

WP1.2 Scalable dynamic and distributed inference

RA: Mengwei Sun,
WP leader: James R. Hopgood,
Academics: Mike E. Davies, Ian K. Proudler
PhD student: Sofie MacDonald



Context and objectives

- ❑ Scalable solutions to approximate inference in distributed and modular sensor networks: signal detection/object tracking problems
- ❑ Scalability issue of existing filters – main concern
- ❑ Two families of Bayesian inference
 - **Data-driven filters:** Dynamic state space model (DSM) is unknown, training data set is provided
 - Propose the Gaussian process-message passing (GP-MP) based algorithm
 - **Model-driven filters:** DSM is given explicitly
 - Propose the adaptive kernel Kalman filter (AKKF)
 - Joint Spatio-Temporal Bias Estimation and Tracking

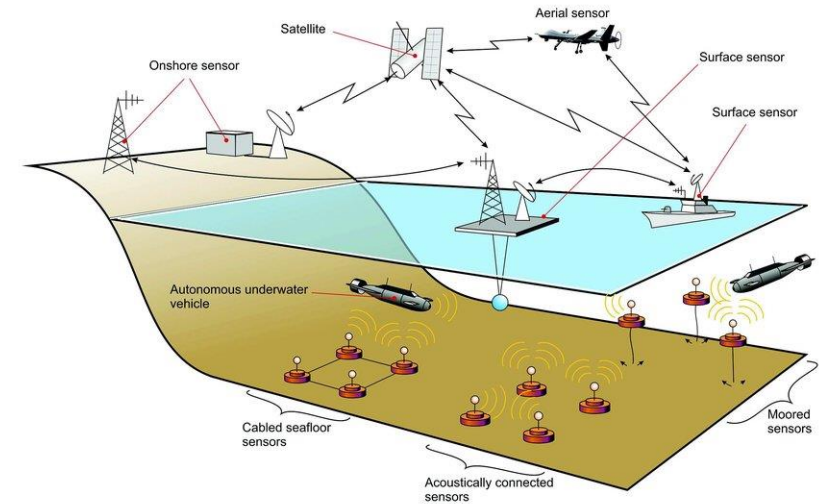


Fig. An example of a distributed sensor network

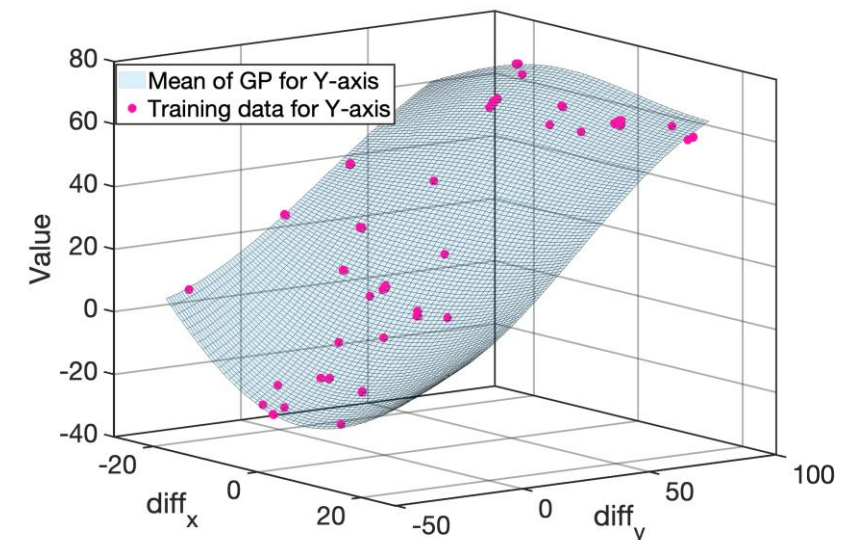


Fig. An example of two-dimensional GPR

Data-driven Bayesian inference – GP-MP based multi-target tracking

❑ Design the Gaussian process – message passing (GP-MP) based algorithm for object tracking

