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Points, Particles and Positions:

Recent Advances in Distributed Processing of Agile Objects

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SIGNetS – Signal and Information Gathering for Networked Surveillance

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SIGNetS

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The Team

- Cambridge University *(Lead Organisation)*:
  - Signal Processing and Communications (SigProC) Laboratory, Department of Engineering.
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- Sheffield University.
  - Department of Automatic Control and Systems Engineering (ACSE)
  - PI Prof. Lyudmila Mihaylova
- Surrey University.
  - Centre for Vision, Speech and Signal Processing (CVSSP), and 5G Innovation Centre (5GIC)
  - PI Prof. Wenwu Wang

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SIGNetS

Signal and Information Gathering for Networked Surveillance

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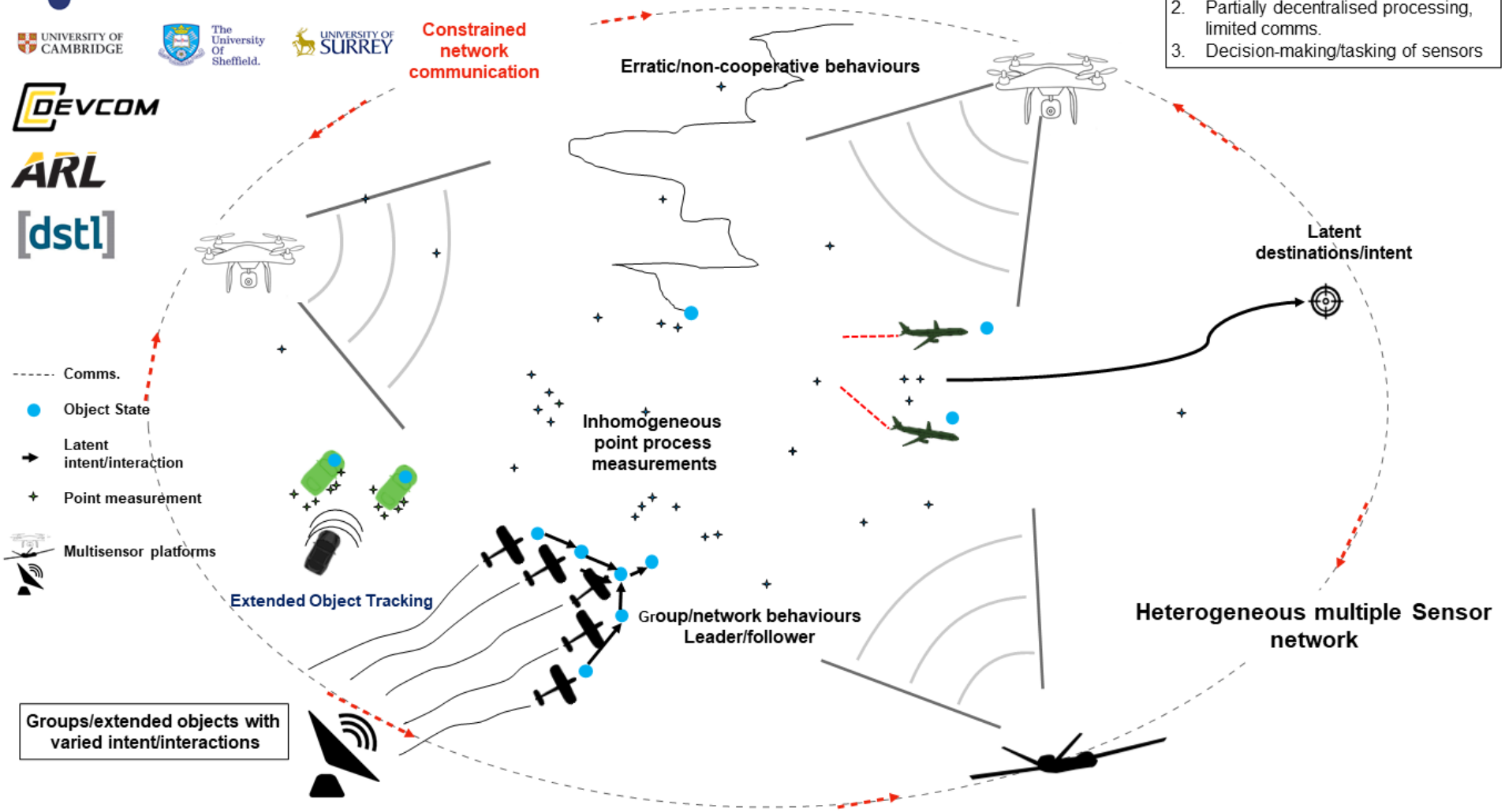
Objectives:
1. Localisation, learning of latent intentions/network structures
2. Partially decentralised processing, limited comms.
3. Decision-making/tasking of sensors



Heterogeneous/multiple sensor data, e.g.
- RADAR
- LiDAR
- Static detectors
- Video
- Road-grid/topological info.

`Allowing networked sensors to see, interpret, and communicate the status of the environment'

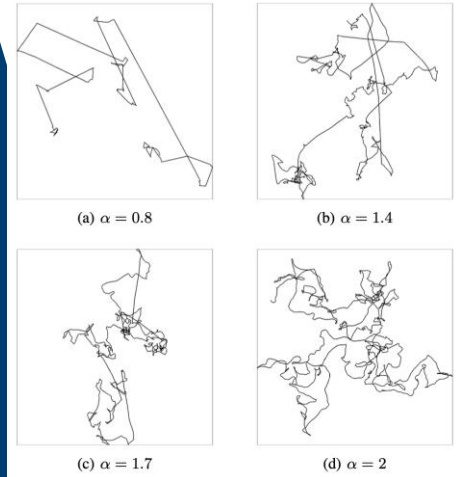
Methodologies:
- **Heterogeneous point processes**
- **Probabilistic network interaction/intent models**
- **Optimal sequential Bayesian inference combined with:**
- **Variational/message passing approximations**
- **Novel communications methods and ML**

Overview of Talk

- Point Process methods for agile targets:
  - Theory
  - Applications in Intent modelling and localisation methods
  - Non-Gaussian Process Regression
- Point Process methods for sensor modelling:
  - Theory
  - Applications in multiple object tracking, object detection, dynamic target/clutter rate inference, and variational Bayes methods

Point Process methods for agile targets

- Irregular Movement (e.g. animal foraging, drones, etc.)



