Sensor Signal Processing for Defence Conference

12th and 13th September 2023

Royal College of Physicians Conference Centre

Adaptive Kernel Kalman Filter for Magnetic Anomaly Detection-based Metallic Target Tracking

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Novelties

- Explore a new application for the Adaptive kernel Kalman filter (AKKF).
  - Joint tracking and magnetic parameters estimation.
  - High-dimensional and high nonlinear problems.
- The simulations evaluate the performance of the AKKF in tracking and estimating magnetic parameters.

Outline

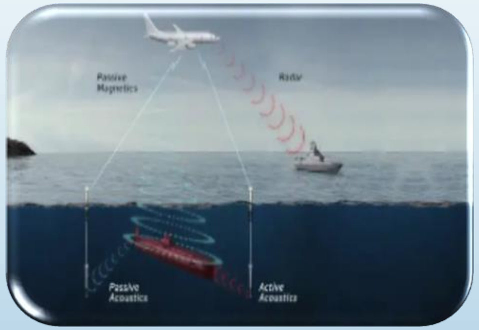
- Background – Magnetic anomaly detection
- System model
- AKKF-based tracking and estimation algorithm
- Simulation Results
- Conclusions

Background – Magnetic anomaly detection (MAD)

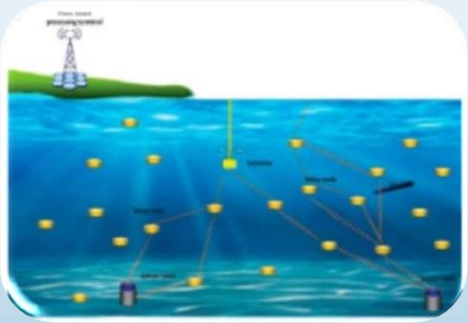
MAD

Detect and locate objects by sensing disturbances in the Earth's magnetic field caused by ferromagnetic materials.

Background – Magnetic anomaly detection (MAD)

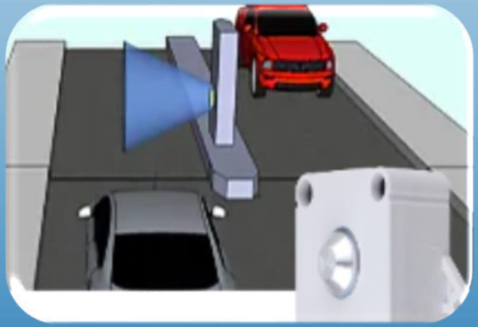


Submarine Detection

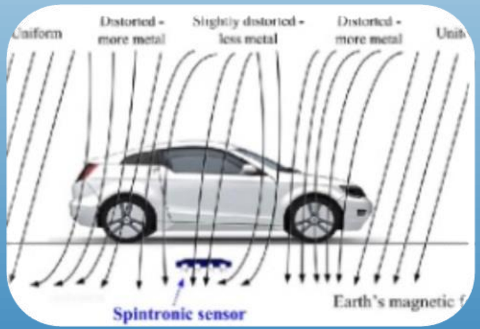


Underwater Surveillance

Archaeology



Access control



Tracking of moving metallic vehicle

Background – Magnetic anomaly detection (MAD)

Advantages

- Passive Operation
- Stealthy Detection
- Secret Agent Mode
- Long Detection Range

