



Hybridisation of Sequential Monte Carlo Simulation with Non-linear Bounded-error State Estimation Based on Interval Analysis Applied to Global Localisation of Mobile Robots

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Agenda

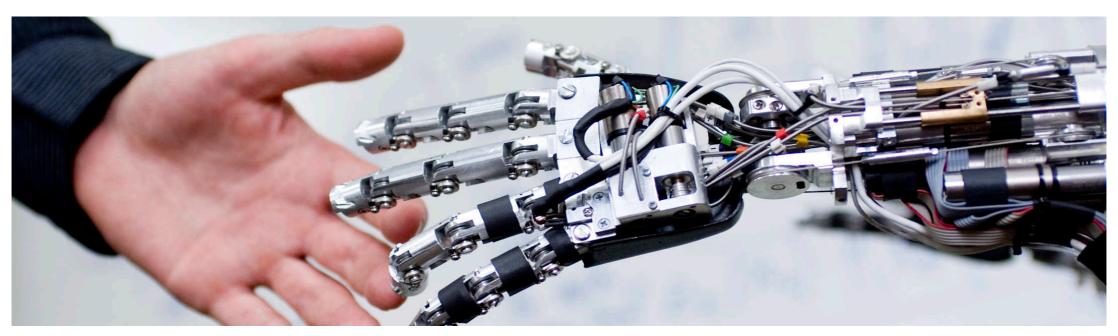
- Introduction
- Sequential Monte Carlo
- Bounded-error estimation
- Hybrid localisation algorithms
- Experiments & Results
- Conclusion





Motivation – Why Robotics?

- Enormous potential to change the world for the better
- Automating dangerous tasks protects human lives & renders operation under inhuman conditions possible
- Releases mankind from mundane & repetitive tasks ⇒ improves quality of life
- Frees time and energy to focus on the more interpersonal tasks & the creative aspects of life

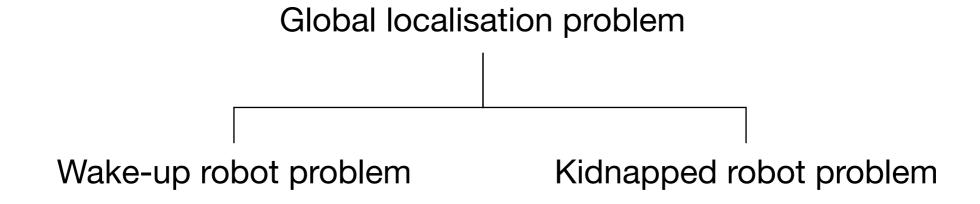


Source: Imperial College London



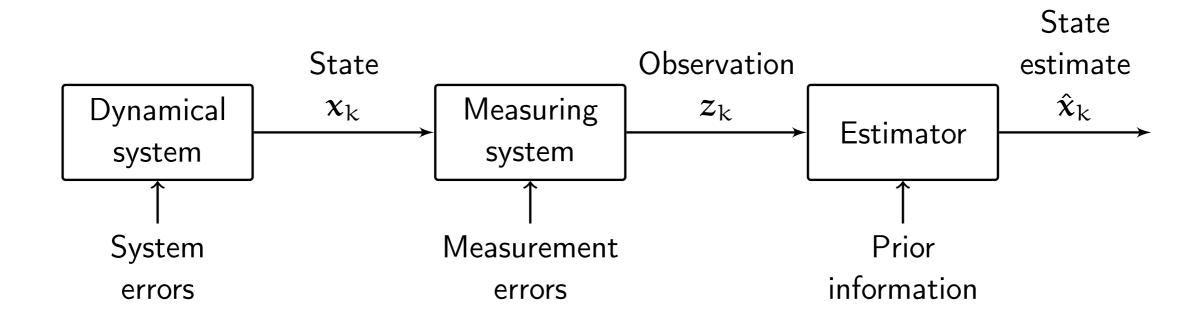
The Global Localisation Problem

- Map: global reference frame + landmarks
- Robot equipped with noisy sensors to measure its distance to each of the landmarks
- Determine the robot's position with respect to the global frame





The Filtering Problem

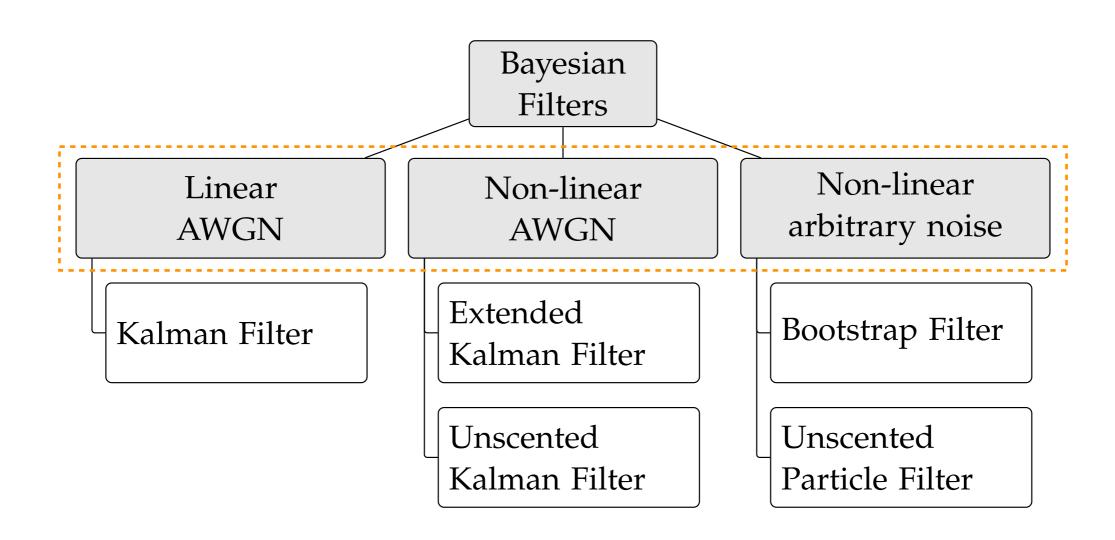


Common solutions:

- Probabilistic estimators ⇒ Bayesian filters
- Bounded-error estimators ⇒ Contractors, SIVIA



