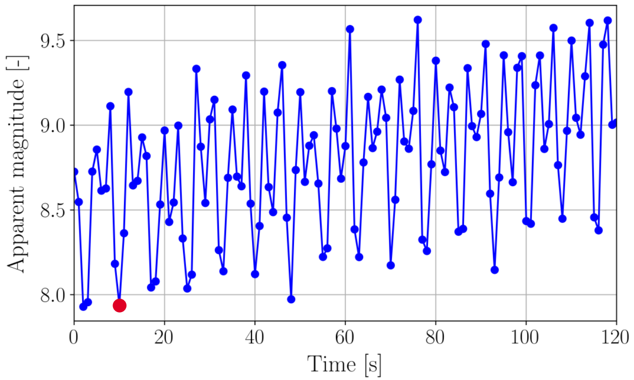
Ground station 2



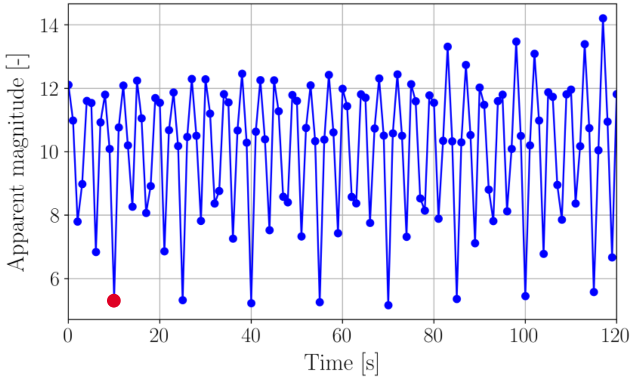
Results. Case 2: multimodal posterior PDF

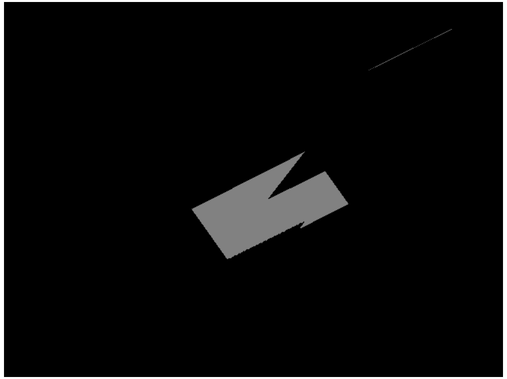
- Case 2B: light curves from 2 ground stations during the same time interval

Ground station 1



Ground station 2

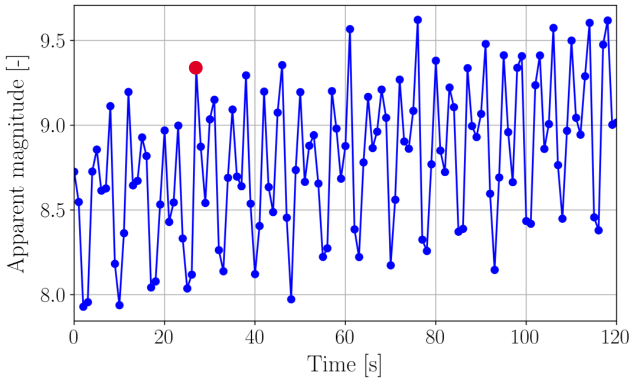


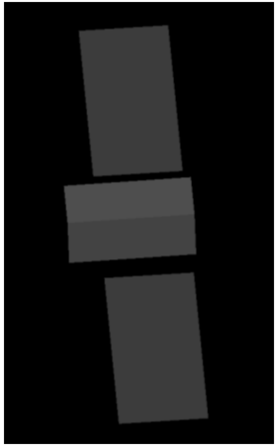


Results. Case 2: multimodal posterior PDF

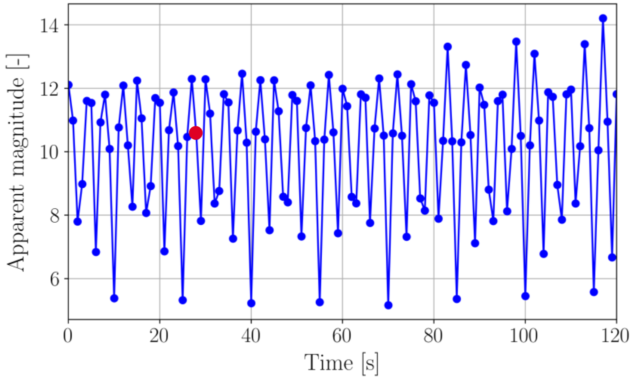
- Case 2B: light curves from 2 ground stations during the same time interval

