

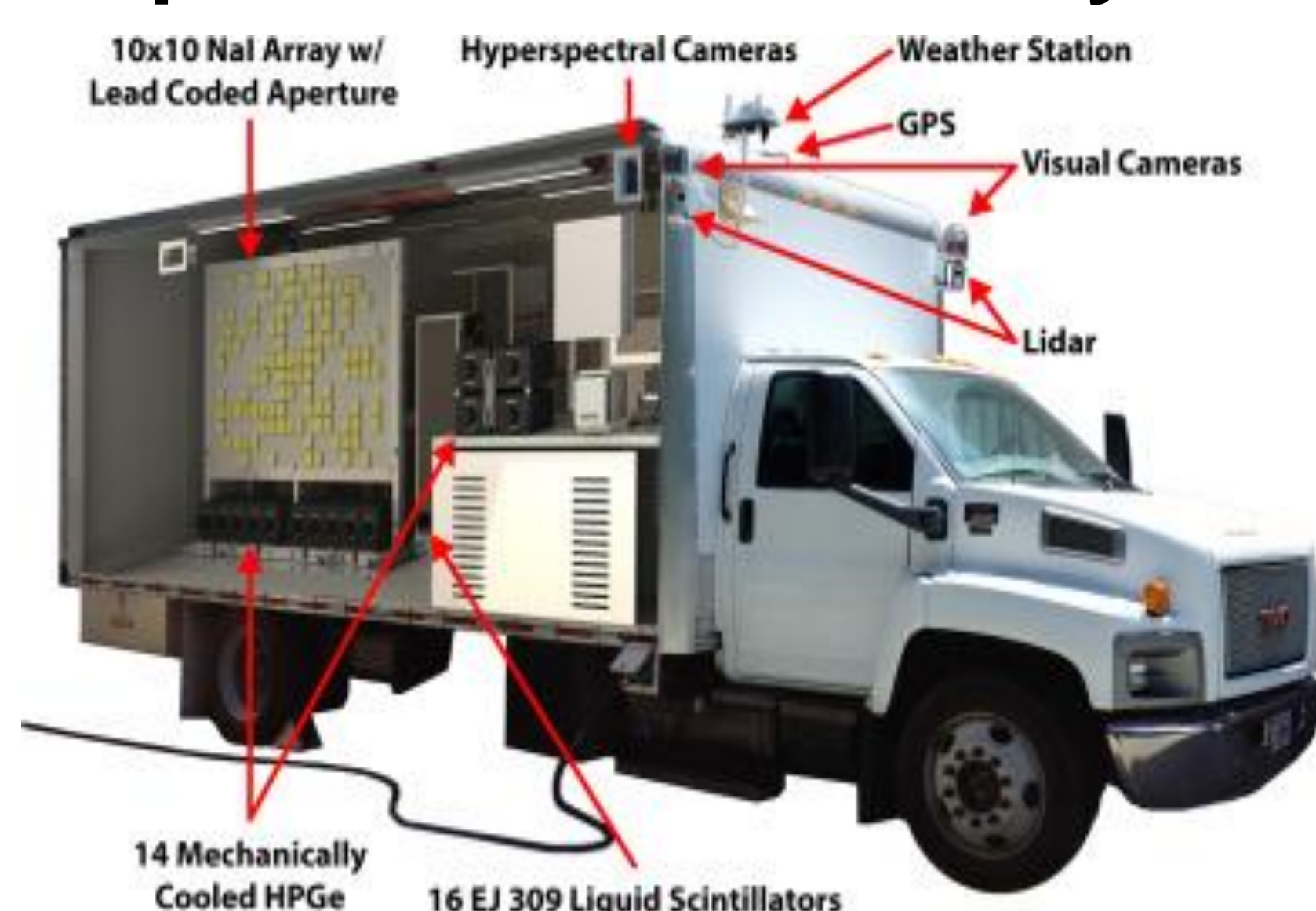
Introduction

Disaster response and scenarios involving stolen nuclear material often require capabilities for rapid radiological search. New source term estimation (STE) algorithms must be developed for performing radiological search in urban environments.