❑ Advantages

- Data-driven DSM
- No need for multiple models
- Scalable multi-target tracking

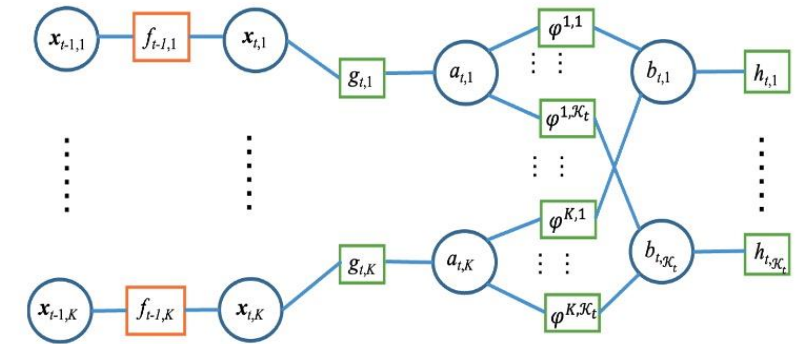


Fig. Factor graphs for single-sensor MTT

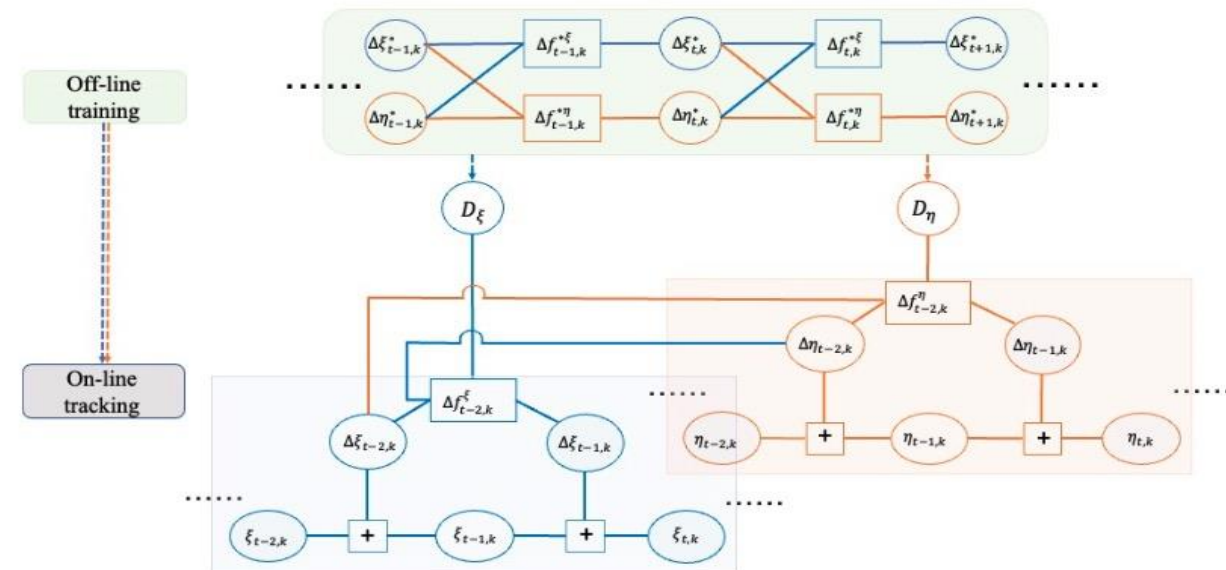


Fig. Factor graph of the proposed joint GP algorithm for state prediction

- M. W. Sun, M. E. Davies, I. Proudler, J.R. Hopgood, "A Gaussian Process based Method for Multiple Model Tracking," 2020 Sensor Signal Processing for Defence Conference (SSPD2020), published.
- M. W. Sun, M. E. Davies, I. Proudler, J.R. Hopgood, "Maneuvering Multi-target Tracking Based on Gaussian Process Regression," IEEE Transactions on Aerospace and Electronic, submitted