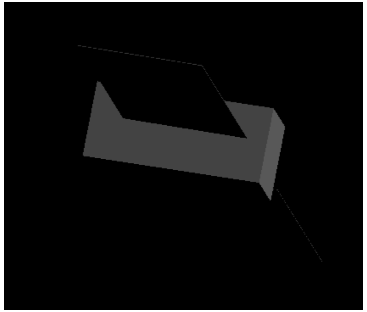
Ground station 1





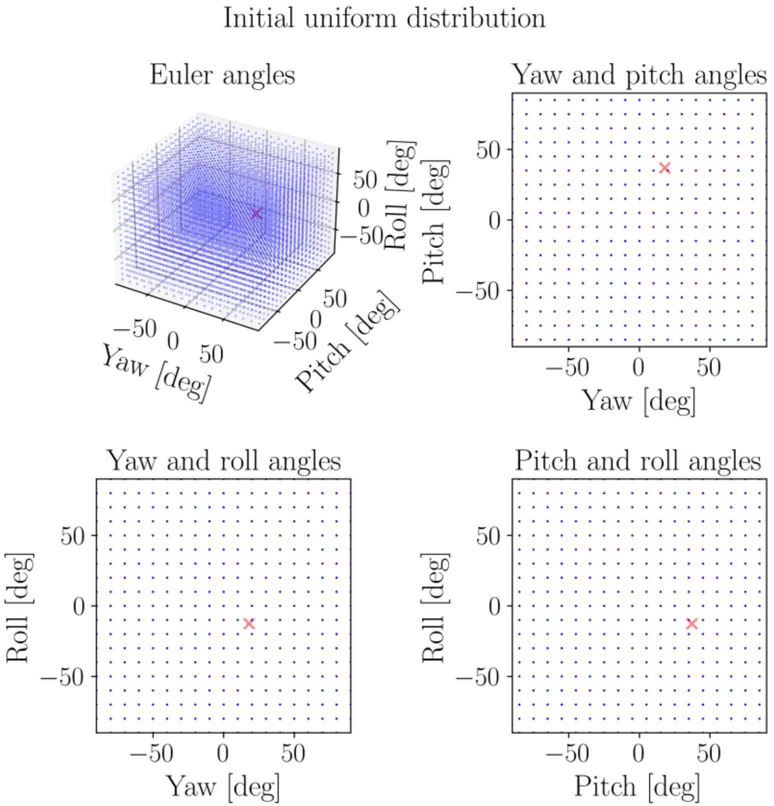
Ground station 2

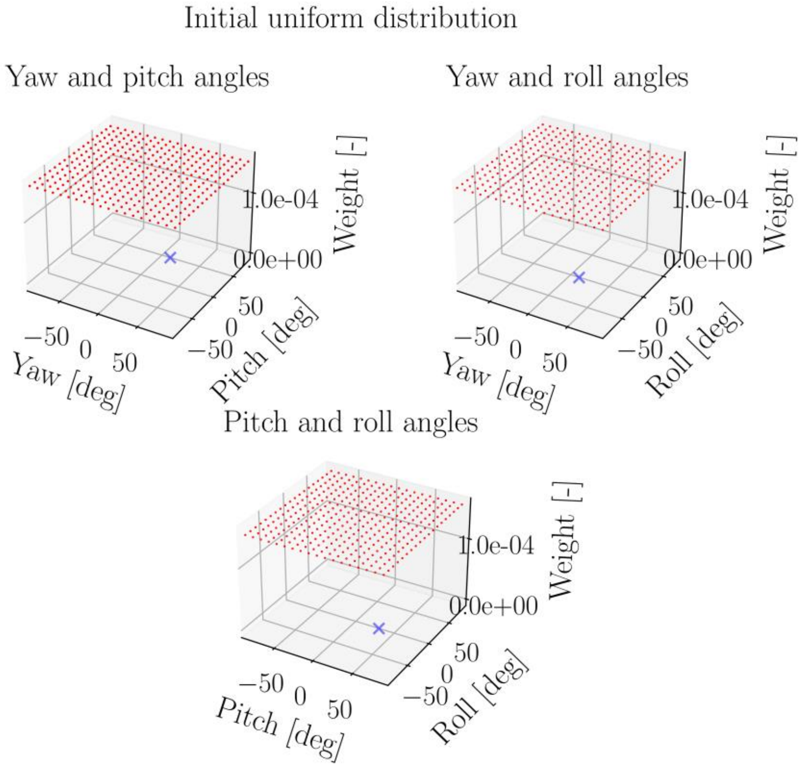