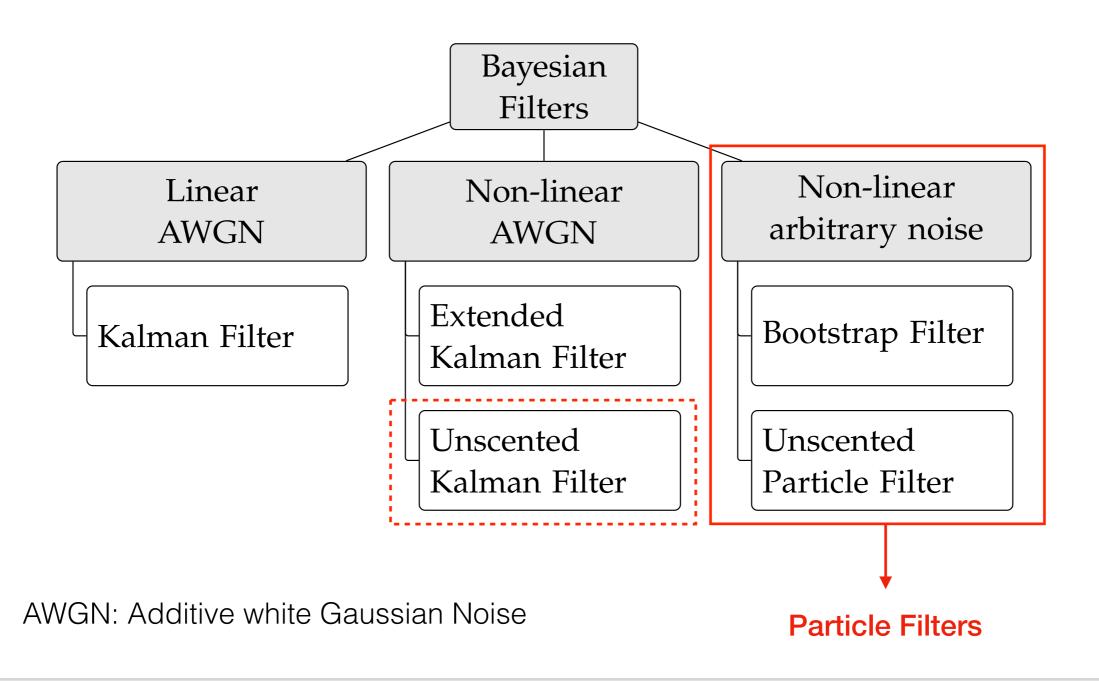
Taxonomy of Bayesian Filters



AWGN: Additive white Gaussian Noise



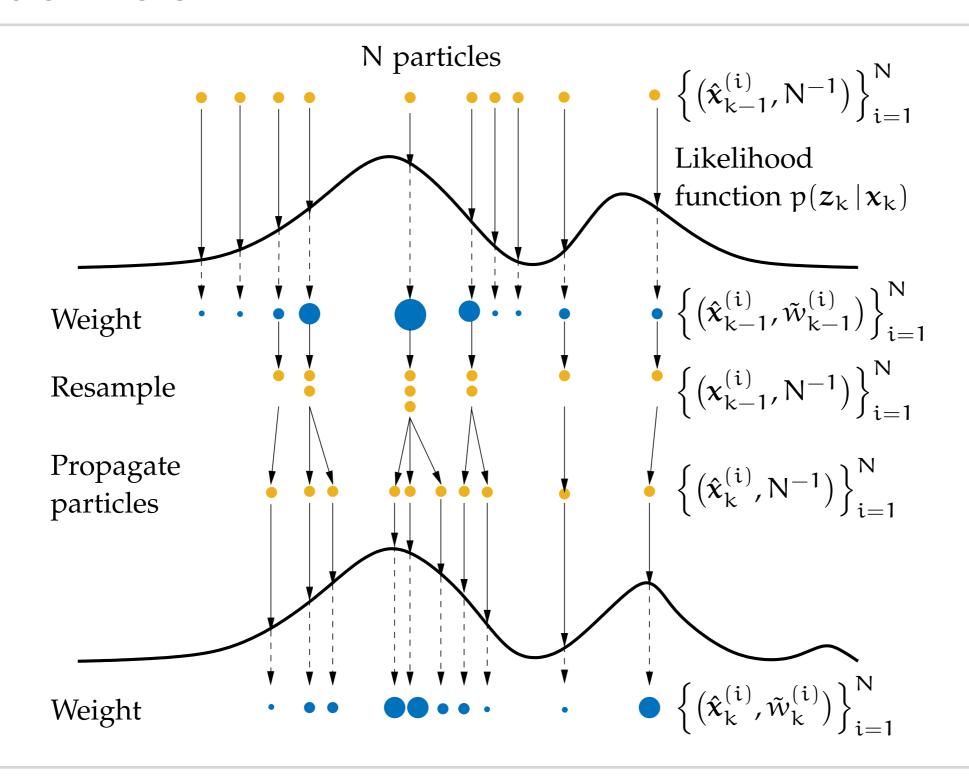
Taxonomy of Bayesian Filters



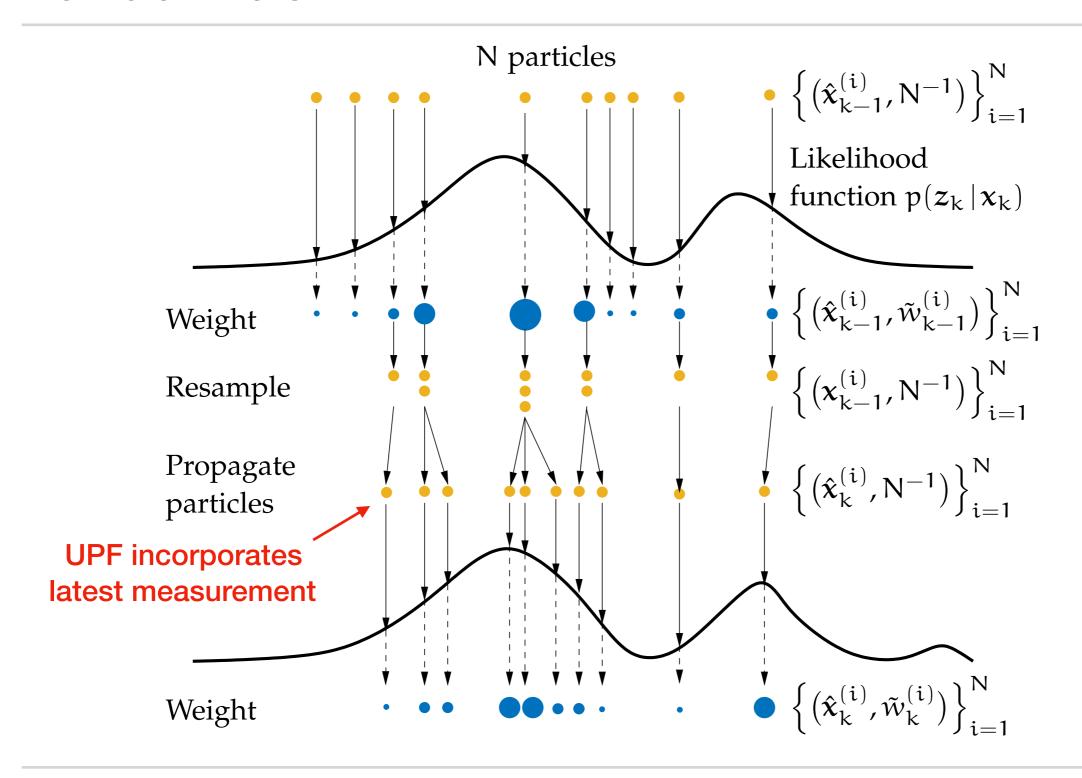
Particle Filters

- Based on sequential Monte Carlo method
- Approximate the posterior probability distribution of the state using a discrete probability distribution (point mass estimate)
- Generate hypotheses of the current state based on the past state (sample from proposal distribution)
- Evaluate the likelihood of these hypotheses using the latest observation (weighting)
- Resample to avoid increasingly skewed posterior distribution

