


A MULTI-BERNOULLI GAUSSIAN FILTER FOR TRACK-BEFORE-DETECT

Elinor Davies, Supervised by Ángel García-Fernández, David Greg (Leonardo), Vassil Alexandrov (STFC)

EPSRC Centre for Doctoral Training in Distributed Algorithms, University of Liverpool, Liverpool, UK

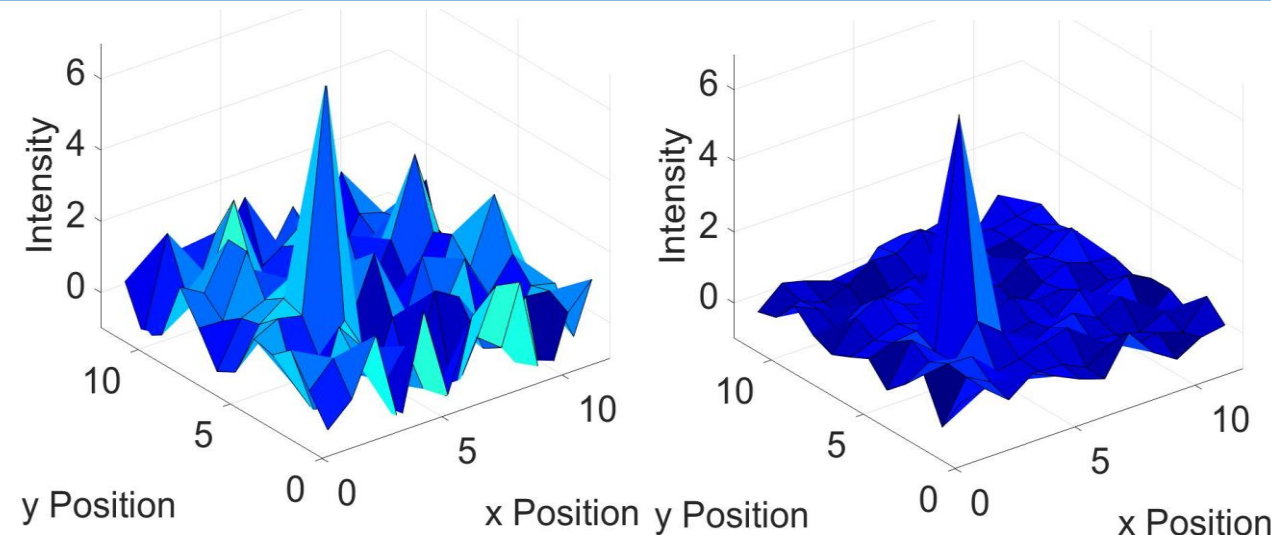
BACKGROUND & AIMS

PROJECT INFORMATION

Project is co-funded by **Leonardo**.  **LEONARDO**
The project focuses on using **Track-Before-Detect** to track objects from **noisy measurement data**.

WHY A DIFFERENT APPROACH?

Typical methods work by **thresholding** measurement data to find **detections**. This becomes problematic in scenarios with **Low Signal-to-noise ratios**.



MULTI-BERNOULLI FILTER?

The **Multi-Bernoulli Filter** identifies **potential targets** that may be present in the **surveillance region**. For this filter it is required to **predict** each potential target's **probability of existence**. Each potential target is **modelled** with a **Bernoulli probability** [1].

$$f_{k|k-1}^l(X_{k|k-1}^l) = \begin{cases} 1 - r_{k|k-1}^l, & X_{k|k-1}^l = \emptyset \\ r_{k|k-1}^l p(x), & X_{k|k-1}^l = \{x\} \end{cases}$$

DEALING WITH MULTIPLE OBJECTS

The filter can be extended for **multiple objects** with **auxiliary variables** [2]. The filter **predicts** the **contribution** of each **potential target** to the **measurement likelihood**. Each **potential target** then undergoes **independent prediction and update** steps.

ONGOING WORK

SENSOR NETWORK

A **multi-sensor** environment is used in which the **surveillance region** is made up of **cells** with a **sensor** positioned at the **midpoint** of **every cell**. This results in a **non-linear measurement function**.

SIGMA-POINT KALMAN FILTER

A **sigma-point Kalman filter** is used to provide a **mapping** between the **state-space** and the **measurements**. **Sigma-points** are used to **predict** the **expected measurement vector** of each potential target, the corresponding **measurement covariance** and **cross covariance** with the target's state-space. Currently an **Unscented Kalman filter** is used.

OBJECTS IN CLOSE PROXIMITY

A challenging scenario is when there are **multiple objects** in **close proximity**. In this project a **bias term** and **additional noise** are introduced to account for any other potential targets.