Model-driven Bayesian inference

– New filter design

- ❑ Kernel mean embedding (KME)
- ❑ Propose the Adaptive kernel Kalman filter (AKKF)

❑ Advantages

- Avoid particle filter resampling step
- Good scalability
- Give a new insight on model-based and data-based filters
- Potential for improving the loopy belief propagation

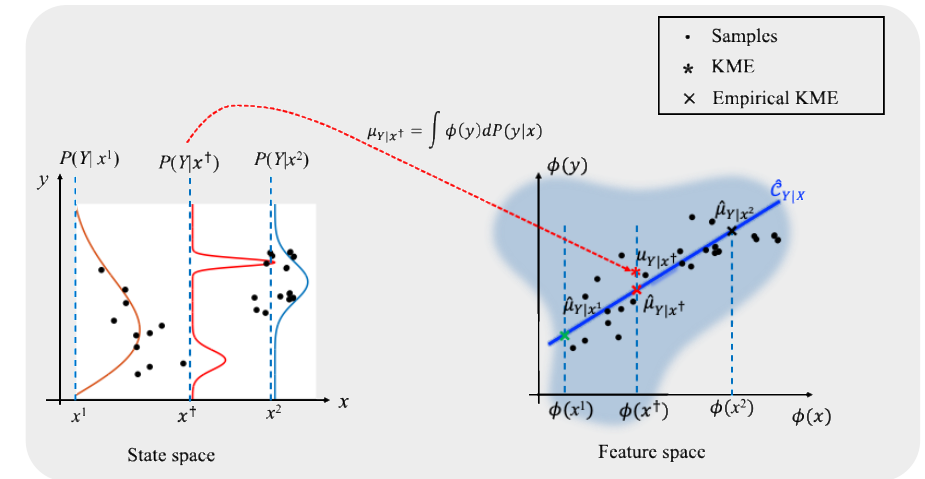


Fig. KME of a conditional distribution

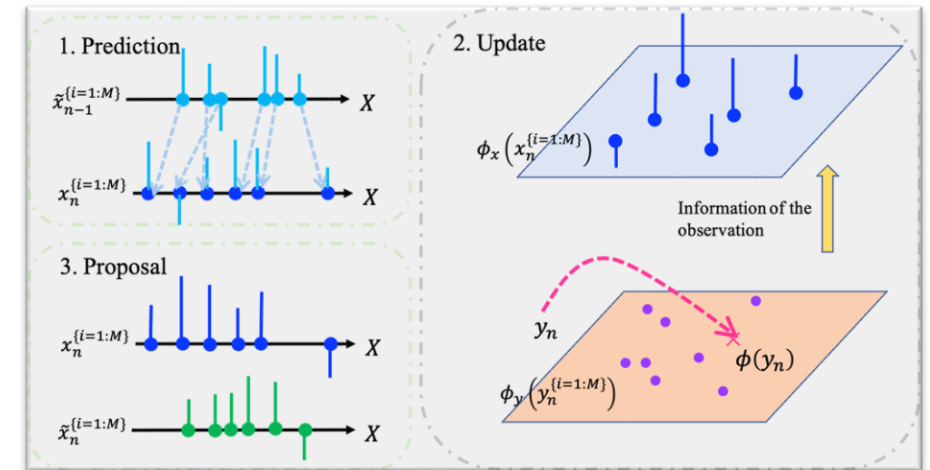


Fig. Realisation of AKKF

- M. W. Sun, M. E. Davies, I. Proudler, J.R. Hopgood, "Adaptive Kernel Kalman Filter," 2021 Sensor Signal Processing for Defence Conference (SSPD2021), published
- M. W. Sun, M. E. Davies, I. Proudler, J.R. Hopgood, "Adaptive Kernel Kalman Filter Multi-Sensor Fusion," 2021 24th International Conference on Information Fusion (FUSION), published.
- M. W. Sun, M. E. Davies, I. Proudler, J.R. Hopgood, "Adaptive Kernel Kalman Filter," IEEE Transactions on Signal processing, Submitted.