Background – MAD-based metallic target tracking

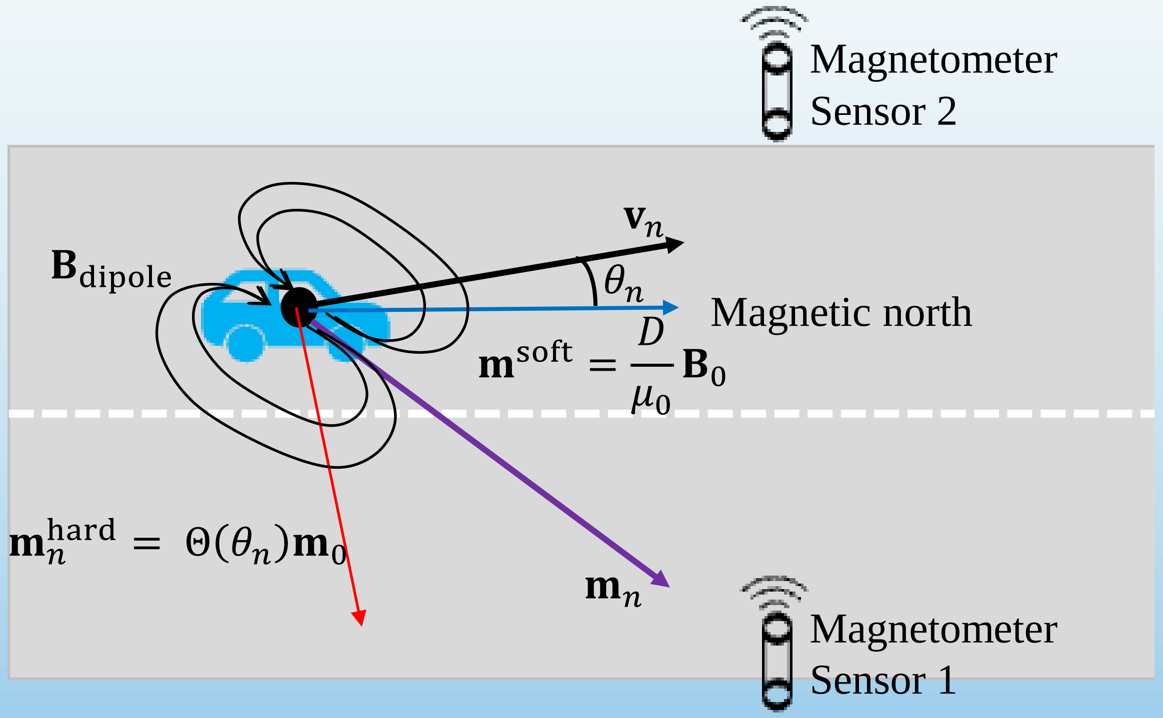
- The magnetic signature → **Unique identifier** → Individual target tracking and differentiation.

- The tracking process:

Measuring the magnetic field → **Analysing changes in the magnetic signatures** → **Determine:**