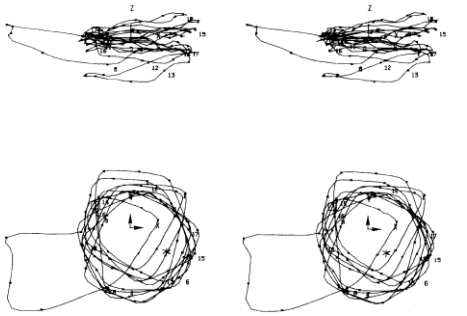
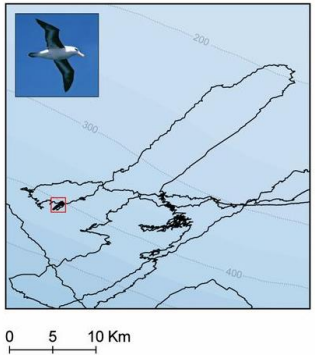
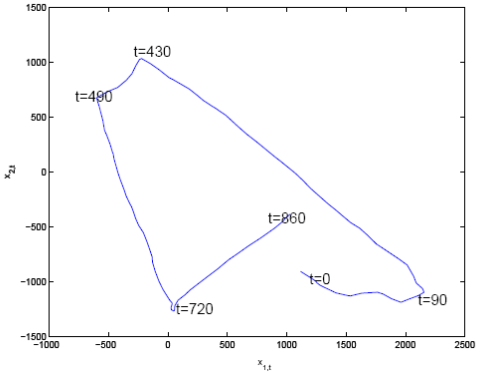


Fig. 1. Stereo plots of the flight path of a fly patrolling the airspace beneath a landmark seen from the side (*top*) and from below (*bottom*). *Star* marks the position of the landmark (a black box suspended from the ceiling). *Arrows* mark the X-, Y-, and Z-direction of the external coordinate system and are 5 cm long. The start of the recorded sequence is marked by an *open square*. Fly positions are marked every 0.2 s and consecutively numbered every second. The whole sequence is 20 s long. The sampling rate is 25/s. The angular separation of the stereo images is 7°

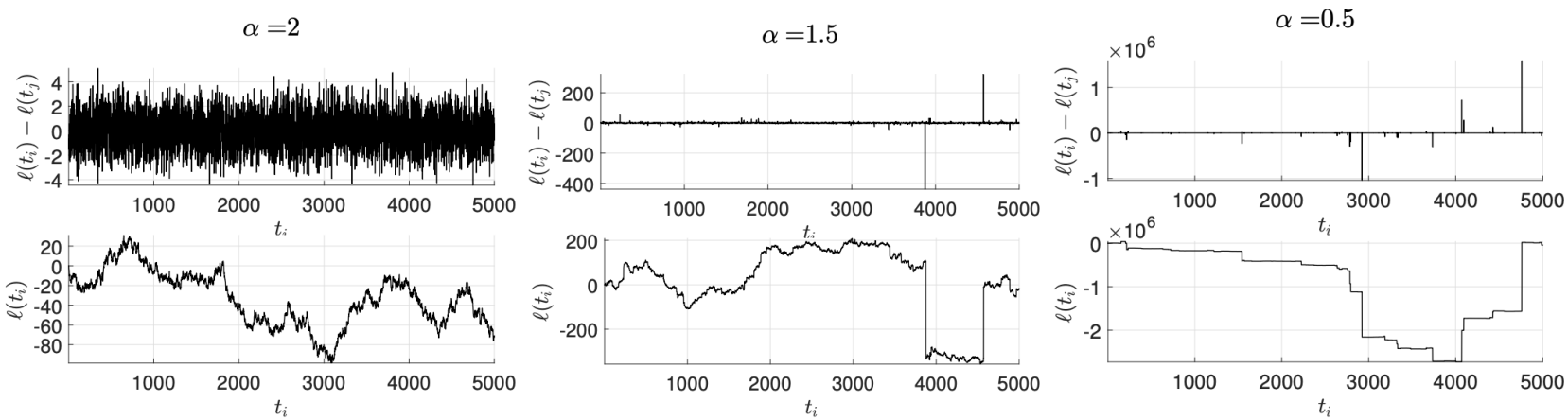




Theory: Levy process models of non-Gaussianity

Gaussian

Non-Gaussian (heavy-tailed)



- Wish to model broad classes of heavy-tailed driving noise to suit application
- Adopt a generic Levy process approach in which driving noise is modelled as *pure jump* processes in continuous time (and observed at random discrete times).
- Elegant and (fairly!) simple alternative to the standard Gaussian (Brownian motion)
- Many possible distributions: alpha-stable, Generalised Hyperbolic (inc. Student-t, normal-Gamma and normal-inverse Gaussian), normal tempered-stable, …

Brownian vs non-Gaussian state space models

- We will be interested in tracking and other models that can be written in a state-space form with state evolution in continuous time:

$$dx(t) = Ax(t)dt + HdW(t)$$

and we will need to be able to characterise transition PDFs for treatment of discrete time measurements:

$$p(x(t)|x(t-\Delta))$$

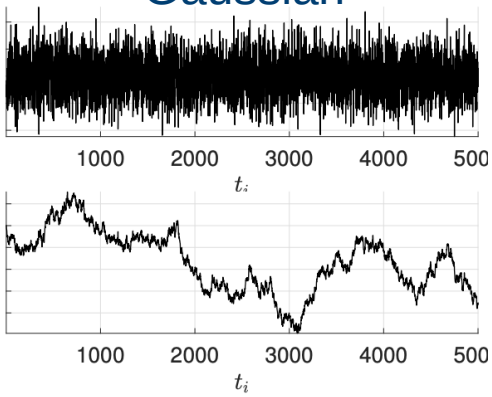
- If $\{W(t)\}$ is Gaussian (Brownian) then all calculations are simple (Kalman filter, standard stuff...)
- We are extending to a non-Gaussian $W(t)$ that moves *only* by small perturbations at random times $\{\tau_i\}_{i=1}^{\infty}$ ('jumps'), using a special conditionally Gaussian class ('Mean and Scale mixture of Gaussians') such that at any jump time τ_i:

$$dW(\tau_i) \sim \mathcal{N}(x_i\mu_W, x_i\sigma_W^2)$$

where $\{x_i\}_{i=1}^{\infty}$ are the jumps of another 'subordinator' process $X(t)$

- Because of the conditionally Gaussian structure we can implement the new models using banks of *standard achitectures* (Kalman filters etc.) inside standard particle filters
- And because of the 'discrete' structure (jumps) it is even easier to compute $p(x(t)|x(t-\Delta))$ than the pure Gaussian case for each Kalman filter