Model-driven Bayesian inference – Applications of the AKKF

• Single target tracking

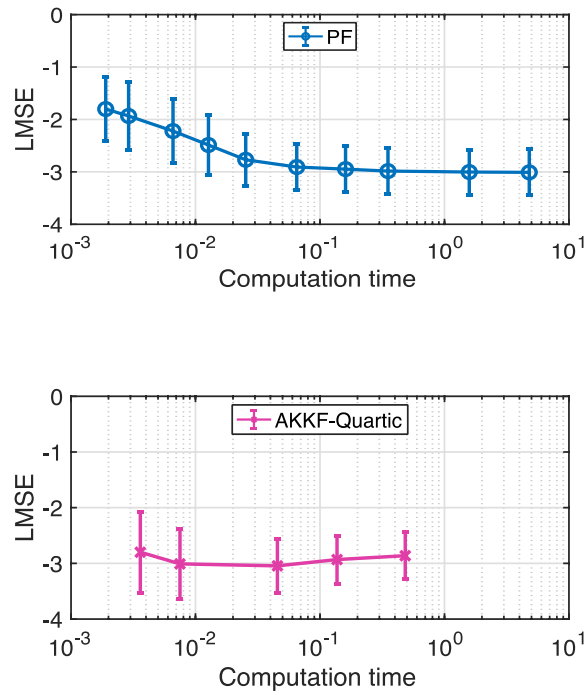
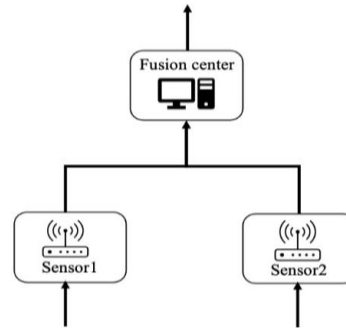


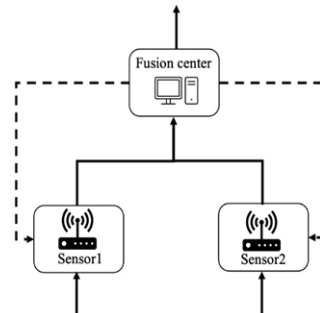
Fig. Comparisons of computation time and tracking performance of the PF and the AKKF

• Multi-sensor fusion



(a)

Centralized fusion



(b)