Objectives

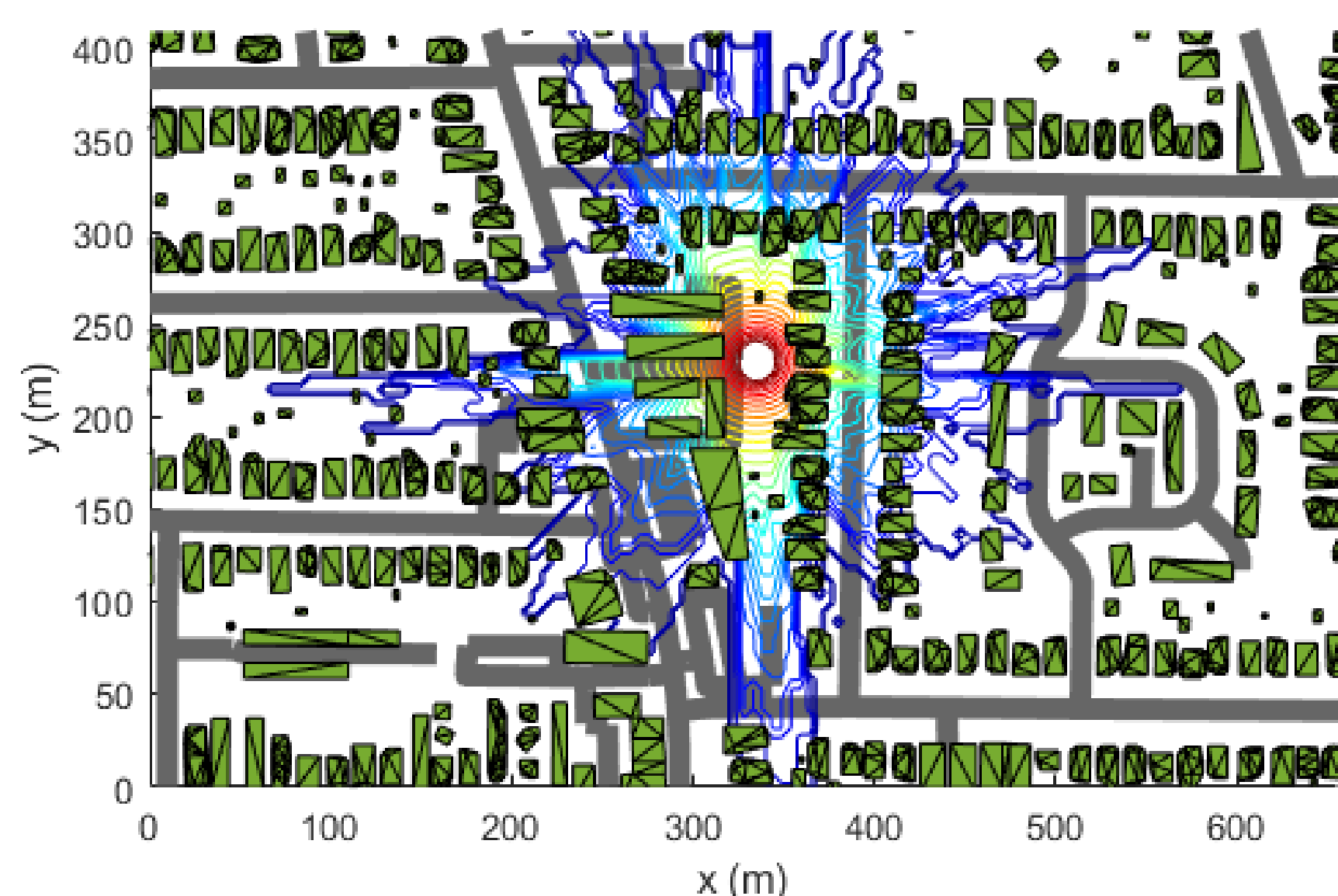
The goal of this study is to investigate STE algorithms for use in obstacle rich environments using teams of UAVs as a mobile sensor array to aid a manned mobile detector system (MMDS) in searching an urban area contaminated by an arbitrary number of point sources.