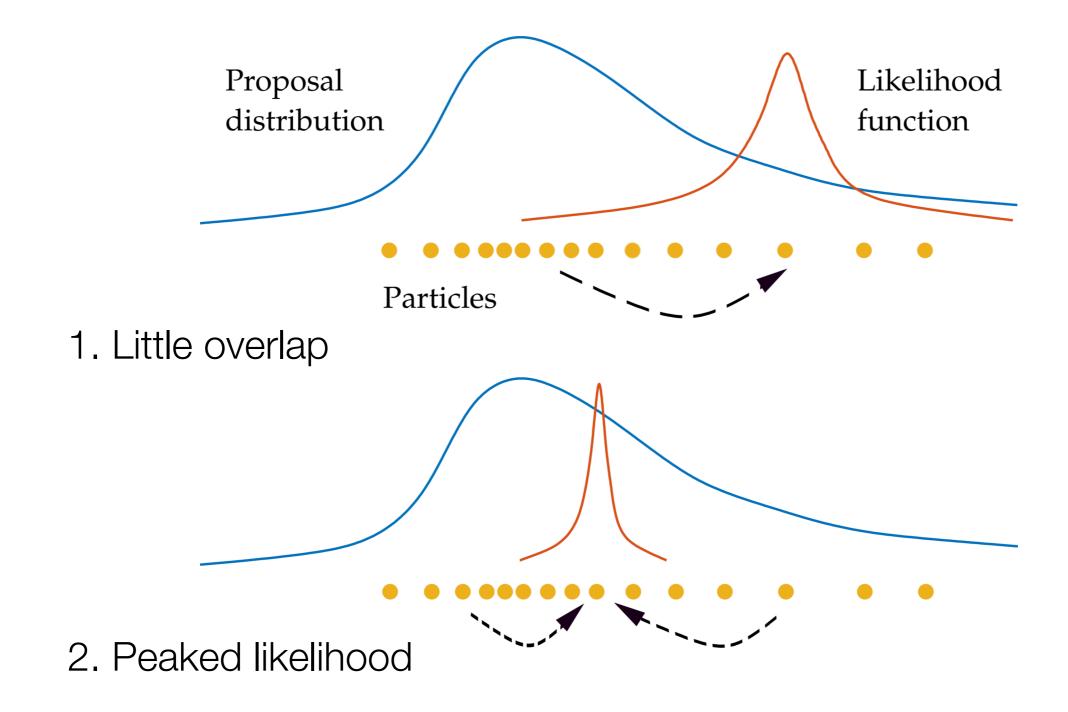
Particle Filters



Particle Filters



Unscented Particle Filter

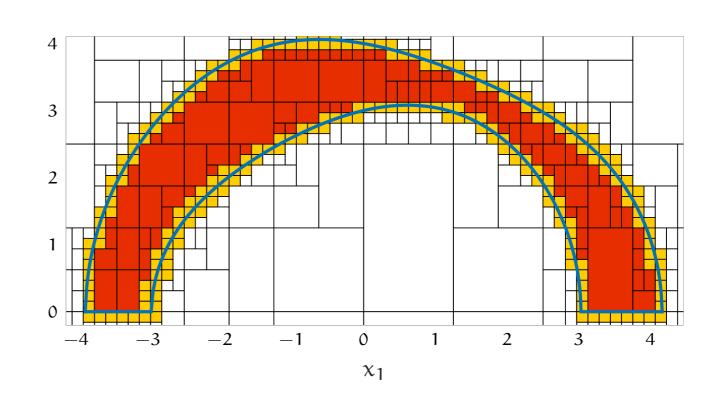


Forward-backward Contractor

- Constraint satisfaction problem $\mathcal{H}: (\mathbf{f}(\mathbf{x}) = 0, \mathbf{x} \in [\mathbf{x}_0])$
 - Set of constraints describing solution set
 - Initial box $[x_0]$ containing all feasible solutions
- Replaces initial box with a smaller box without discarding feasible solutions and without bisecting it
- Implemented by the HC4 algorithm (Frédéric Benhamou et. al, 1999)
- Demands little computational resources

Set Inverter Via Interval Analysis

- Set inversion problem $S = f^{-1}(Y) = \{x \in \mathbb{R}^n \mid f(x) \in Y\}$
- Initial box to which the solution set is guaranteed to belong
- Bisect and test ⇒ narrow down the solution set
- Arbitrarily precise
- Computationally more demanding than the contractor





Probabilistic vs. Bounded-error Localisation

Probabilistic filters

- Point estimate of position, e.g. minimum mean-squared error estimate
- No correct solution ensured ⇒ divergence possible

Bounded-error estimators

- Region that is guaranteed to contain the true robot position
- Constant probability over confined region ⇒ information yield may not be sufficient in practice

Novel Hybrid Localisation Algorithms

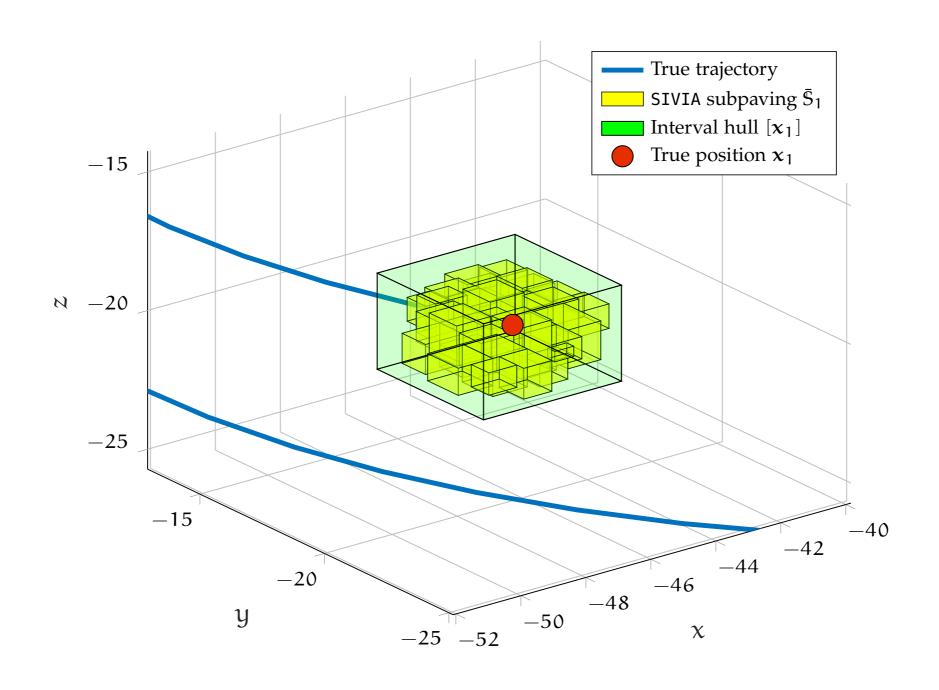
- Rationale is to perform Monte Carlo Localisation over a limited region of the search space
- Increase the particle density in regions of high observation likelihood without increasing the absolute number of particles
- Enhance the localisation accuracy and speed of convergence
- Bounded-error estimate is only computed once in the beginning and once after kidnapping
- Reduce computational complexity compared to previous methods (Neuland et. al 2014)