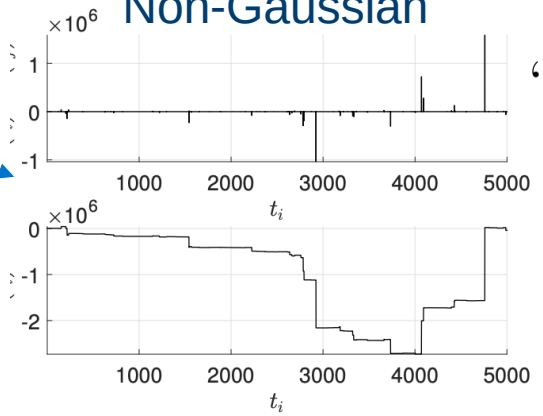
Gaussian



'$dW(t)$'

$W(t)$

Non-Gaussian



'$dW(t)$'

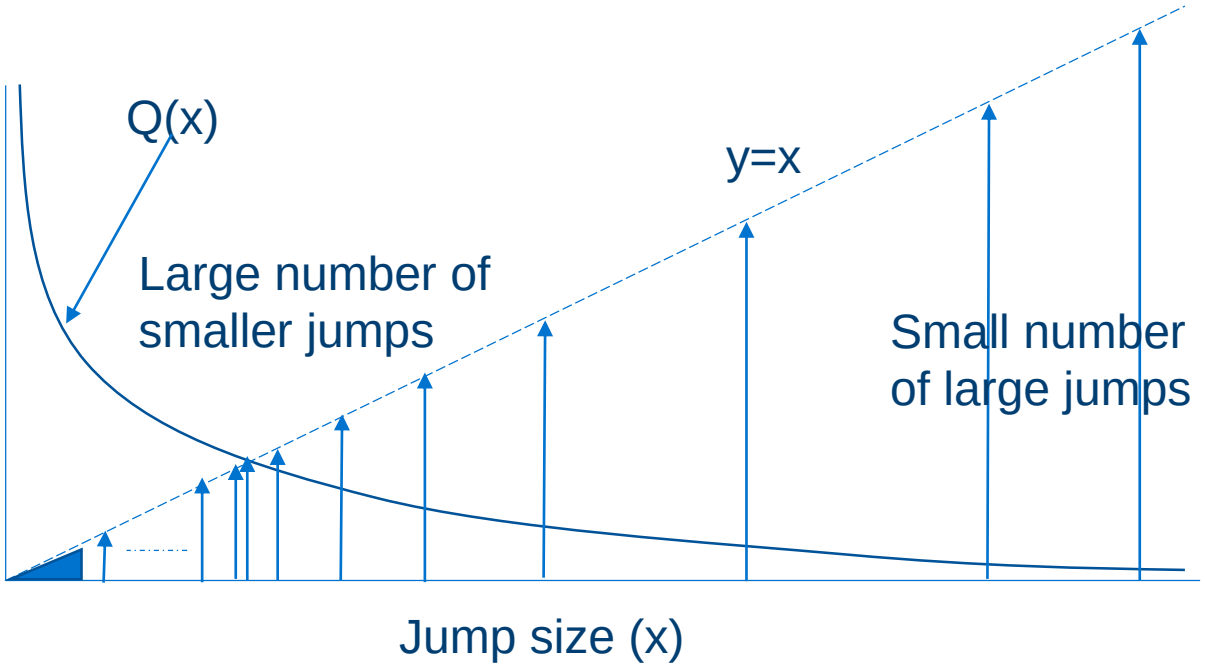
$W(t)$

See Also: (α-stable case): $dW(\tau_i) \sim \mathcal{N}(x_i\mu_W, x_i^2\sigma_W^2)$

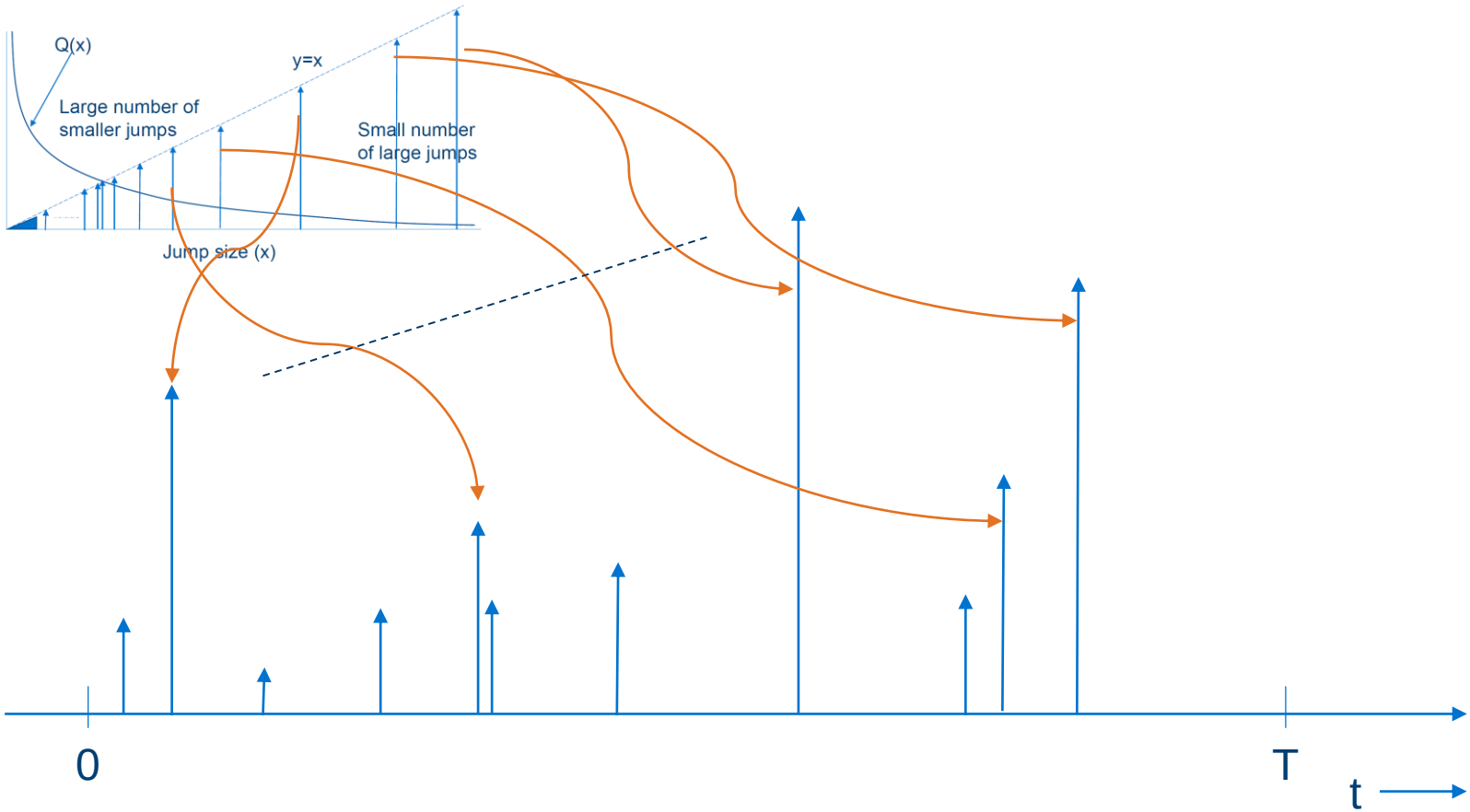
The Lévy State Space Model (1919) Godsill, Riabiz, Kontoyiannis https://arxiv.org/abs/1912.12524