Semi-Decentralized fusion

Fig. Different fusion schemes

• Multi-target tracking

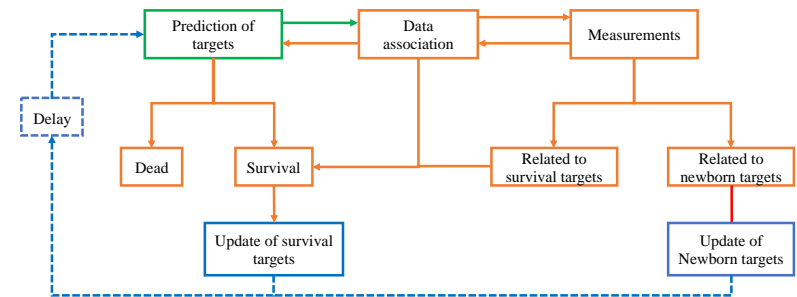


Fig. Flow diagram of the proposed AKKF based BP algorithm

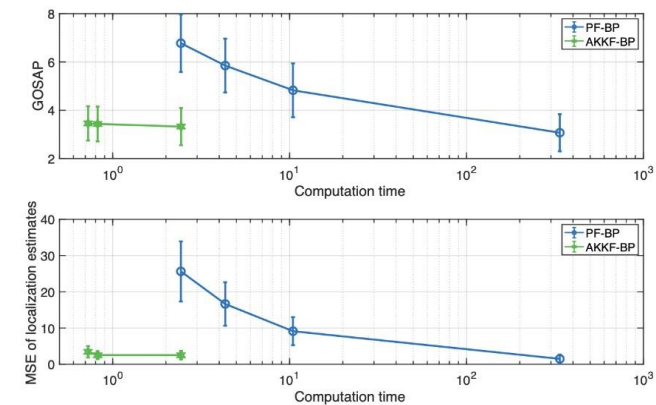


Fig. GOSAP and localization estimation error of the detected targets comparisons

Model-driven Bayesian inference

– Joint Spatio-Temporal Bias Estimation and Tracking

❑ **Problem:** Sensor calibration for reliable object tracking without a global frame of reference

❑ **Proposed solutions:** Grid-based search method with likelihood function to test the bias state space.

❑ **Advantages**

- Tracking performance improvement
- Registration errors are corrected
- Increase in accuracy over object tracking with only a single sensor

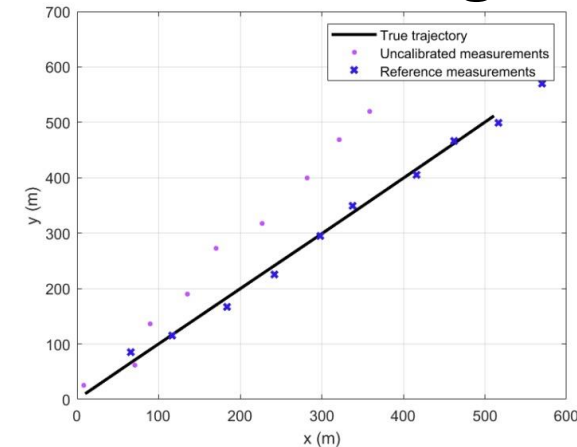


Fig. Before fusion and correction

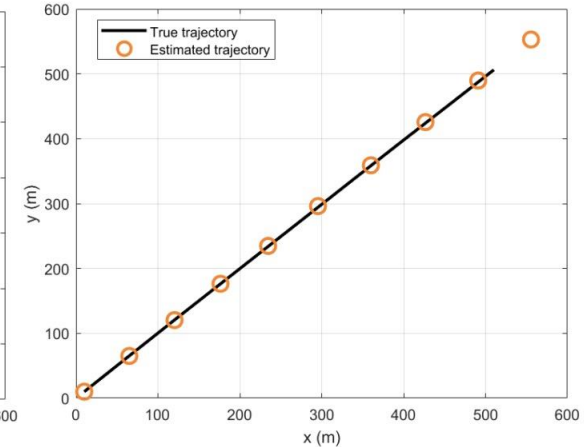


Fig. After fusion and correction

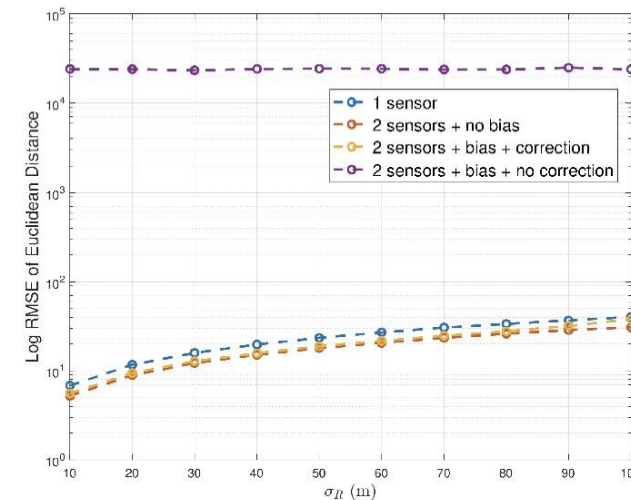


Fig. Tracking performance vs σ_R