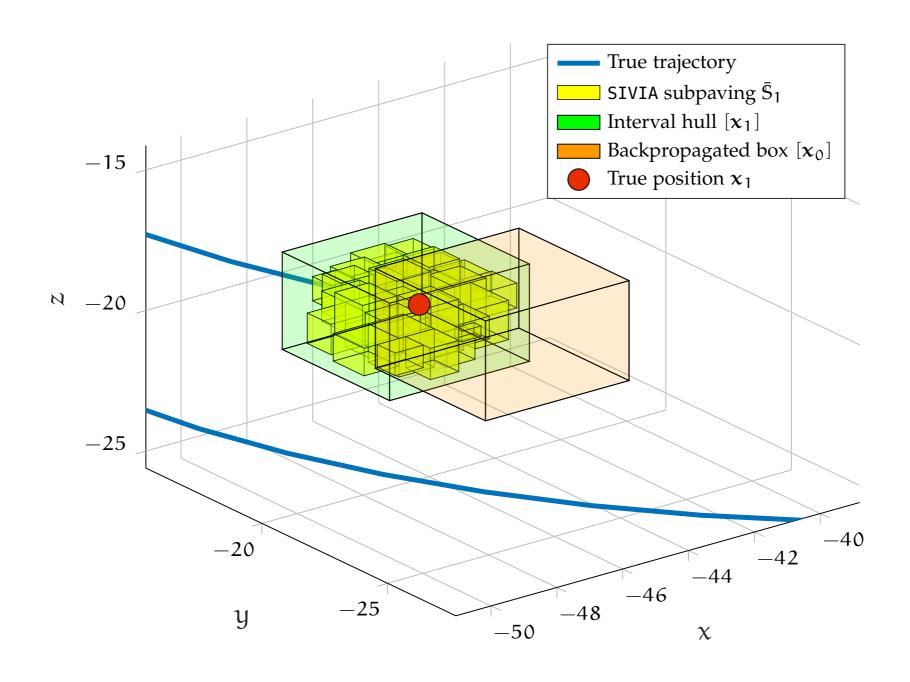
Novel Hybrid Localisation Algorithms

- Satisfaction of given constraints that are based on geometrical considerations of the environment are tested
- The particles not satisfying the constraints receive a weight of zero
- Zero-weighted particles are not resampled
- When all particles have a weight of zero, the robot has been kidnapped ⇒ localisation failure
- Global localisation process is restarted

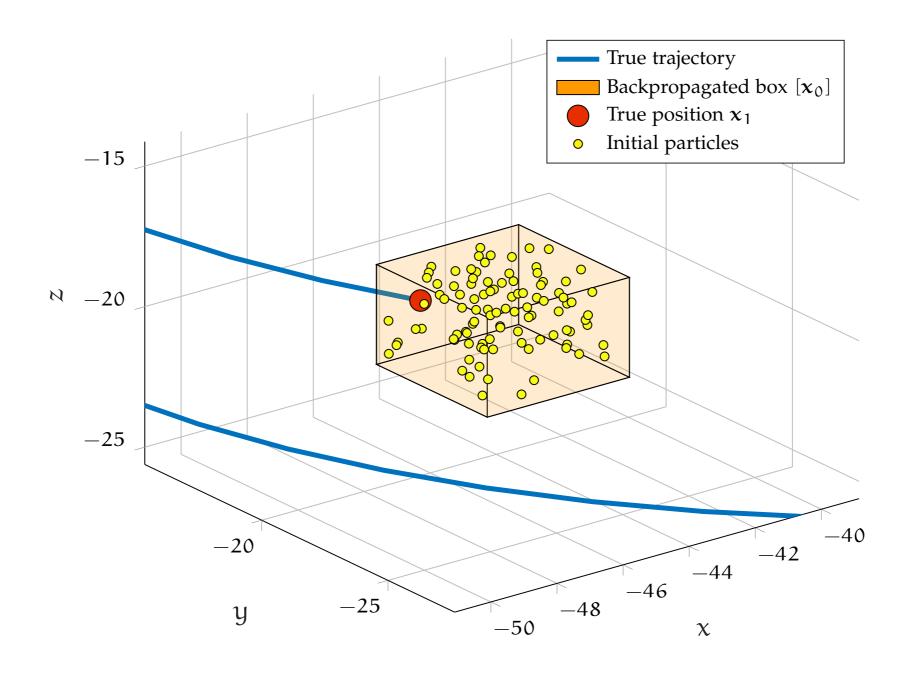
Novel Hybrid Algorithms – Bounded-error estimation



Novel Hybrid Algorithms – Backward propagation



Novel Hybrid Algorithms – Sample from Initial Distribution

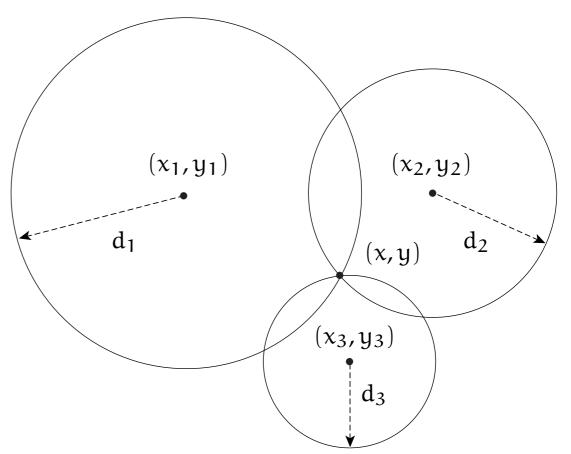




Constraints

- Lateration
- Euclidean distance
- Inflate measurement model

$$\begin{split} [z_k] &= \begin{bmatrix} \left[d_{1,k} - \xi \sigma_d, d_{1,k} + \xi \sigma_d \right] \\ \left[d_{2,k} - \xi \sigma_d, d_{2,k} + \xi \sigma_d \right] \\ \vdots \\ \left[d_{n_z,k} - \xi \sigma_d, d_{n_z,k} + \xi \sigma_d \right] \end{bmatrix} \\ &= [\mathbf{h}_k] \big([\mathbf{x}_k], 0 \big) \\ &= \begin{bmatrix} \sqrt{([\mathbf{x}_k] - \mathbf{x}_1)^2 + ([\mathbf{y}_k] - \mathbf{y}_1)^2 + ([\mathbf{z}_k] - \mathbf{z}_1)^2} \\ \sqrt{([\mathbf{x}_k] - \mathbf{x}_2)^2 + ([\mathbf{y}_k] - \mathbf{y}_2)^2 + ([\mathbf{z}_k] - \mathbf{z}_2)^2} \\ \vdots \\ \sqrt{([\mathbf{x}_k] - \mathbf{x}_{n_z})^2 + ([\mathbf{y}_k] - \mathbf{y}_{n_z})^2 + ([\mathbf{z}_k] - \mathbf{z}_{n_z})^2} \end{bmatrix} \end{split}$$

