Real-Time Radiological Source Term Estimation for Multiple Sources in Cluttered Environments

S. Kemp[1], S. Kumar[1], C. Bakker[2], M. Duce[1], J. Rogers[1]

[1]Georgia Institute of Technology, [2]PNNL

9 Feb 2023

Introduction

Problem Statement: Perform Source Term Estimation in a cluttered environment for an arbitrary number of radioactive point sources of varying activities and isotopes.

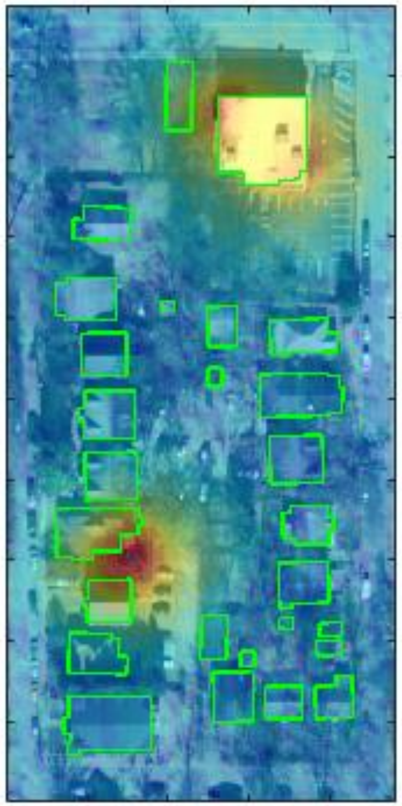
Goal: Develop an algorithm to accomplish this in real time and validate it with Monte Carlo simulations and hardware results.

Introduction

Source Term Estimation (STE):

- How many are there?
- Where are they?
- What is their activity?
- What isotope?

Cluttered Environment: Obstacles are present. Obstacle/terrain information is known or can be approximated.



Example environment with obstacles outlined in green and radiation field due to 3 sources.

Applications and Motivation

Radiological security and mishandling of nuclear material

Lost radioactive capsule in Australia (25 Jan 2023) [CNN]
Cs-137 Sealed source recovery at University of Washington (2 May 2019) [energy.gov]

Trafficking, nuclear smuggling detection, and deterrence

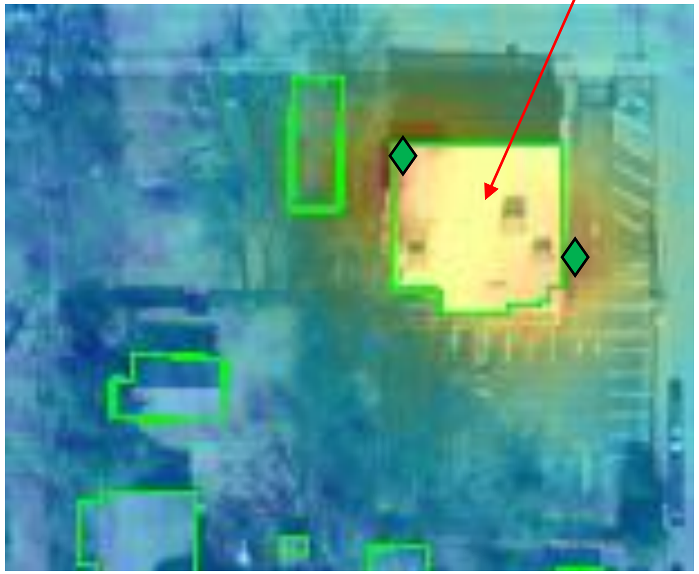
190 incidents of trafficking reported on the ITDB in 2019. [IAEA]

Disasters and nuclear verification

Fukushima nuclear disaster
[Reuters]

Prior Work Limitations

Measurements here will have 2 sources contributing



- **Obstacles**
- **Source cardinality**
  - Single source (~83% of papers)
  - Non-interacting sources (~14% of papers)

Particle Filter

- Ristic, B., Morelande, M., & Gunatilaka, A. (2010). Information driven search for point sources of gamma radiation. *Signal Processing*, *90*(4), 1225-1239.