- **Location**
- **Speed**
- **Direction of the metallic targets**

System Model

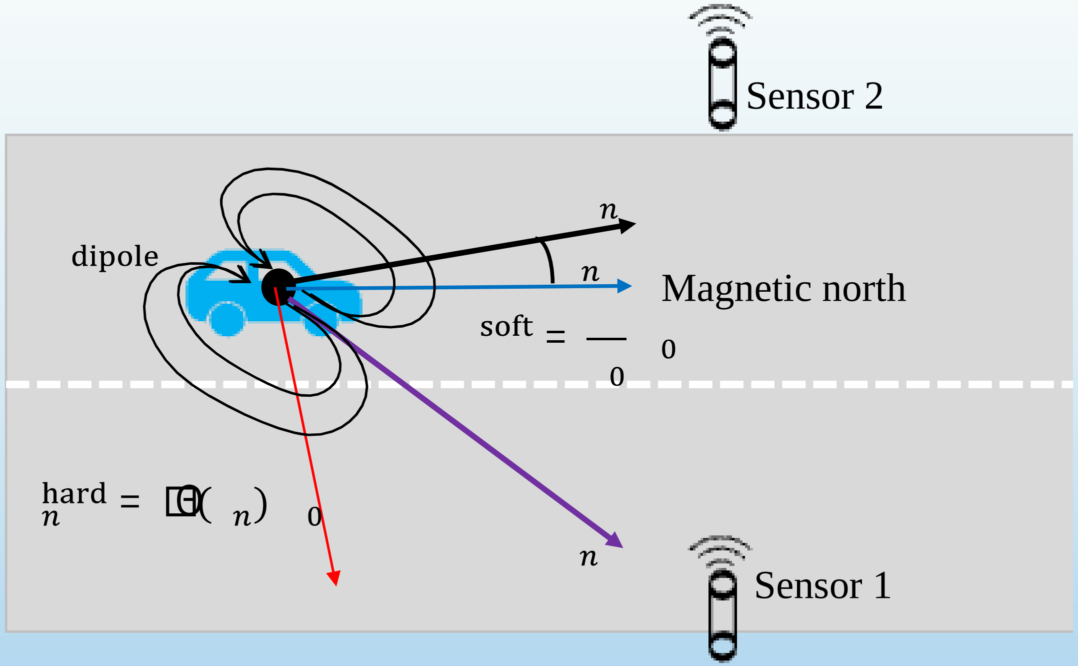


- Motion model: nearly constant velocity model
- The magnetic moment of the metallic objects

$$\mathbf{m}_n = \mathbf{m}_n^{\text{hard}} + \mathbf{m}_n^{\text{soft}} = \Theta(\theta_n)\mathbf{m}_0 + \frac{D}{\mu_0}\mathbf{B}_0,$$

- Ferromagnetic content (hard iron)
- Deflection of the Earth's magnetic field (soft iron)
- Scalar constant *D*
- Permeability of the vacuum μ_0
- Earth's magnetic field $\mathbf{B}_0$

System Model



❑ Measurement model

$$
\begin{aligned}
\mathbf{y}_{n,k} &= h_k(\mathbf{x}_n, \mathbf{m}_n) + \mathbf{e}_{n,k} \\
&= \mathbf{B}_0 + \frac{\mu_0}{4\pi} \frac{3\left(\mathbf{r}_{n,k} \cdot \mathbf{m}_n\right)\mathbf{r}_{n,k} - \| \mathbf{r}_{n,k} \|^2 \mathbf{m}_n}{\| \mathbf{r}_{n,k} \|^5} + \mathbf{e}_{n,k}.
\end{aligned}
$$

Bayesian methods

Purpose