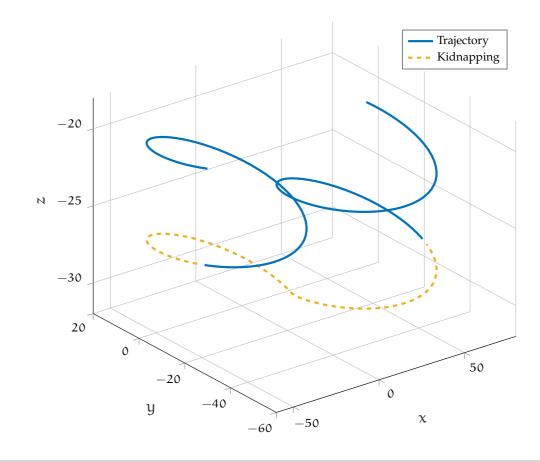


Experiments

- Existing simulations from an autonomous underwater robot generated by the MORSE Simulator
- Added landmarks and computed distance measurements

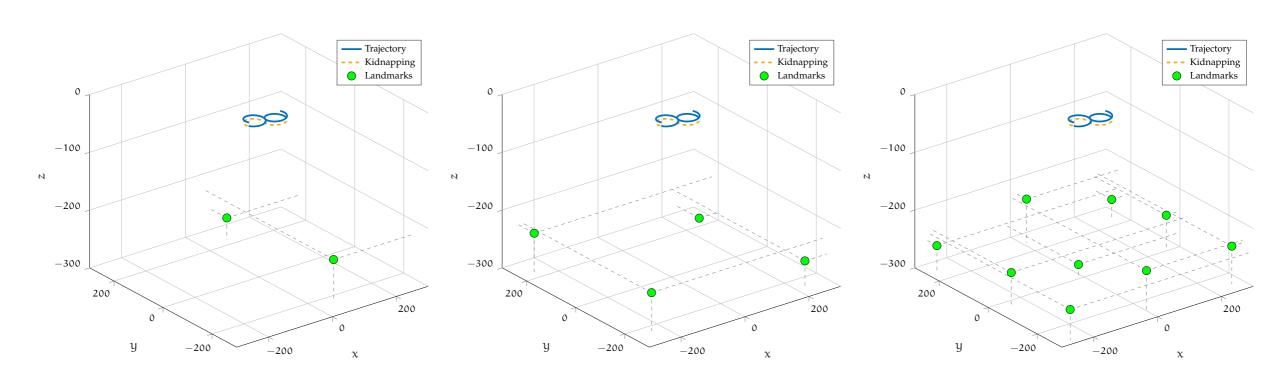


UAV Redermor, source: Groupe d'Etude Sous-Marine de l'Atlantique

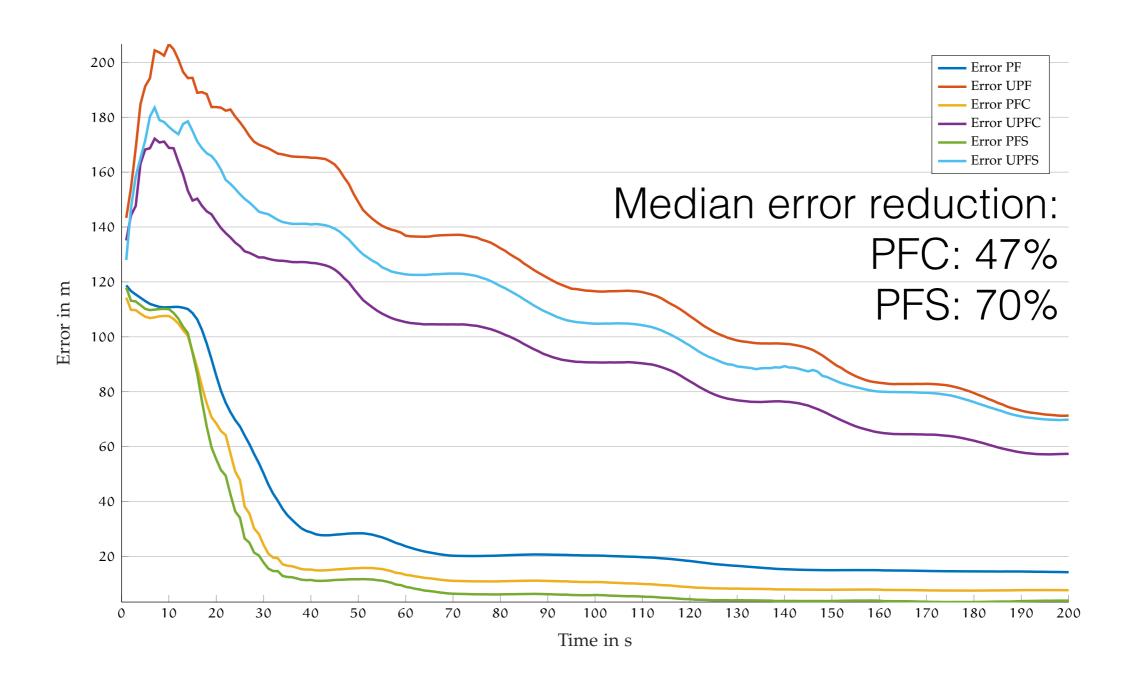


Experiments

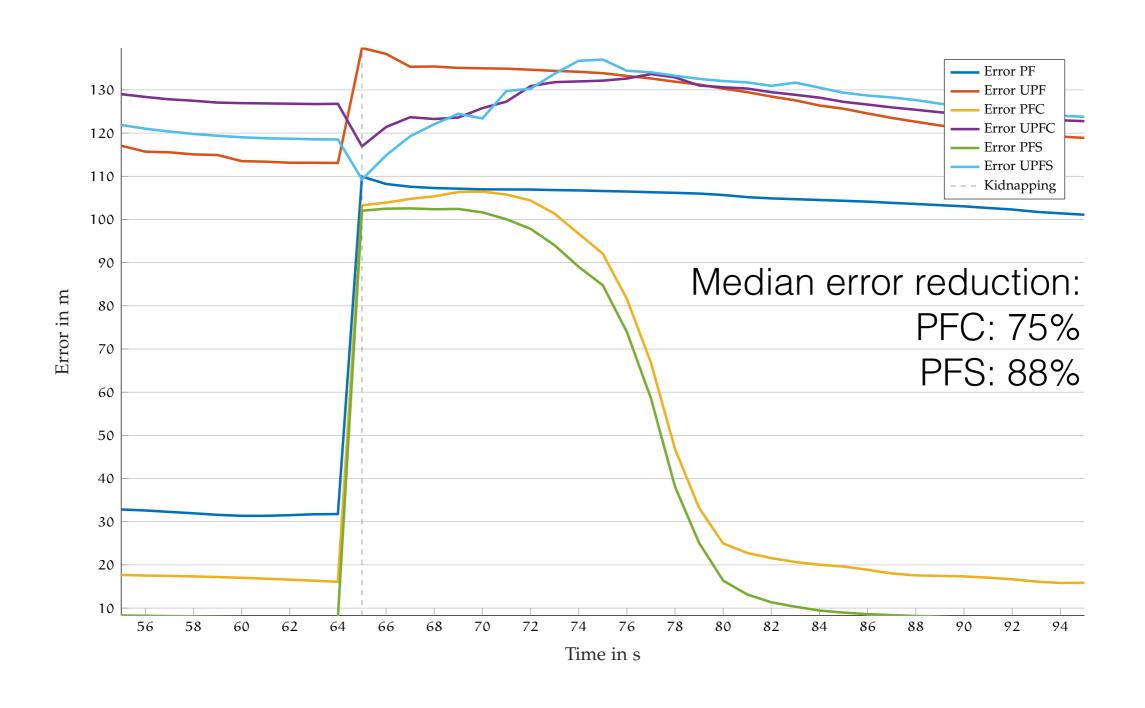
- Three scenarios with two, four and nine landmarks on the seabed, with and without kidnapping, 100 runs
- 10 000 particles for the bootstrap particle filters
- 100 particles for the unscented particle filters