Limitations

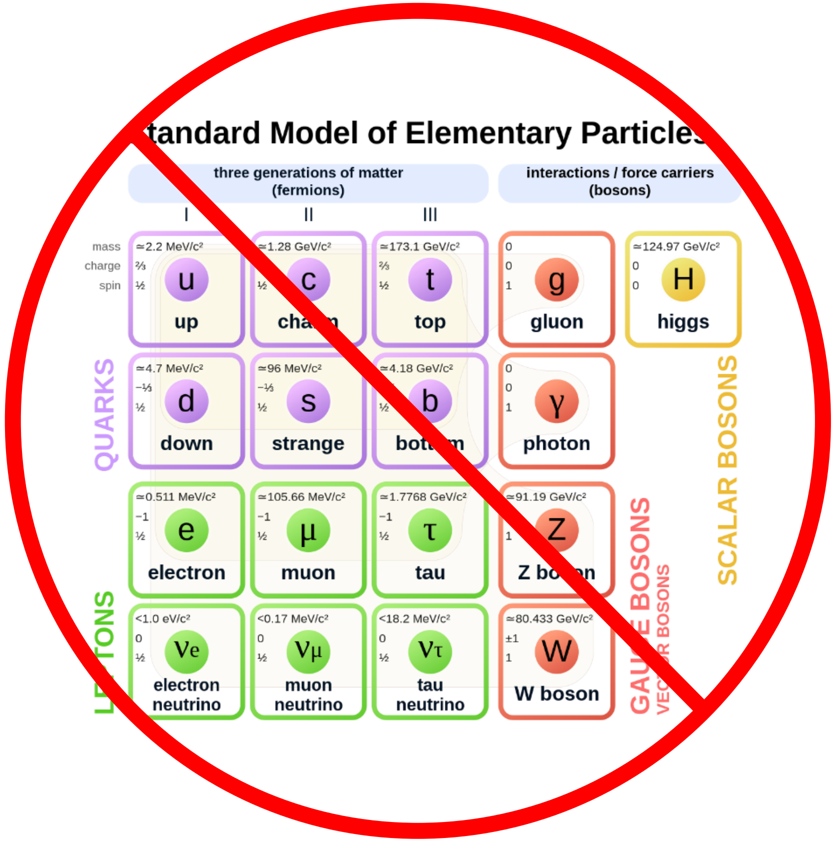
- No obstacle considerations
- Computationally intractable for >3 sources
- Degeneracy