Theory: Levy process models of non-Gausianity

- The Jumps $\{x_i\}_{i=1}^{\infty}$ are characterised by a Poisson process with non-uniform intensity function Q(x), the `Levy Density':

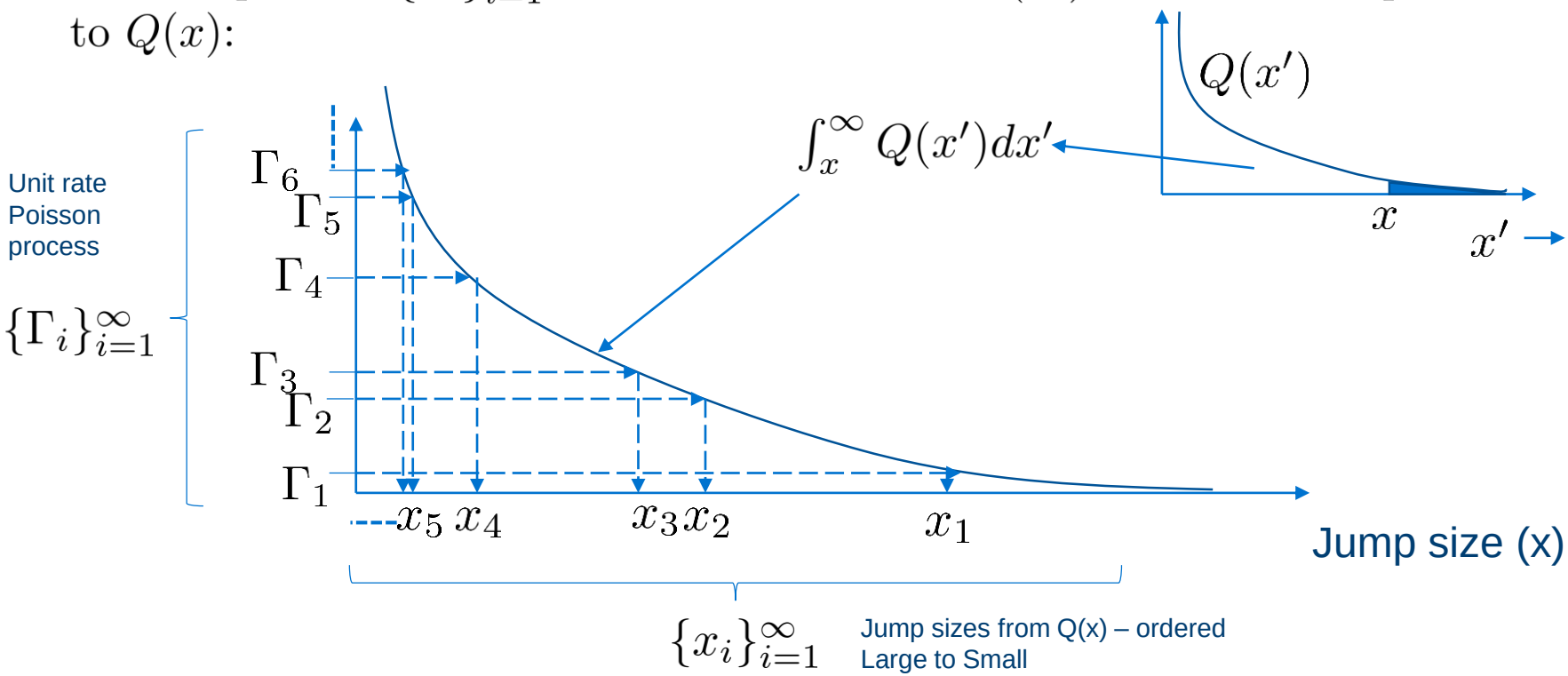


- Jumps are then uniformly randomly scattered across the time axis:



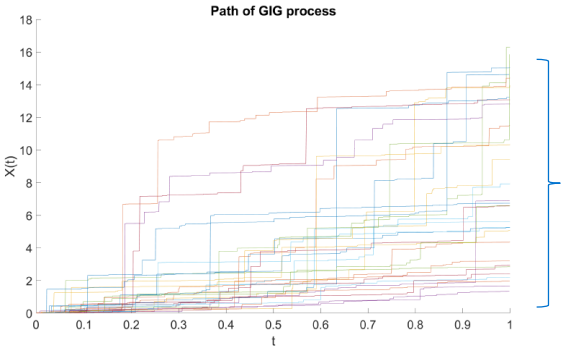
How to sample from Q(x)?

- In general $\int_0^\infty Q(x)dx \to \infty$ so can't sample directly
- The classical method (Fergusson and Klaas 1970's) starts with a uniform Poisson process $\{\Gamma_i\}_{i=1}^\infty$ and finds a function $h(\Gamma_i)$ that converts process to $Q(x)$:

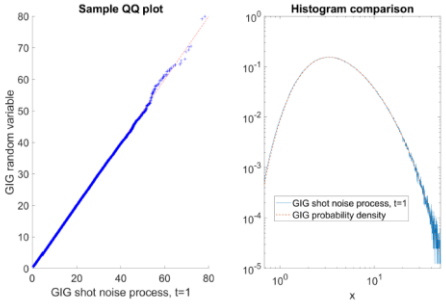


- Turns out the optimal function $h()$ is the inverse of $\int_x^\infty Q(x')dx'$.
- Can think of this as the direct analogue of sampling random variables using the *inverse CDF* method
- Also turns out that $h()$ can't be calculated for most of the processes we wish to use (e.g. the Generalised Inverse Gaussian (GIG))
- A lot of the fun then has been in developing effective alternative strategies for these cases:

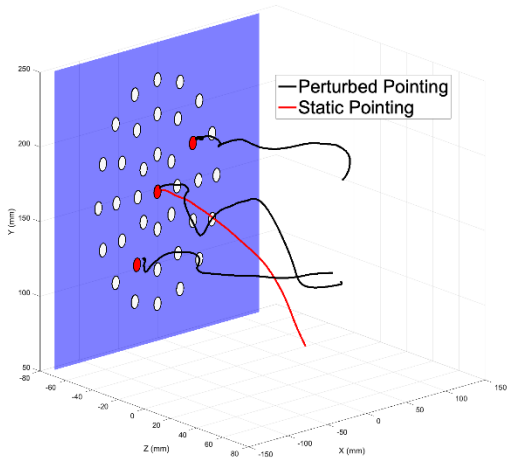
  Godsill and Kindap (2021) Point process simulation of generalised inverse Gaussian processes and estimation of the Jaeger integral, Stats and Comp.