Results – 2 Landmarks – Wake-up Robot Problem

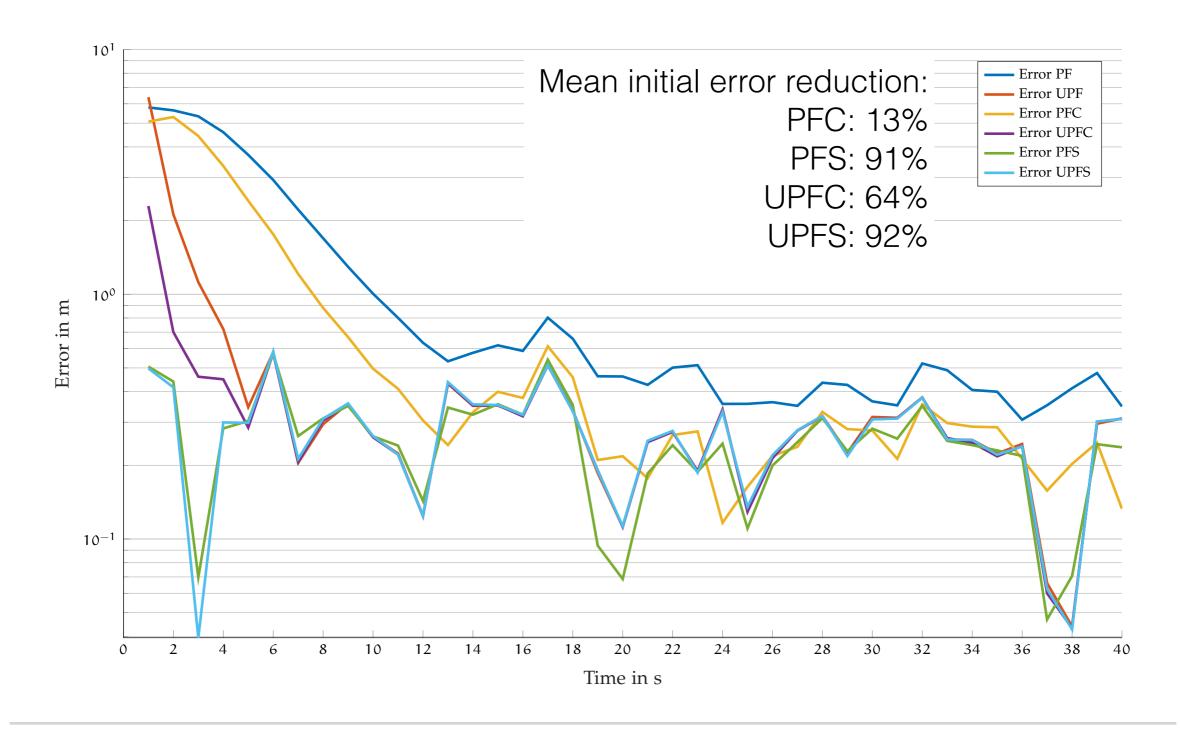


Results – 2 Landmarks – Kidnapped Robot Problem

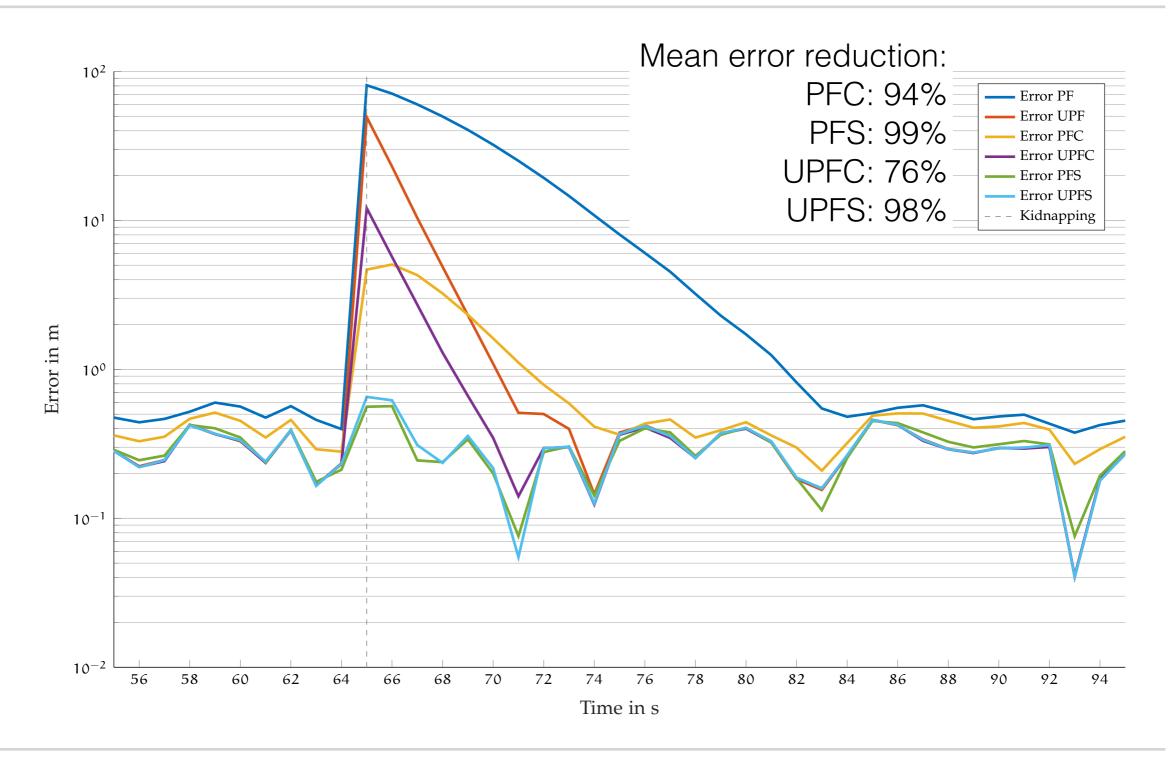