Results. Case 2: multimodal posterior PDF

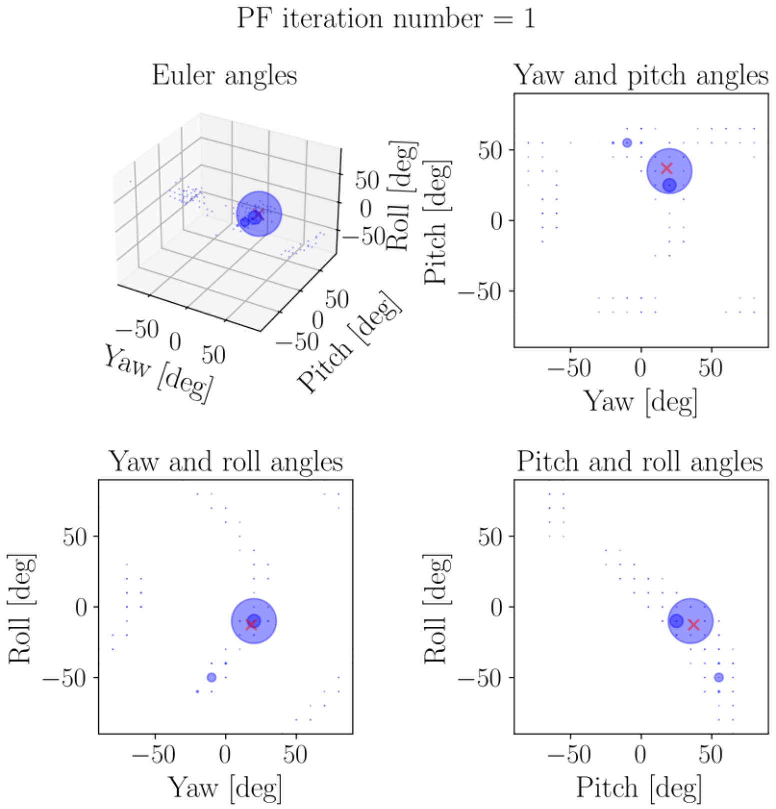
- Case 2B: particle filter execution