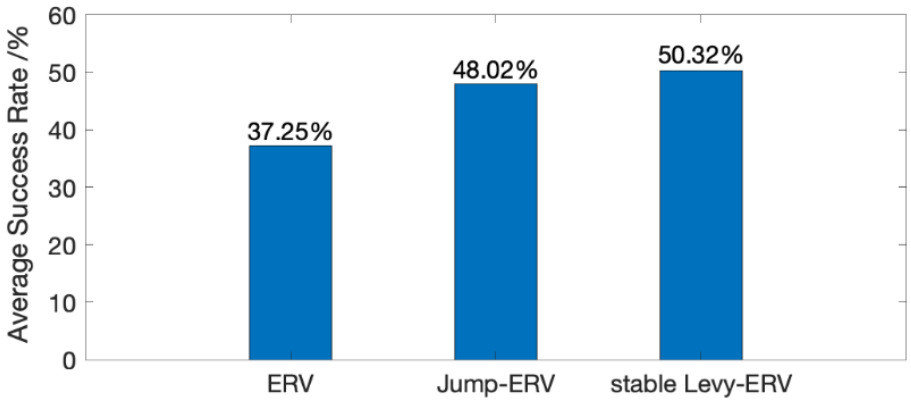


Study pdf at t=1:



Example: Intentionality analysis for perturbed pointing task in-vehicle





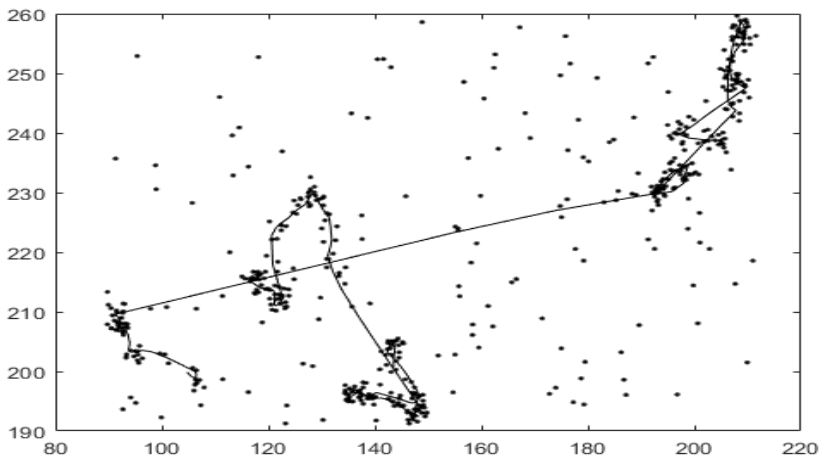
Result for perturbed pointing data from automobile UI systems:

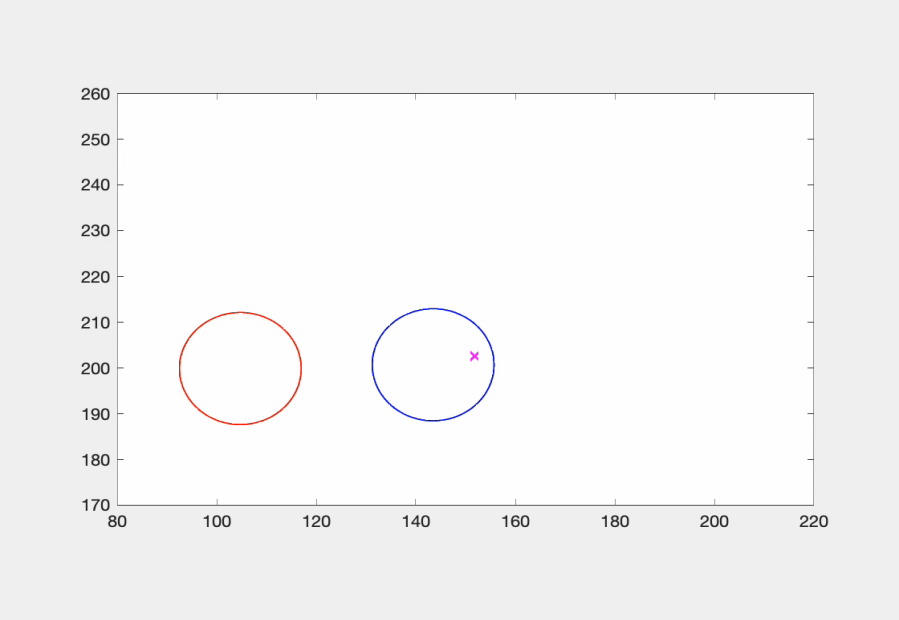
Gan, R., Ahmad, B. I., & Godsill, S. J. (2021). Levy State-Space Models for Tracking and Intent Prediction of Highly Maneuverable Objects. *IEEE TRANSACTIONS ON AEROSPACE AND ELECTRONIC SYSTEMS, 57* (4), 2021-2038.

Example: α-stable Lévy State-Space Model for multiple objects in clutter

`Langevin' dynamics:

$$d\dot{X}(t) = -\lambda \dot{X}(t)dt + dW(t)$$





Black lines are ground truth; crosses are measurements; colored lines are estimates plus 95% confidence ellipse

A new idea – the non-Gaussian Process (NGP) model

[Work with Yaman Kindap]

- Here we apply the same Levy process principles to a Gaussian process (GP) model.