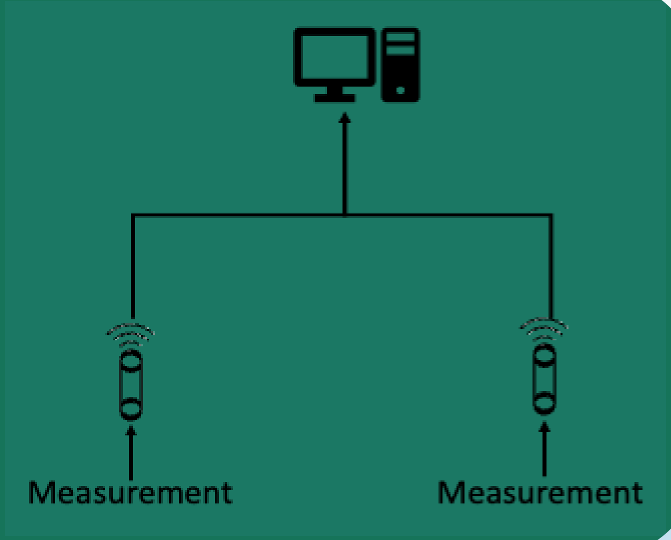
Track the target's movement and simultaneously estimate its magnetic moment based on measurements at two magnetometers.

Hidden states

Position and velocity ($\mathbf{x}_n$), magnetic dipole moment ($\mathbf{m}_0$), scalar constant (D)

Bayesian methods

Framework



Posterior pdf

$$p(\mathbf{X}_n \mid \mathbf{y}_{1:n,1:2}) = p(\mathbf{x}_n, \mathbf{m}_n, \mathbf{m}_0, D \mid \mathbf{y}_{1:n,1:2}) = p\left(\mathbf{y}_{n,1:2} \mid \mathbf{x}_n, \mathbf{m}_n, \mathbf{m}_0, D\right)$$
$$\times \frac{\iiiint p\left(\mathbf{x}_n|\mathbf{x}_{n-1}\right) p\left(\mathbf{m}_n|\mathbf{x}_n, \mathbf{m}_{n-1}, \mathbf{m}_0, D\right) p\left(\mathbf{m}_0, D\right) p\left(\mathbf{x}_{n-1}, \mathbf{m}_{n-1}, \mathbf{m}_0, D \mid \mathbf{y}_{1:n-1,1:2}\right) d\mathbf{x}_{n-1} d\mathbf{m}_{n-1} d\mathbf{m}_0 dD}{p\left(\mathbf{y}_{n,1:2} \mid \mathbf{y}_{1:n-1,1:2}\right)}$$