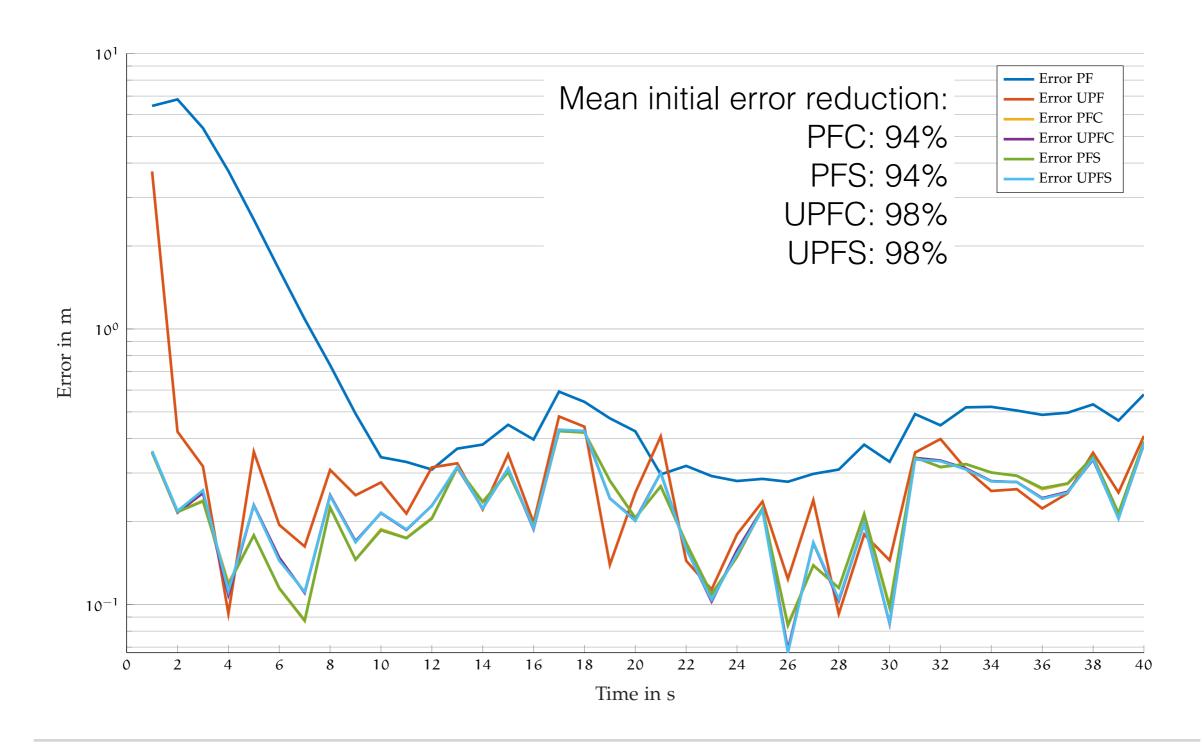
Results – 4 Landmarks – Wake-up Robot Problem



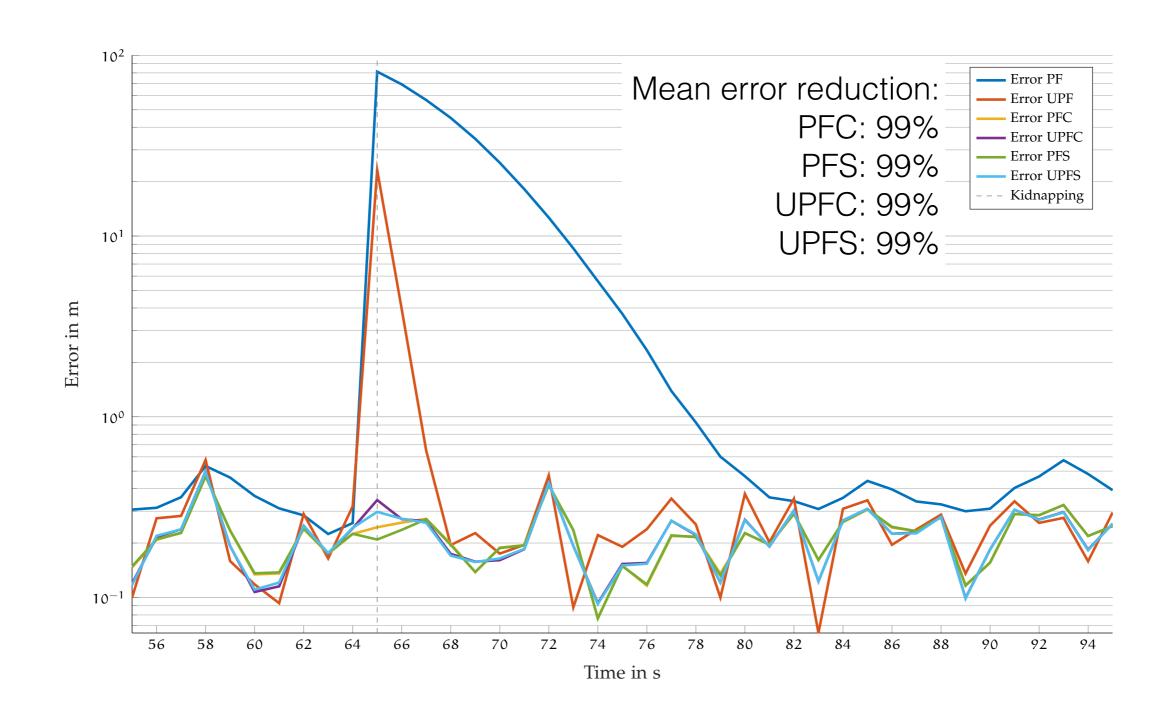
Results – 4 Landmarks – Kidnapped Robot Problem