- We take a standard GP {W(t)} with covariance function

$$cov(W(t), W(t')) = C(t, t')$$

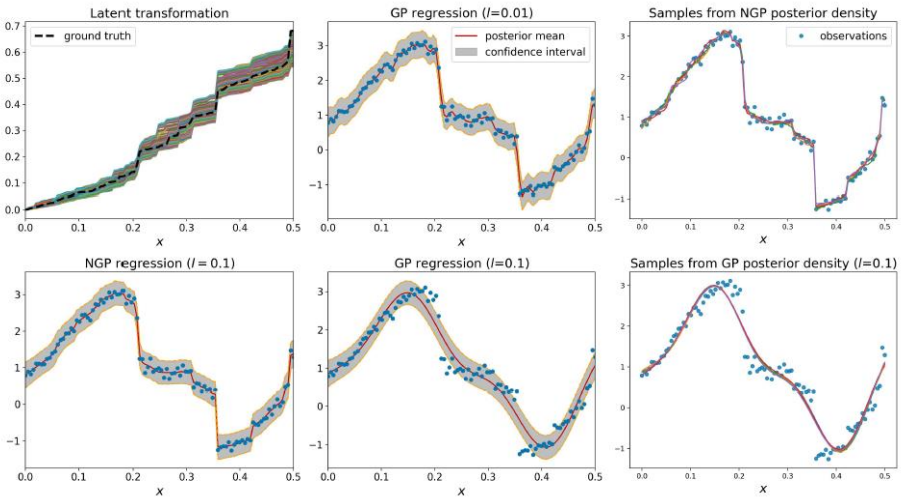
- We use the same class of `subordinator' jump process {X(t)} to modulate locally the covariance function (`time-change' operation):

$$cov(W(t), W(t')) = C(X(t), X(t'))$$

- This allows for non-Gaussian perturbations to the process, but retains once again the structure of a bank of standard GPs, each with a differently modulated covariance function. Examples…

Preliminary examples

X(t) W(t)



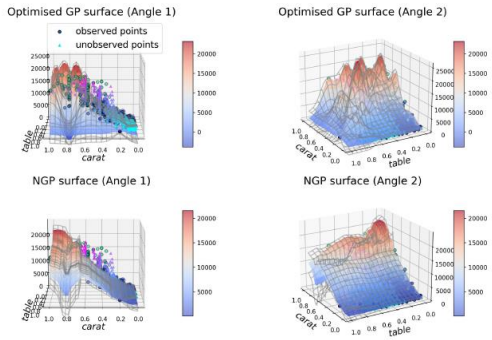


Figure 3: Regression analysis results for NGP and GP models with for the diamond price data set using a TS subordinator. The posterior means are plotted as a surface and the ±3 standard deviation surface is overlaid on the mean as a wireframe plot.

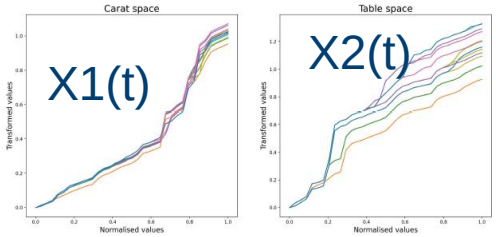


Figure 4: Posterior subordinator samples for a TS subordinator.

Spatial Tracking models using the NGP are currently under development

Poisson point process tracking

Non-homogeneous Poisson process (NHPP) measurement model

- We see clusters of point detections around object locations X_i
- Each object's detections Z are assumed drawn from a non-homogeneous Poisson point process (NHPP) with intensity $\lambda_i(Z|X_i)$ - 0 or more measurements for each object (realistic...)
- Clutter detections also a Poisson process $\lambda_0(Z)$
- The Union property of Poisson processes means that all detections from all K objects and clutter are still Poisson:

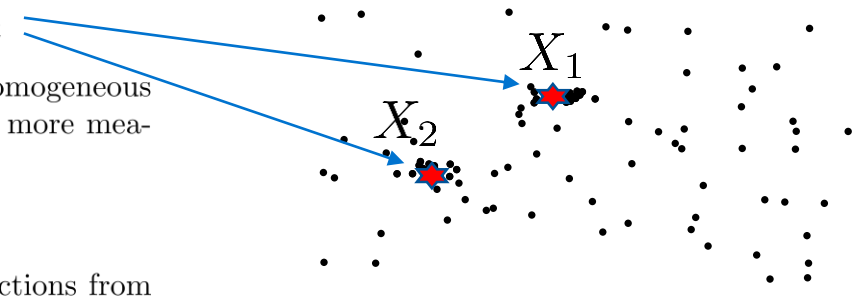
$$\lambda(Z|X) = \sum_{i=0}^{K} \lambda_i(Z|X_i)$$

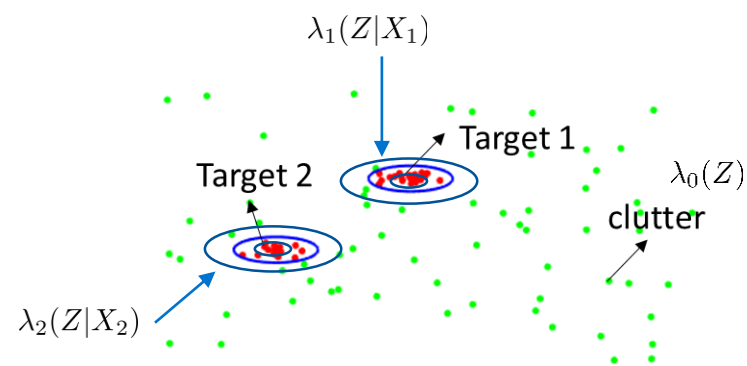
- Simple likelihood function and no data association required! This was the insight of:

  Gilholm, Godsill, Maskell and Salmond (2005), "Poisson models for extended target and group tracking," in Proc. SPIE

- We now augment the model with data association variables θ - very simple computationally (sequential MCMC) and allows parallelisation. In particular:

$$p(\theta_j = i|Z_j, X) = \frac{\lambda_i(Z_j|X_i)}{\sum_{i=0}^{K} \lambda_i(Z_j|X_i)}, \quad i = 0, ..., K$$





Applications of the NHPP model…

NHPP Application 1:

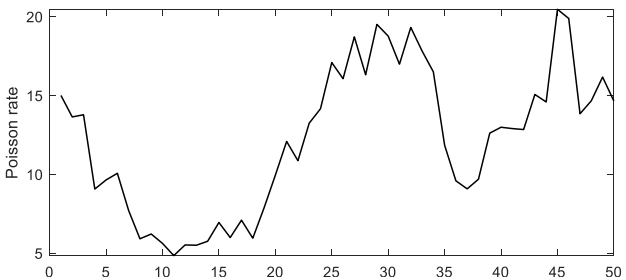
Q. Li, J. Liang and S. Godsill, "A scalable sampling-based scheme for data association and multi-target tracking under mixed Poisson measurement process", ICASSP 2022, Singapore,