Bayesian methods – particle filter (PF)

$$p(\mathbf{X}_n \mid \mathbf{y}_{1:n,1:2}) \approx \frac{1}{M}\sum_{i=1}^{M} w_n^{\{i\}}\, \delta(\mathbf{x}_n - \mathbf{x}_n^{\{i\}}, \mathbf{m}_n - \mathbf{m}_n^{\{i\}}, \mathbf{m}_0 - \mathbf{m}_{0,n}^{\{i\}}, D - D_n^{\{i\}}).$$

Computational cost

The computational cost of the PF grows exponentially with the number of state variables

Particle degeneracy

Difficult to obtain a sufficient number of particles to represent the posterior pdf accurately

Tracking/estimation performance

Poor estimation accuracy and instability in the estimates

Bayesian methods – Adaptive kernel Kalman filter (AKKF)

Applications so far

- Single target tracking
- Sensor fusion
- Multi-target tracking

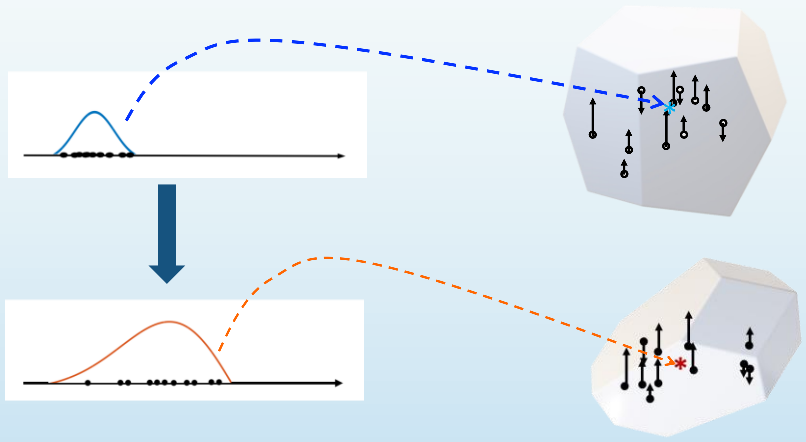
Potential applications

- Joint tracking and parameters estimation

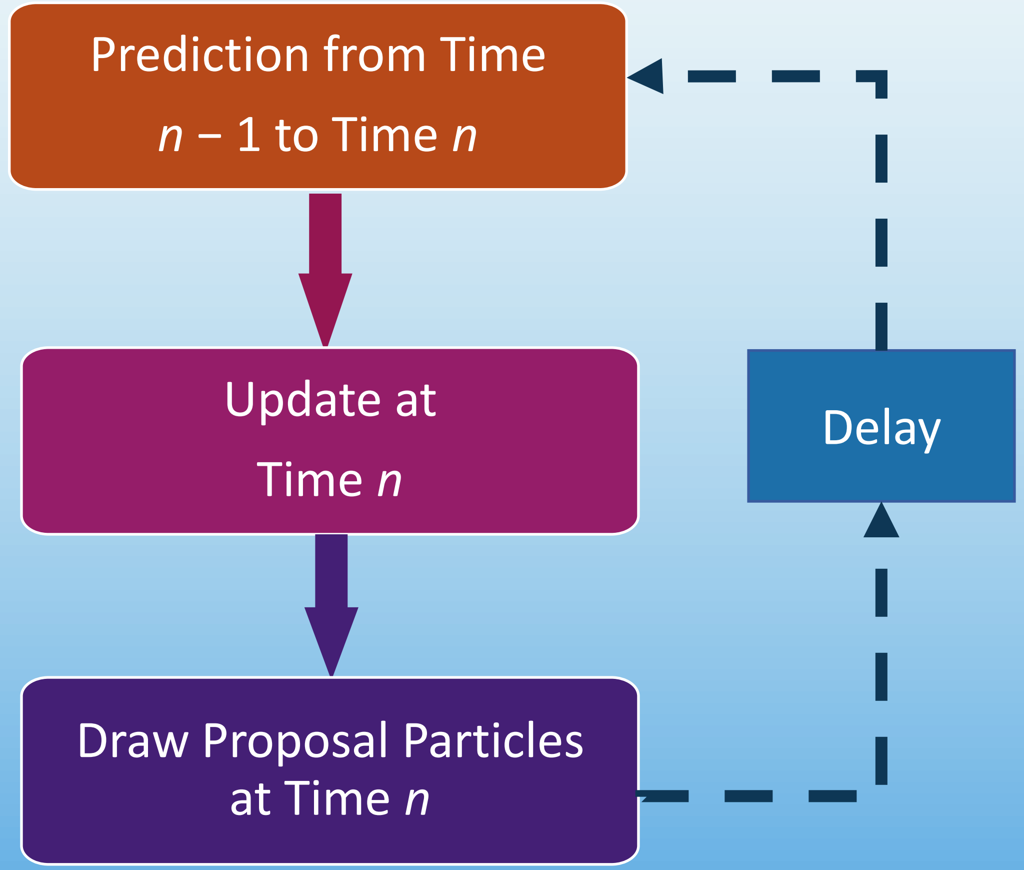
Objectives

- Validity of the AKKF for fixed parameter estimation
- Validity of the AKKF for high-dimensional tracking/estimation problems

Bayesian methods – Adaptive kernel Kalman filter (AKKF)