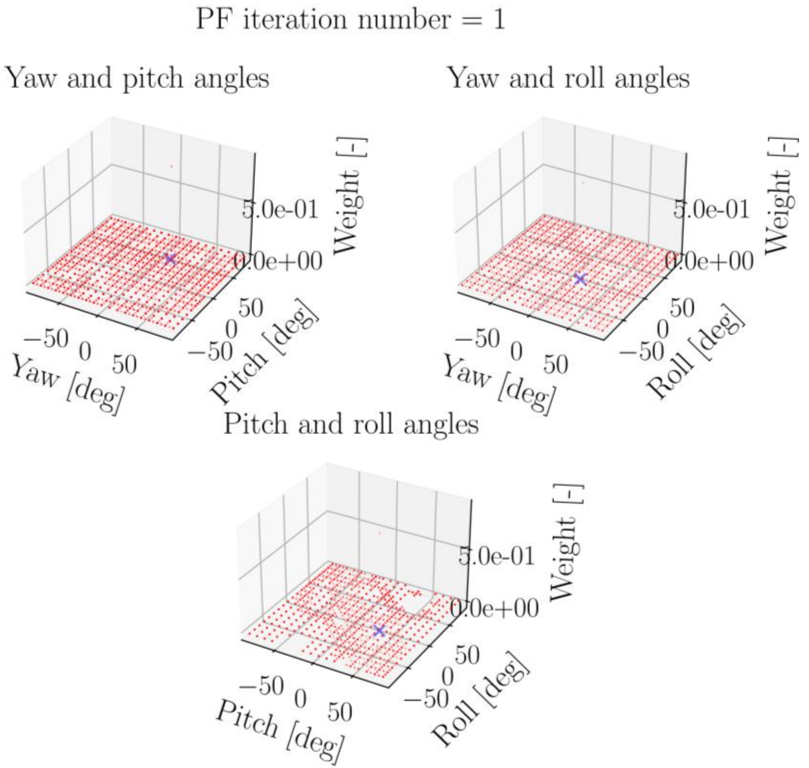




Results. Case 2: multimodal posterior PDF

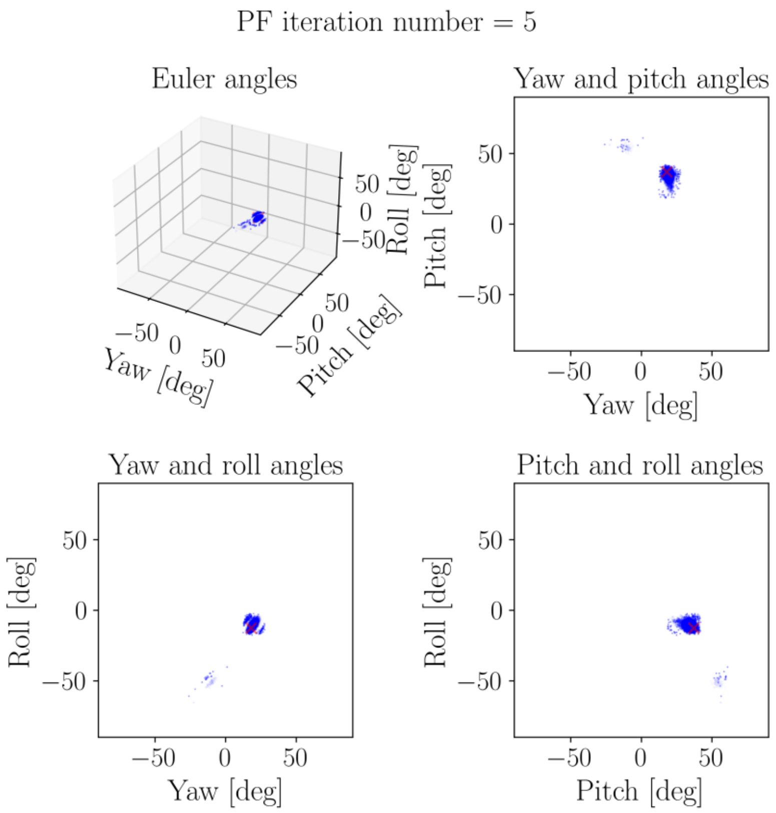
- **Case 2B: particle filter execution**