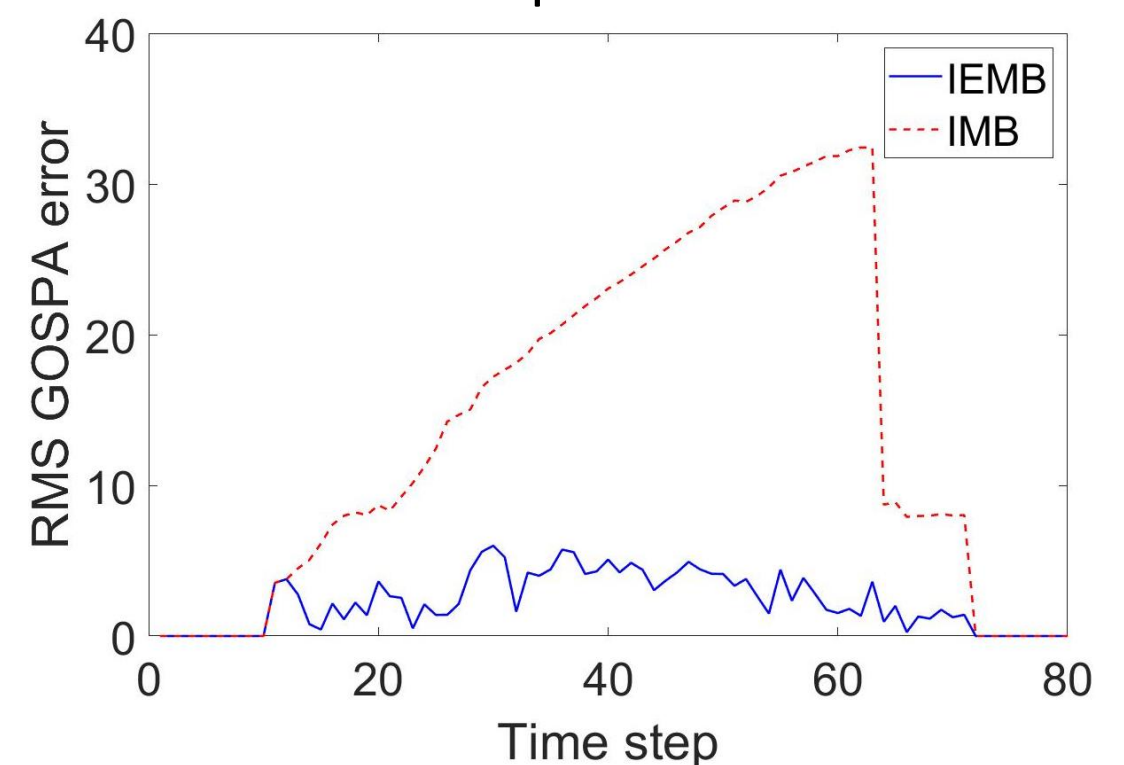
$$p(z_k) \approx N(z_k; h(x^u) + \tilde{z}_{corr}^u, R + S_{corr}^u)$$

CONDITIONAL MOMENTS

Each target's **expected measurement vector** and **measurement covariance** is **weighted** using its **probability of existence** to give its **likelihood contribution**. The **bias term** and **additional noise** are found by **summing contributions** from all **other targets**.

PRELIMINARY RESULTS

The Root Mean Squared GOSPA error



In this approach (**IEMB**), compared to methods which ignore other targets (**IMB**), the number of **false targets** is greatly **reduced**. This produces a **lower RMS GOSPA error** [3].

FUTURE WORK

- ❑ **Parallelisation** of the filter where the recursions for the independent potential targets operate on separate processors.
- ❑ Implement **alternatives** to the **Unscented Kalman filter** including **particle filters** or the **iterated posterior linearisation filter**.
- ❑ Investigate the possibility of switching **auxiliary variables** between **Bernoullis** at each time step.
- ❑ To test filter using data **real data** collected from sensor.

CONCLUSION

This project will create a filter that works in noisy environments where there is a **low signal-to-noise ratio**. It should be capable of tracking **multiple objects** in **close proximity** to each other **simultaneously**. The use of **parallel computing** techniques means the potential of **highly accurate** results while maintaining desirable **run-times**.

REFERENCES

- [1] B. Ristic, B.-T. Vo, B.-N. Vo, and A. Farina, "A Tutorial on Bernoulli Filters: Theory, Implementation and Applications," IEEE Transactions on Signal Processing, vol. 61, no. 13, pp. 3406–3430, Jul. 2013.
- [2] Á. F. García-Fernández, L. Svensson, J. L. Williams, Y. Xia, and K. Granström, "Trajectory Poisson multi-Bernoulli filters," in IEEE Transactions on Signal Processing, vol. 68, pp. 4933–4945, Mar. 2020.
- [3] A. S. Rahmathullah, A. F. García-Fernández, and L. Svensson, "Generalized optimal sub-pattern assignment metric," in 20th International Conference on Information Fusion, 2017, pp. 1–8.