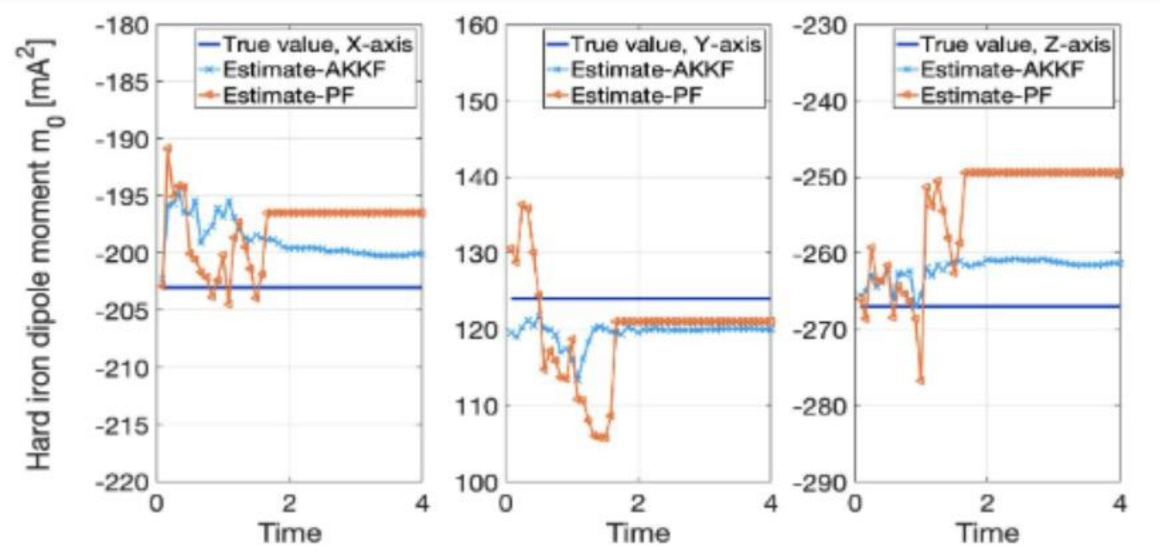


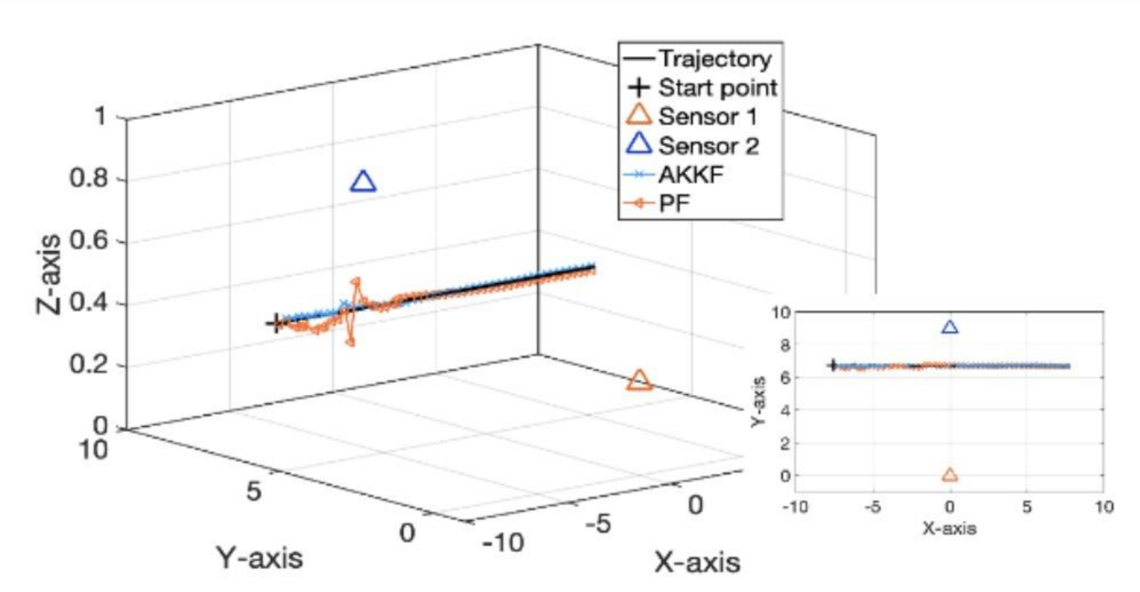
- Embed the joint pdf into high-dimensional kernel space as an empirical Kernel mean embedding.

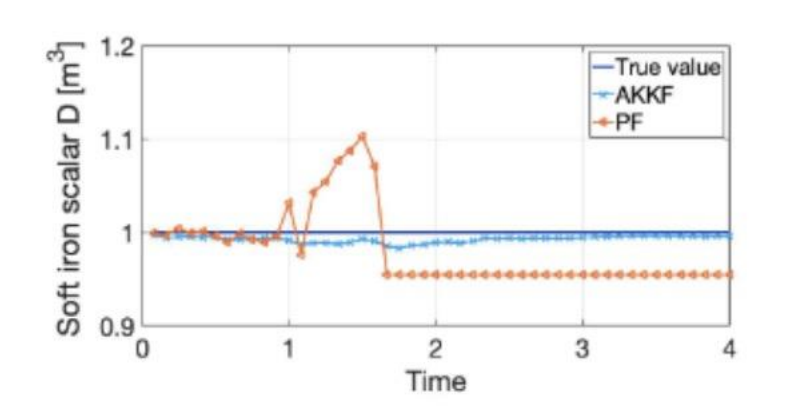


- Executed in both the data state space and kernel feature space
  - Based on the system model, the particles are propagated and updated in the data space.
  - KMEs of predictive/posterior pdfs are predicted and updated in the kernel feature space.