Time-varying Poisson rate estimation for both targets and clutter

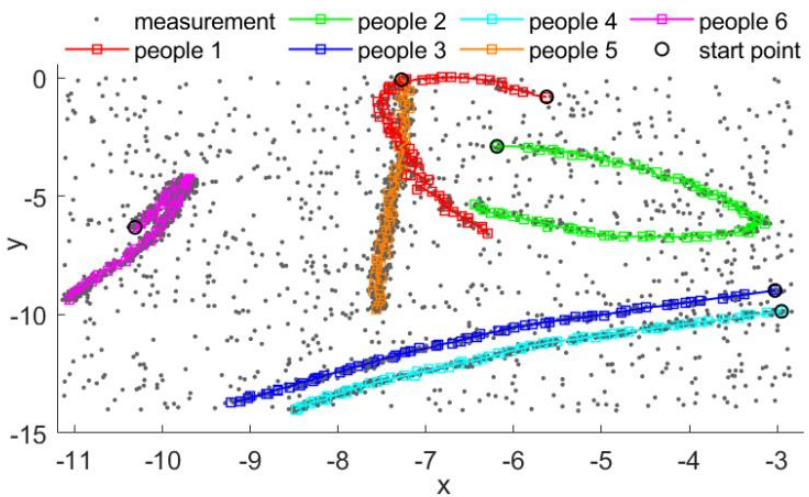
Poisson rates $\Lambda_{i,n}$ are unknown and/or time-varying

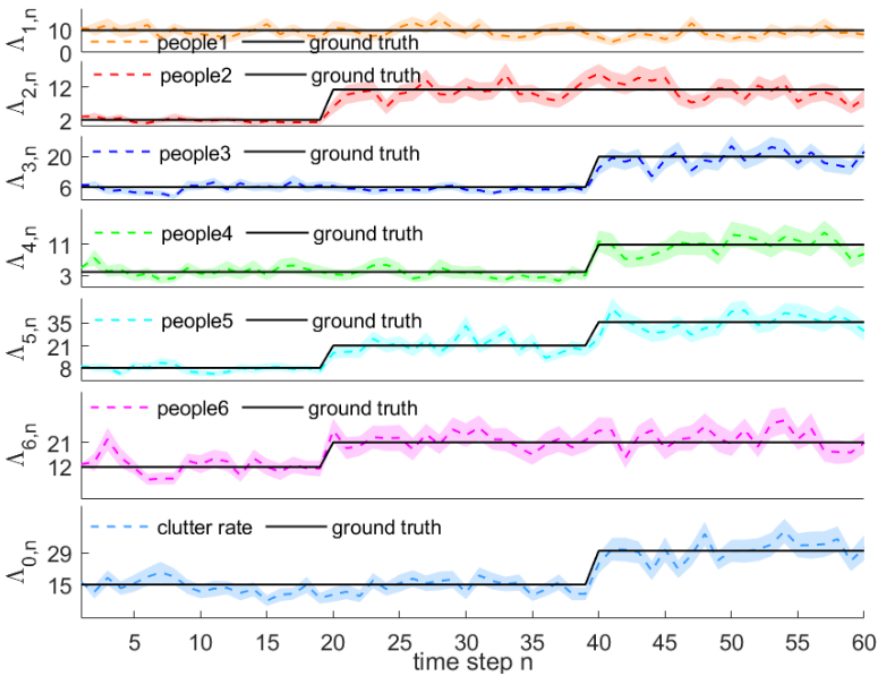
Introduce a novel Markov transition density for $\Lambda_{i,n}$ (GIG)

Implement using Sequential Markov chain Monte Carlo (S-MCMC)



MOT Challenge dataset results:



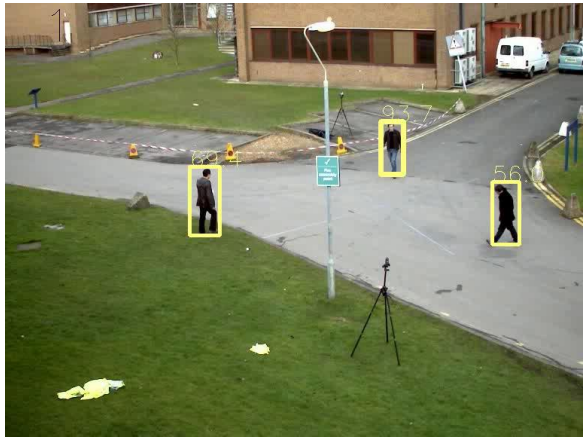


method	OSPA (mean $\pm 1\sigma$)	track loss(%)	CPU time (s)
online PMHT	6.19±3.09	30.0	8.58
RB-AbNHPP	1.30±0.08	0.00	0.40

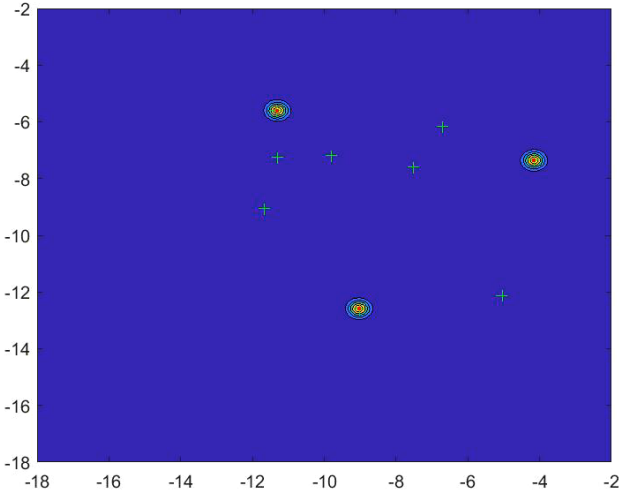
NHPP Application 2:

Tracking of a varying number of objects using reversible jump S-MCMC

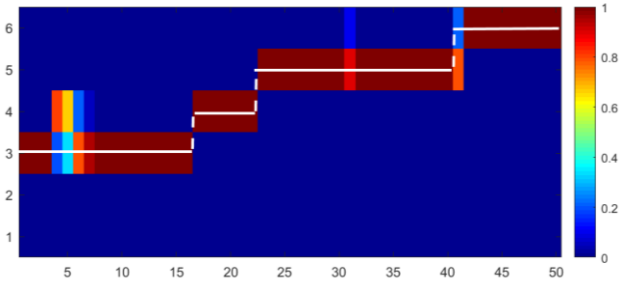
MOT15 benchmark data sets for multiple person tracking



Tracked Posterior density for objects:



Cardinality inference:



[4] https://motchallenge.net/data/MOT17/

R. Gan, Q. Li and S. Godsill, "A Variational Bayes Association-based Multi-object Tracker under the Non-homogeneous Poisson Measurement Process", FUSION 2022