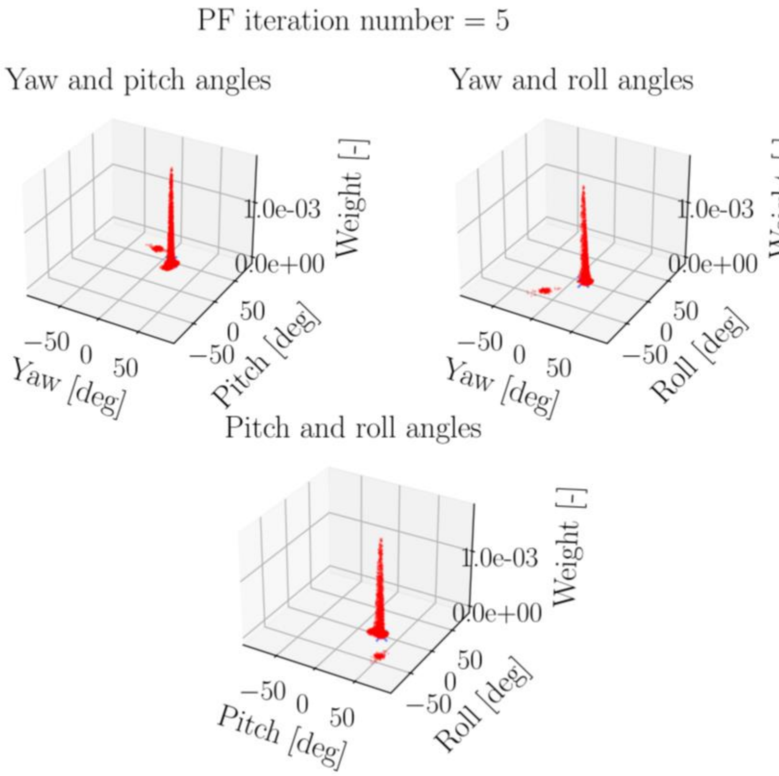




Results. Case 2: multimodal posterior PDF

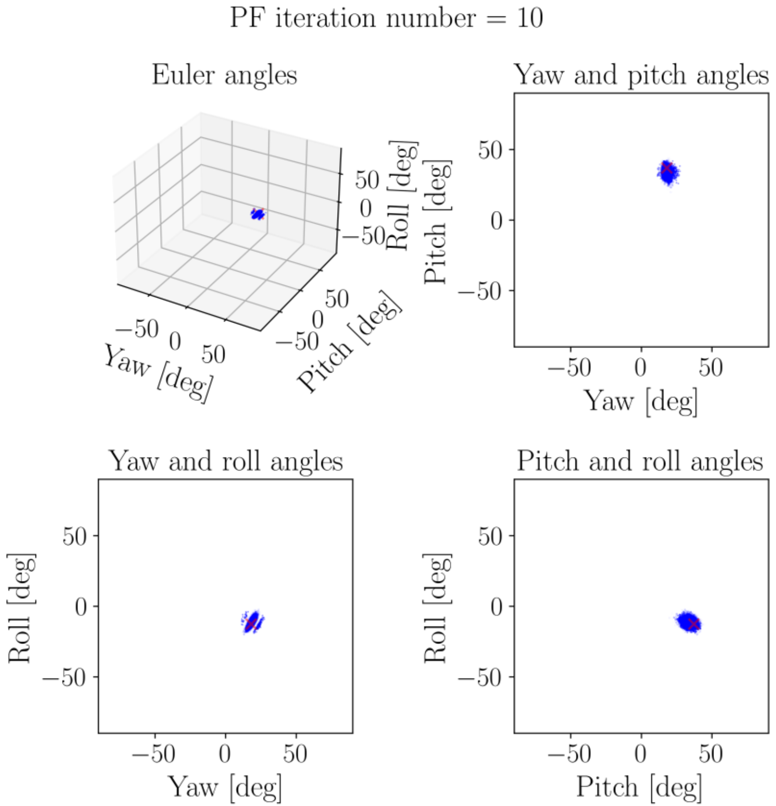
- Case 2B: particle filter execution