Example Mobile Detector System



Credit: Bandstra, Mark S., et al. "RadMAP: The Radiological Multi-Sensor Analysis Platform."

Count Rates with Obstacle Occlusion

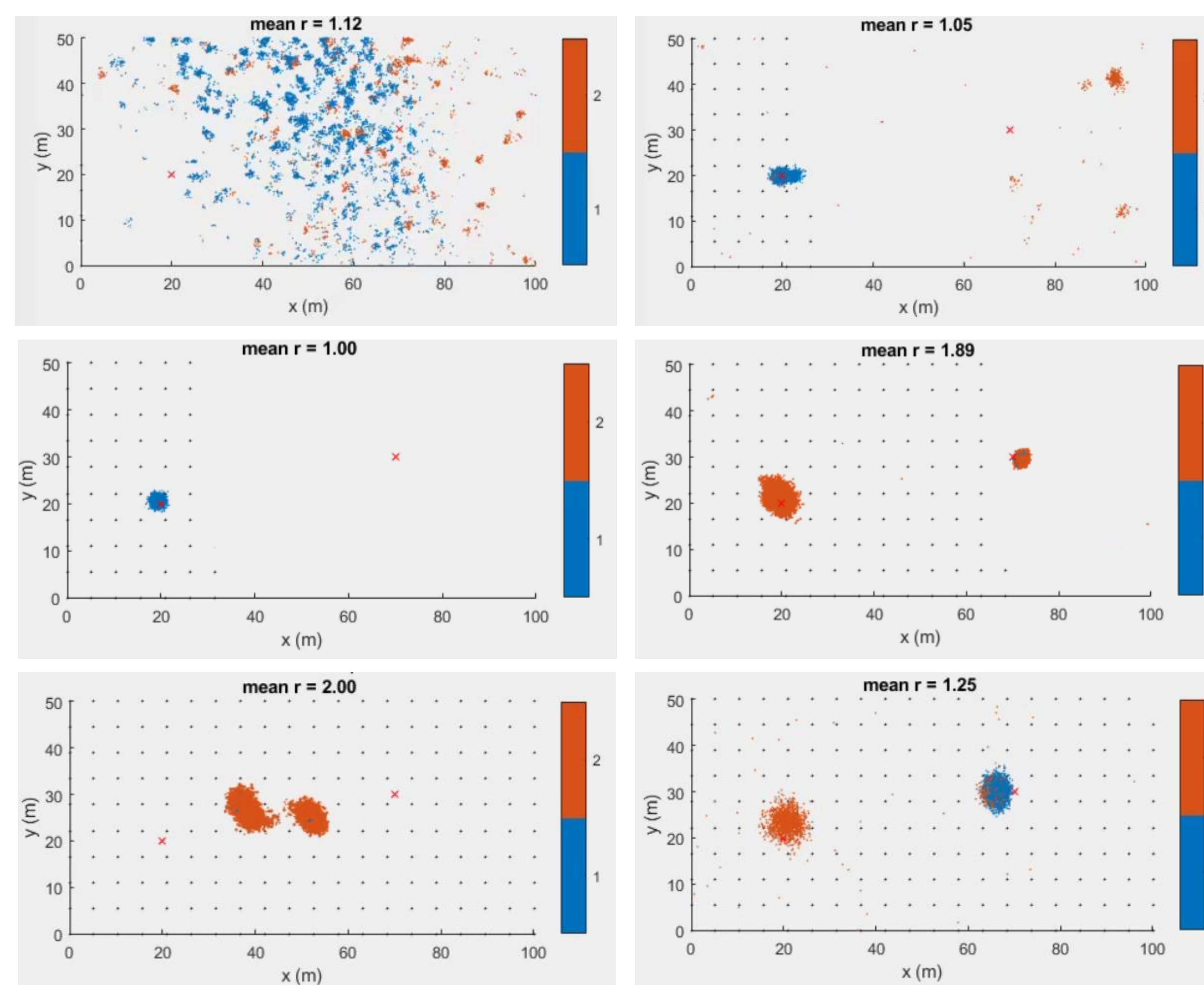


Green shapes are buildings. Grey lines are roads. Colored contours indicate count rate due to a point source.

Challenges

- Degeneracy: many particles have insignificant weight.
- Sample impoverishment: particles become too concentrated.
- Amnesia: locally good particles outcompete globally good particles
- Discontinuity: obstacles create discontinuity in weight gradient

Degeneracy, Impoverishment, and Amnesia



(left column) Progression of PF degeneracy leading to sample impoverishment. (right column) Progression of PF suffering from observability induced amnesia.

Methods

$$r_0 \sim \mathcal{U}(r_{min}, r_{max}), (x_0, y_0) \sim \mathcal{U}(\mathcal{A}),$$

$$\varphi_0 \sim \mathcal{U}(\varphi_{min}, \varphi_{max})$$

$$\mathbf{X}_r = [x, y, \varphi]$$

For each new measurement, z :

$$\pi = \ell_S \left(\ell_{S-1} \left(\dots \ell_2 \left(\ell_1 \pi_0 / c \right) \right) \right)$$