Best Student paper award

Variational Bayes Association-based Multi-object Tracker

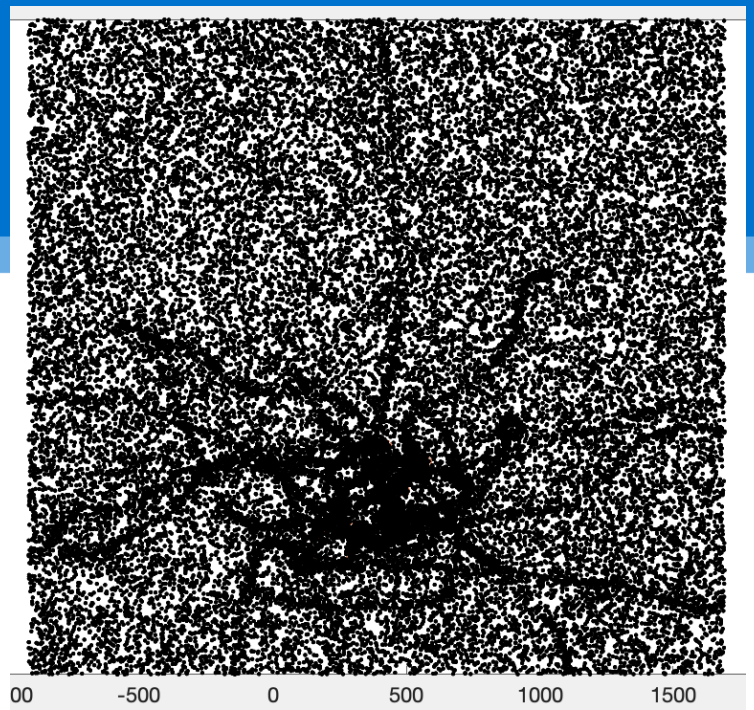
- Ideal filtering density under NHPP model:

$$p(X_n, \theta_n | Z_{1:n})$$

- Variational Approximation:

$$q_n(X_n, \theta_n) = q_n(X_n) q_n(\theta_n) \approx p(X_n, \theta_n | Z_{1:n})$$

- Scalable and parallelisable since update operations may be further split between the elements of X_n and θ_N
- Tracking performance is comparable to S-MCMC-based trackers, but much faster. Significantly outperforms other fast approximate trackers.
- Distributed versions are currently under development...



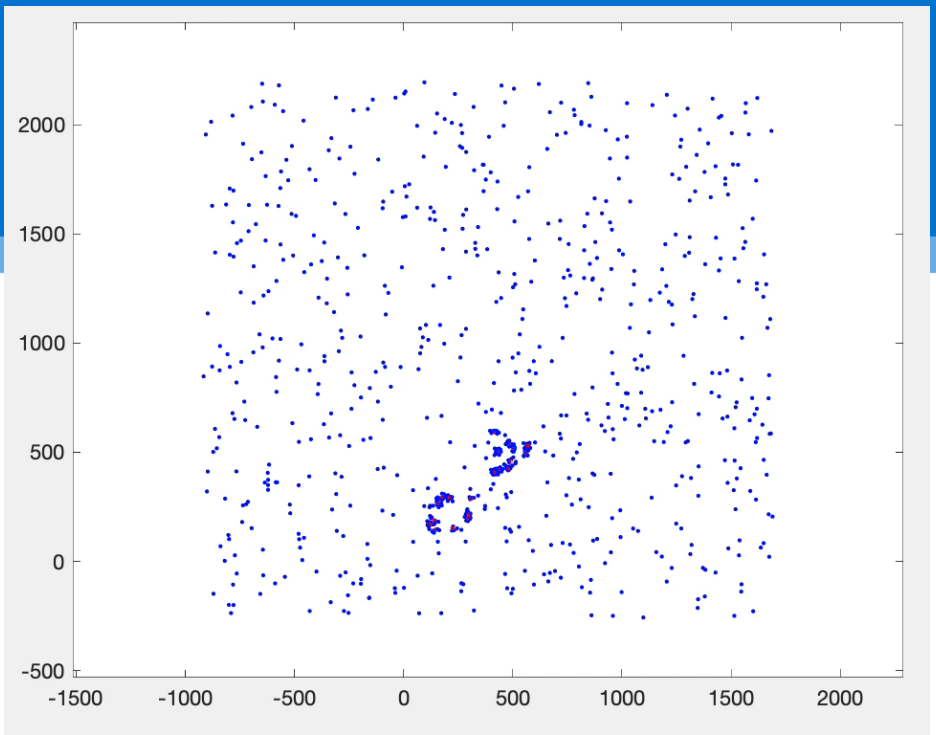
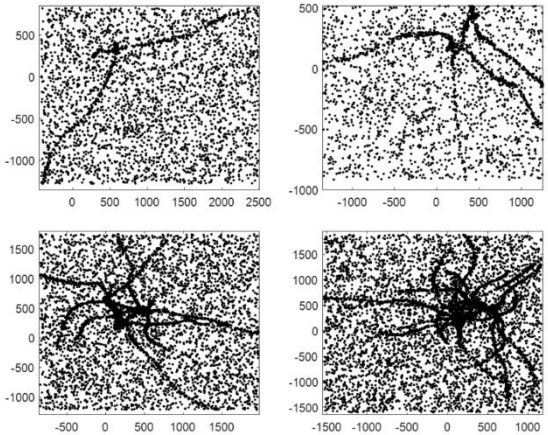


TABLE I: Tracking performance comparisons

dataset	K	RMSE (mean $\pm 1\sigma$) | track loss percentage (%) | CPU time (s)				
		PF-NHPP	Gibbs-AbNHPP	ET-JPDA	VB-AbNHPP$^{(1)}$	VB-AbNHPP
1	2	7.69±0.64 | 0.00 | 4.05	5.50±0.34 | 0.00 | 0.22	7.49±1.06 | 4.50 | 5e-4	5.64±0.58 | 0.00 | 3e-6	5.51±0.43 | 0.00 | 6e-6
2	4	N/A | 51.8 | 15.9	5.63±0.13 | 0.00 | 0.57	8.40±2.97 | 8.75 | 2e-3	5.91±0.37 | 0.25 | 6e-6	5.75±0.29 | 0.00 | 1e-5
3	10	–	6.06±0.25 | 0.10 | 0.67	9.41±1.99 | 16.3 | 0.01	6.50±0.50 | 2.20 | 8e-6	6.03±0.32 | 0.70 | 2e-5
4	20	–	6.25±0.26 | 0.65 | 2.31	N/A | 22.6 | 0.03	7.31±0.70 | 4.05 | 1e-5	6.30±0.40 | 1.90 | 3e-5



Conclusions…