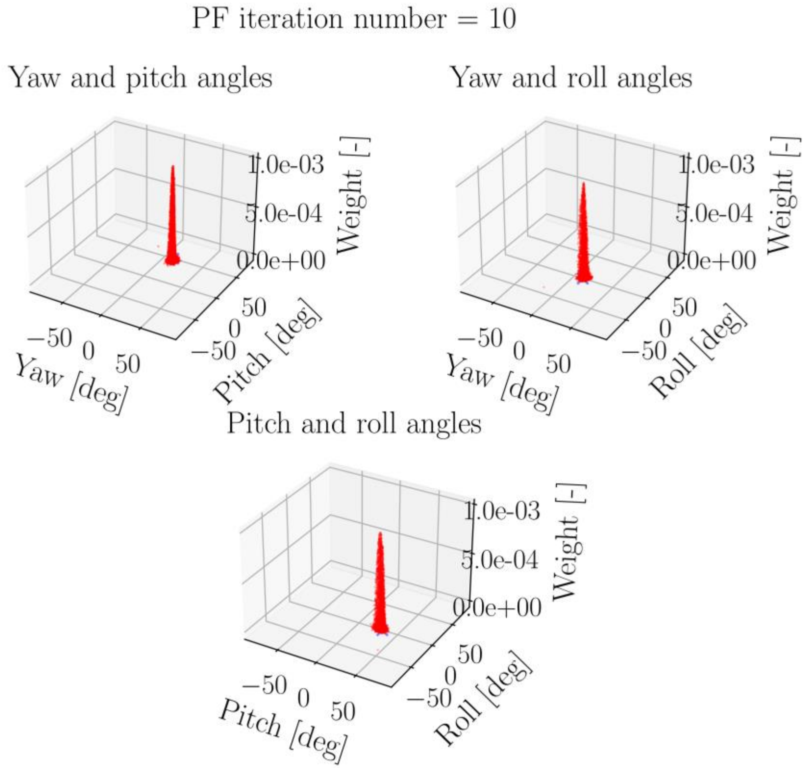




Results. Case 2: multimodal posterior PDF

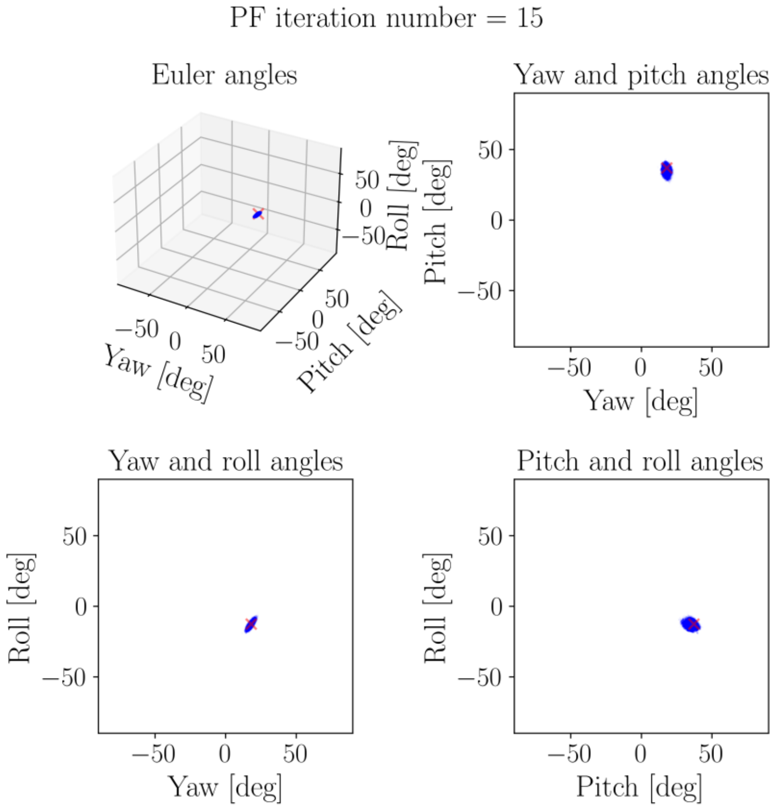
- **Case 2B: particle filter execution**