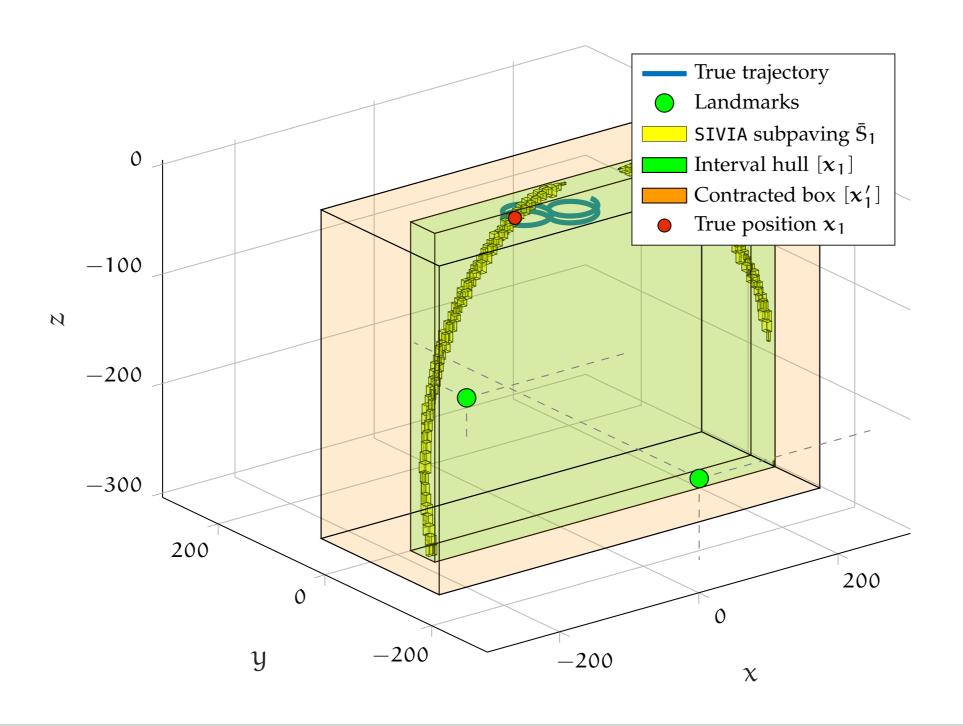
Results – 9 Landmarks – Wake-up Robot Problem



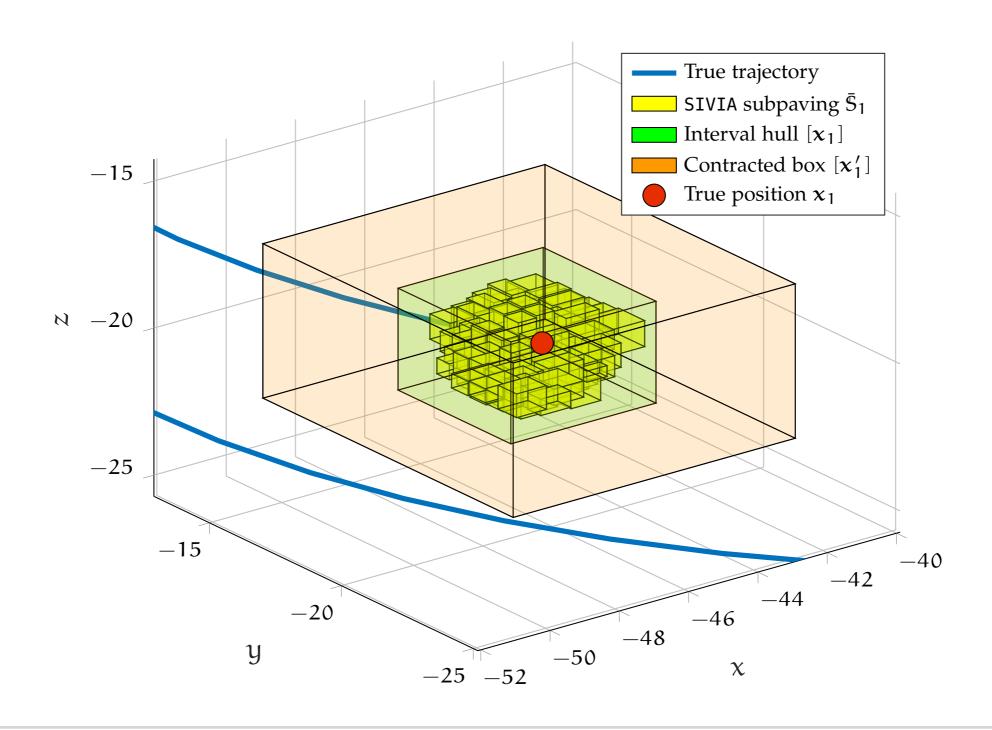
Results – 9 Landmarks – Kidnapped Robot Problem



Results – 2 Landmarks – HC4 vs. SIVIA



Results – 9 Landmarks – HC4 vs. SIVIA



Conclusion

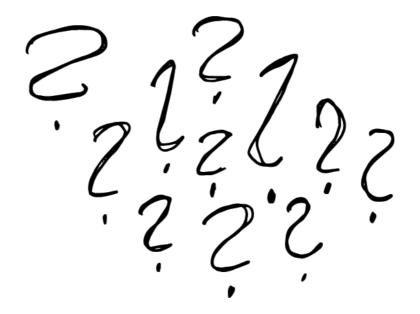
- All four new hybrid filters are generally able to solve the wake-up and kidnapped robot problem more accurately than the conventional filters
- Improvement of up to 88% in the median estimation error
- Mean initial estimation error reduced by up to 94%
- Mean error after kidnapping is reduced by up to 99%
- Improvement is particularly pronounced when 4 or 9 landmarks are present
- With 4 landmarks UPFC better than PFC at 100 times fewer particles.
- Instead of 200 bounded-error estimations 1 + 1 per kidnapping for the estimated scenarios sufficient
- The four novel filters are applicable to any landmark-based localisation scenario



Future Work

- Dynamically replace the particle filter by a Kalman filter when:
 - One subpaving results from the bounded-error estimation
 - The volume of the confined region is smaller than some threshold
 - Particle variance is smaller than some threshold ⇒ filter converged
 - Tracking ⇒ uni-modal Gaussian distribution appropriate
- Dynamically vary measurement noise covariance of unscented Kalman filter to influence the impact of the UKF on the proposal distribution ⇒ keep benefits of UPF when more than 2 landmarks are available but do bootstrap filtering when only 2 landmarks are available

Questions?



References

- [27] Renata Neuland, Jeremy Nicola, Renan Maffei, Luc Jaulin, Edson Prestes and Mariana Kolberg. "Hybridization of Monte Carlo and Set-membership Methods for the Global Localization of Underwater Robots". In: *International Conference on Intelligent Robots and Systems*. Sept. 2014.
- [28] Renata Neuland, Renan Maffei, Luc Jaulin, Edson Prestes and Mariana Kolberg. "Improving the Precision of AUVs Localization in a Hybrid Interval-Probabilistic Approach Using a Set-Inversion Strategy". In: *Unmanned Systems* 02 (Oct. 2014), pp. 361–375.
- [106] Luc Jaulin, Michel Legris and Frédéric Dabe. "GESMI, un logiciel pour l'aide à localisation de mines sous-marines". In: *JIME* (2006).