Simulation

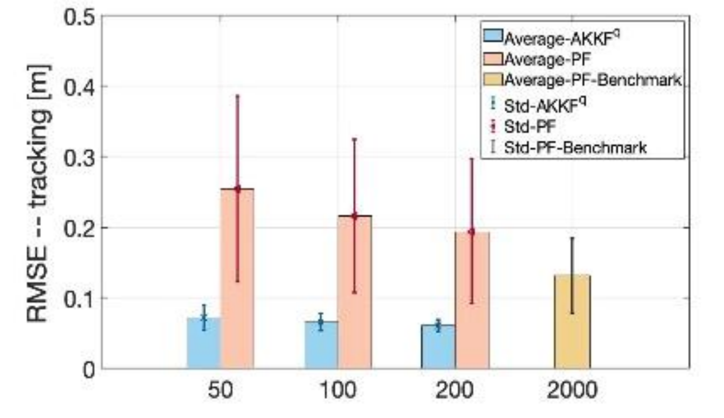


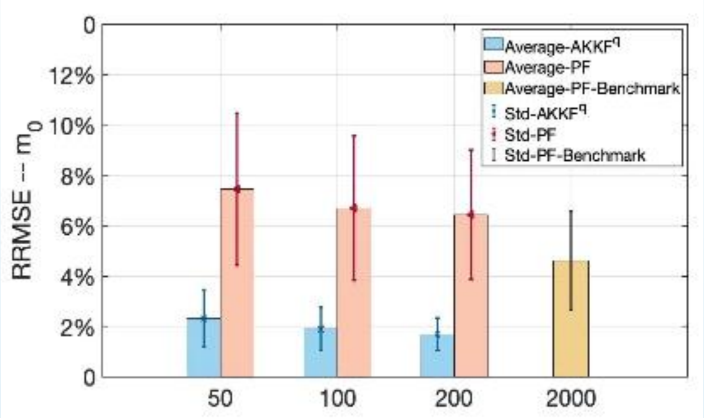


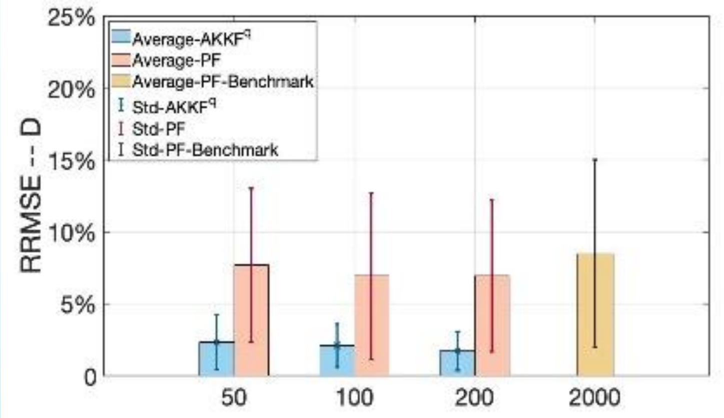


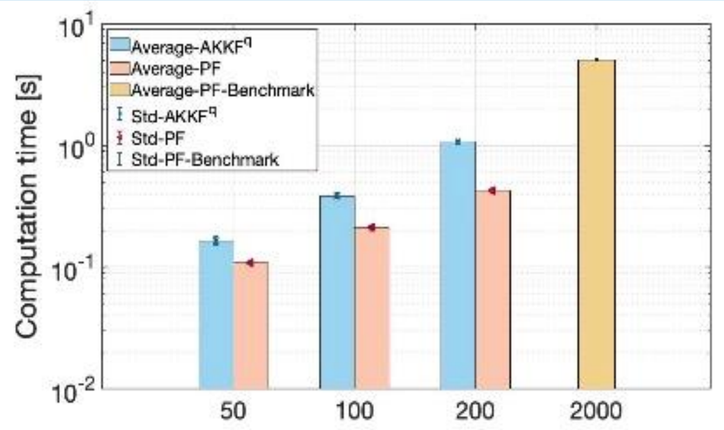
- The AKKF uses $M^{AKKF} = 100$ particles, while $M^{PF} = 2000$ particles are used for the PF.
- The AKKF with a smaller number of particles achieved favourable tracking and estimation performance compared to the PF with a large number of particles.

Simulation









- Compared to the PF with the same number of particles, the AKKF shows improved performance.
- Compared to the benchmark performance: the AKKF shows satisfactory tracking and estimation performance with significantly reduced computational complexity.

Conclusion

Summary

- ❑AKKF utilisation for joint tracking and magnetic parameters estimation

Advantages

- Efficiency for high nonlinear and high dimensional problems
- Lower computation complexity

Thank You
For Your Attention

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