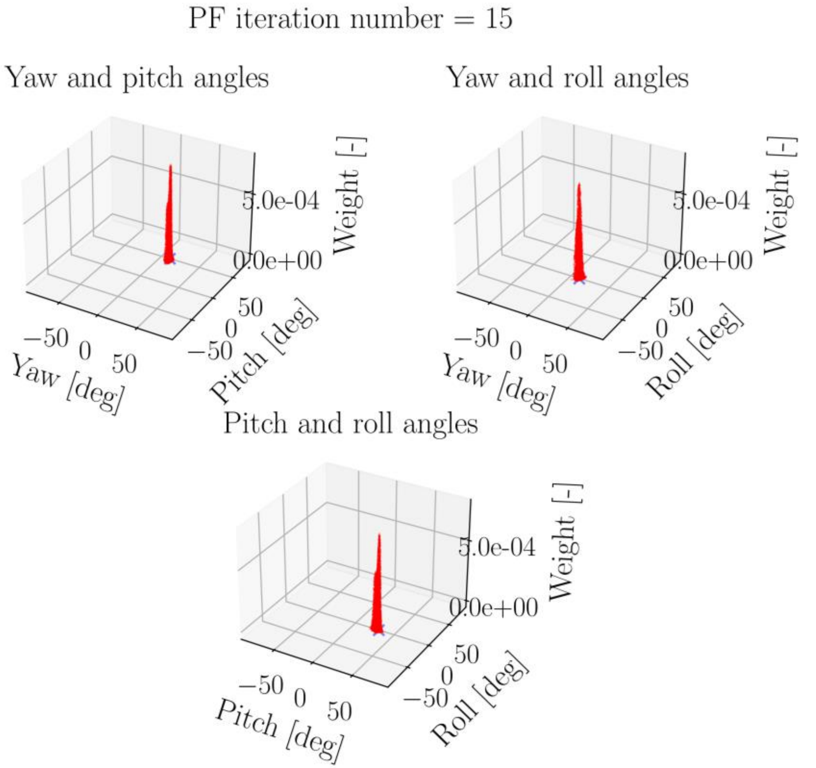




Results. Case 2: multimodal posterior PDF

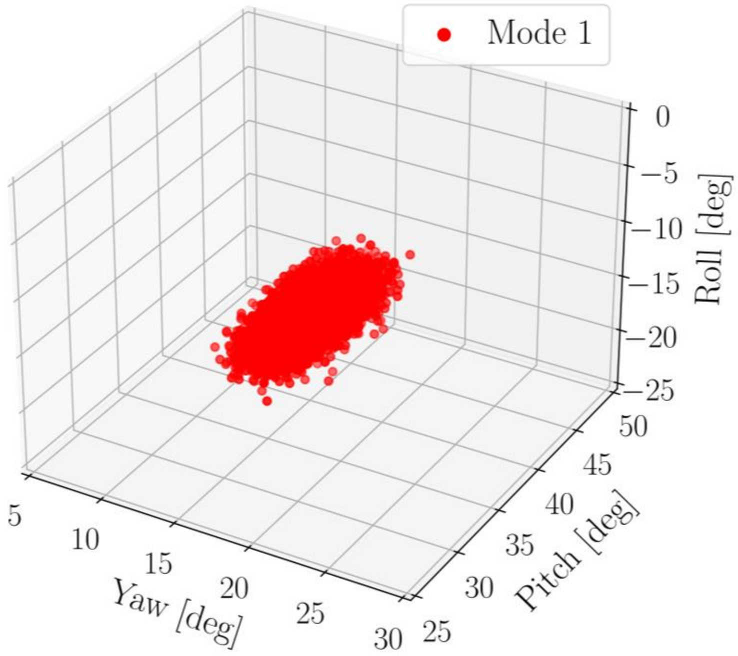
- **Case 2B: particle filter execution**





Results. Case 2: multimodal posterior PDF

- **Case 2B: cluster and posterior PDF analyses**



True attitude: $\boldsymbol{x}_0 = [18,\ 37,\ -12.5]\ \mathrm{deg}$

Mode 1
$W = 1.0$
$\boldsymbol{x}_0 = [17.74,\ 35.66,\ -13.03]\ \mathrm{deg}$
$\boldsymbol{\sigma} = [0.01,\ 0.02,\ 0.02]\ \mathrm{deg}$

Conclusions and future work

Conclusions and future work

- **Conclusions**
  - Understand the challenges of light curve inversion for attitude estimation
  - Identify the limitations of sequential particle filters
  - Develop the pseudo-batch particle filter with reinitialisation
  - Analyse simulated test cases with single and multimodal posterior PDFs
  - Use stereoscopic measurements to mitigate measurement ambiguities
- **Future work**
  - Improve the computational performance of the particle filter
  - Relax assumptions regarding the RSO's attitude law and physical properties
  - Extend analyses using real light curves

Thank you

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Comunidad de Madrid

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