$$(\ell_1, \ell_2, \dots, \ell_S) \text{ s.t. } \ell = \prod_{j=1}^S \ell_j$$

$$w = C[\mathcal{P}(z; \lambda(\mathbf{X}_r))]$$

$$\mathbf{X}_r^* = \text{RESAMPLE}(\mathbf{X}_r, w)$$

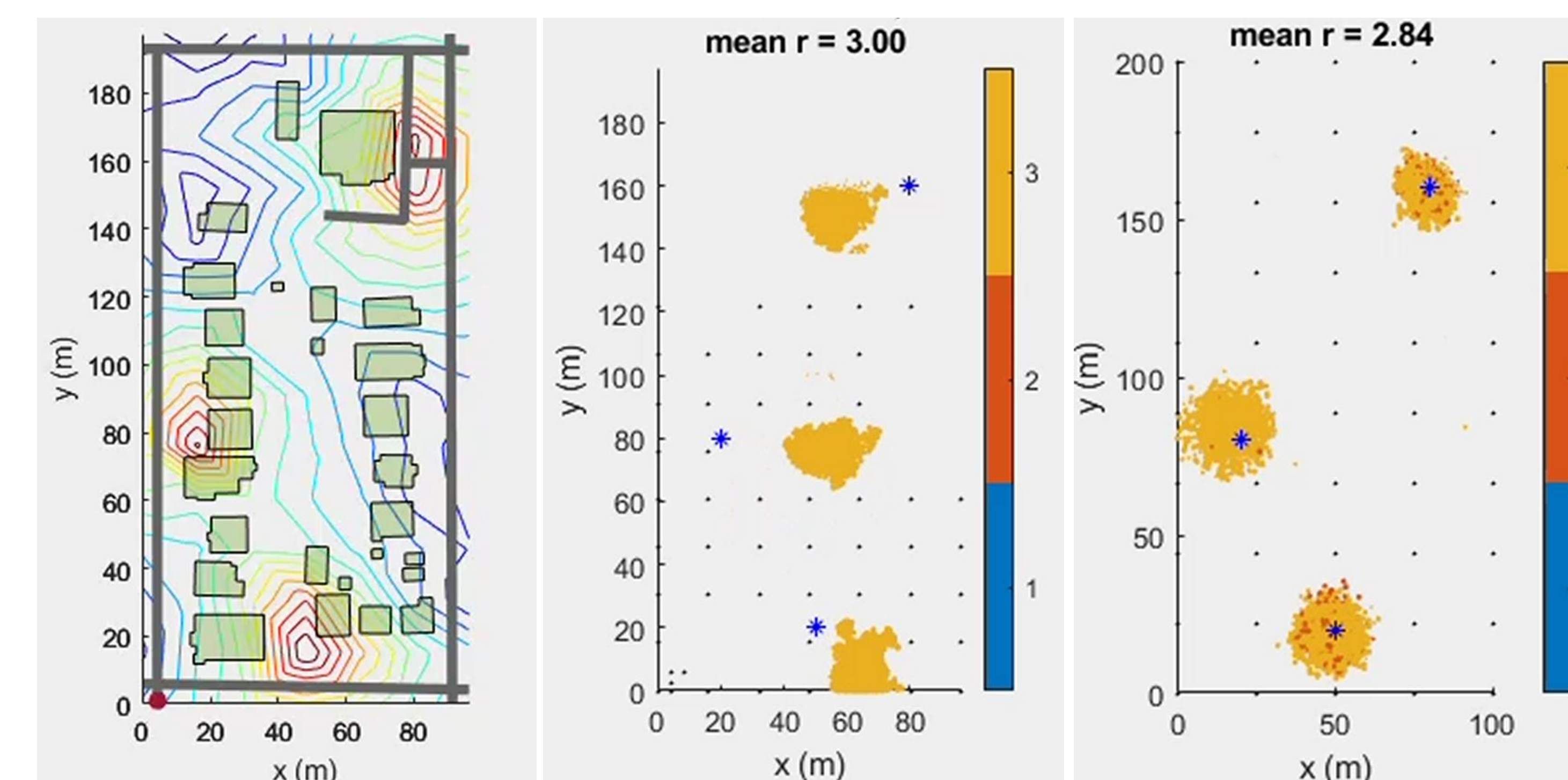
$$\mathbf{X}_r^* = \mathbf{X}_r + \mathcal{N}(0, \sigma^2)$$

Particles initialized from uniform distributions

Progressive Correction (PC) to combat degeneracy. [2]

Particle weights calculated. Particles are resampled and regularized.

Particle Filter in Obstacle Rich Environment



(left) Illustration of the search space with count rate contours. (middle) PF incorporating obstacle attenuation. (right) PF in obstacle free version of the space.

Results and Conclusions

- PC mitigates degeneracy and sample impoverishment
- Obstacles severely degrade PF performance.
- Runtime of current algorithm with obstacles is on the order of minutes per iteration.
- Need more advanced techniques for dealing with PFs in large, discontinuous state spaces.

Future Work

- Importance sampling to fight sample impoverishment [3].
- Add periodic actively sampled retraining to combat amnesia.
- GPU acceleration will be used on the obstacle occlusion calculations to speed up the STE likelihood function.
- Multi vehicle simulations and limited hardware experiments will be conducted using the final STE algorithm.

Acknowledgements

- Satvik G. Kumar for his work on acceleration and optimization on the obstacle attenuation computations.

References

1. Bandstra, Mark S., et al. "RadMAP: The Radiological Multi-Sensor Analysis Platform." Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, North-Holland, 20 Sept. 2016. www.sciencedirect.com/science/article/pii/S0168900216309780?via%3Dihub.
2. Ristic, B., Morelande, M., & Gunatillaka, A. (2010). Information driven search for point sources of gamma radiation. Signal Processing, 90(4), 1225-1239.
3. Chopin, N. (2004). Central limit theorem for sequential Monte Carlo methods and its application to Bayesian inference. The Annals of Statistics, 32(6), 2385-2411.