Lit review 2

					High-Level Team Goal(s)	Team Size		Agent Configuration		Computation Strategy		Inference Framework					Path Planning Strategy		
Year	Paper Title	Journal	Journal Link	Impact Factor		Single	Multi	Homo-	Hetero-	Centralized	Decentralized	Bayesian	Other:	Satvik's Column	Algorithm	Adaptive Model?	POMDP	Other:	Cost Formulation
2009	Information Driven Search for Point Sources of Radiation	Signal Processing	https://www.sciencedirect.co	4.662	Estimate #, location, and strength of radiation point sources	☑	☑	☑	☐	☑	☐	☑			SMC	☐	☑		Renyi Divergence
2019	Unmanned Aerial Vehicle Based Hazardous Materials Response: Information-theoretic Hazardous Source Search and Reconstruction	IEEE Robotics and automation magazine	https://ieeexplore.ieee.org/xp	5.143	Full STE of isotropic plume in steady-state	☑	☐	☑	☐	☑	☐	☑			SMC	☐	☑		KL Divergence
2017	Adaptive Bayesian Sensor Motion Planning for Hazardous Source Term Reconstruction	IFAC-papersonline	https://www.sciencedirect.co	CS 2.1	Determine location + release rate of a single source (steady-state)	☑	☐	☑	☐	☑	☐	☑			Metropolis-Hastings MC	☐	☑		Negative Shannon Ent
2013	Gas source localization with a micro-drone using bio-inspired and particle filter-based algorithms	Advanced Robotics	https://www.tandfonline.com/	1.699	Gas source localization in turbulent environment + wind vector estimation	☑	☐	☑	☐	☑	☐	☑			SMC	☐	☐	Non-information-theore	N/A
2019	Information-Based Search for an Atmospheric Release Using a Mobile Robot: Algorithm and Experiments	IEEE Transactions on Control Systems Technology	https://ieeexplore.ieee.org/xp	5.845	Get location + strength of single release with ground robot	☑	☐	☑	☐	☑	☐	☑			SMC	☐	☑		KL Divergence
2010	Information-rich Path Planning with General Constraints using Rapidly-exploring Random Trees	AIAA	https://arc.aiaa.org/journal/ai	2.127	Plan paths in real time that maximize information content in dynamic target tracking	☑	☑	☑	☐	☑	☑	☑			(Some centralized filter)	☐	☐	RRT-based	Fisher Information Mat
2018	Source term estimation of a hazardous airborne release using an unmanned aerial vehicle	Journal of field robotics	https://onlinelibrary.wiley.com	3.767	3D source localization + emission rate of a single gas source	☑	☐	☑	☐	☑	☐	☑			SMC	☐	☐	Sweeping	N/A
2018	Real-time distributed non-myopic task selection for heterogeneous robotic teams	Autonomous Robots	https://www.springer.com/jou	3	(See the title)	☐	☑	☐	☑	☐	☑	☐	(Accommodates uncertainty, but no inference)		N/A	☐	☐	Monte Carlo Tree Sear	Edge and node costs (v
2017	An Adaptive Online Co-Search Method With Distributed Samples for Dynamic Target Tracking	IEEE Transactions on Control Systems Technology	https://ieeexplore.ieee.org/xp	5.845	Single or multi-agent tracking of single or multiple targets with unpredictable motion	☑	☑	☑	☐	☑	☐	☑			Recursive Bayesian Est	☑	☐	Adaptive Online Co-sea	(Not information-theore
2014	Post-disaster Remote Sensing and Sampling via an Autonomous Helicopter	Journal of field robotics	https://onlinelibrary.wiley.com	3.767	Helicopter + ground robot system (the ground robot doesn't facor in too much) for mapping 3D environ	☑	☐	☐	☑	☑	☐	☑	2 methods (1st for accuracy) Spatially variant dec		Richardson Lucy MLE //	☐	☐	none they just do a "za	N/A
2012	Radiation Mapping in Post-Disaster Environments Using an Autonomous Helicopter	Remote Sensing	https://www.mdpi.com/journa	4.848	Helicopter for mapping 3D environments, mapping radiation, and source term estimation.	☑	☐	☑	☐	☑	☐	☑	RBE and Radiation contour mapping (contour ana		RBE and Radiation cont	☐	☐	none "archimedean spiral" search pattern	
2016	A PSO-Based Approach with Fuzzy Obstacle Avoidance for Cooperative Multi-Robots in Unknown Environments	ICIA	https://ieeexplore.ieee.org/xp	-	Team exploration of unknown environment with fuzzy obstacle avoidance	☐	☑	☑	☐	☑	☐	☐	None		Simply keeps track of ex	☐	☐	Particle swarm optimiza	potential field based on
2019	Asymptotically Optimal Planning for Non-myopic Multi-Robot Information Gathering	Robotics: Science and Systems			Reduce uncertainty of uncertain environment with a team of sensing robots	☐	☑	☑	☐	☑	☐	☑			Kalman filter (ricatti map	☐	☐	stochastic optimal contr	covariance matrix deter
2018	Anytime Planning for Decentralized Multirobot Active Information Gathering	IEEE Robotics and Automation Letters	https://ieeexplore.ieee.org/xp	3.741	Reduce uncertainty about a physical process with a robot team	☐	☑	☑	☐	☐	☑	☑			Distributed Kalman filter	☐	☑	uses reduced value iter	log-determinant of cova
2017	Online information gathering using sampling-based planners and GPs: An information theoretic approach	IROS			Online information gathering for single robot with obstacle avoidance and continuous state space	☑	☐	☑	☐	☑	☐	☑			Gaussian processes-bas	☐	☐	Informative RRT*	Path execution time div
2018	Distributed Multi-Robot Cooperation for Information Gathering Under Communication Constraints	ICRA			Information gathering with continuous state space and accounting for communication constraints. Robo	☐	☑	☑	☐	☐	☑	☑			Gaussian processes-bas	☐	☐	RRT + share with neigh	Sum of entropies of nei
2019	Multi-modal active perception for information gathering in science missions	Autonomous Robots	https://www.researchgate.net/journal/Autonomo		Physical phenomenon classification with team of robots. Catered toward NASA/Mars rover applications	☐	☑	☑	☐	☑	☐	☑			General Bayesian infere	☐	☐	Monte Carlo Tree Sear	(approximate) Shannon
2019	Information-Guided Robotic Maximum Seek-and-Sample in Partially Observable Continuous Environments	IEEE Robotics and Automation Letters	https://ieeexplore.ieee.org/xp	3.741	Informative sample collection in challenging real-world environments	☑	☐	☑	☐	☑	☐	☑			Gaussian process mode	☐	☑	using Monte Carlo Tree	Maximum-Value Inform
2018	Potential Game-Based Non-Myopic Sensor Network Planning for Multi-Target Tracking	IEEE Access	https://ieeexplore.ieee.org/xp	3.367	Render non-myopic target tracking more computationally tractable (scales linearly with number of plann	☐	☑	☑	☐	☑	☐	☑			1 EKF per target	☐	☐	Potential Game Formul	Entropy - conditional en
2016	Decentralized control of multiple unmanned aircraft for target tracking and obstacle avoidance	ICUAS			The objective of the controller is to let the multiple aircraft move independently to the positions where th	☐	☑	☑	☐	☐	☑	☑	Fischer information matrix		Fischer Information matr	☐	☐	"Navigation Function"	composed of a goal fun
2019	Non-myopic scheduling method of mobile sensors for manoeuvring target tracking	IET radar sonar and navigation	https://ietresearch.onlinelibra	1.965	Develop a Non-Myopic scheduling method for controlling sensors on a battlefield	☐	☑	☑	☐	☑	☐	☐	Interacting multiple model (IMM) algorithm for estimating target motion state			☐	☑		Nonmyopic scheduling
2019	Distributed Source Seeking and Robust Obstacle Avoidance Through Hybrid Gradient Descent	IEEE Aerospace Conference			Estimate the gradient of a source from multi agent scalar measurements then use a hybrid distributed c	☐	☑	☑	☐	☐	☑	☐	Distributed gradient estimation			☐	☐	Distributed hybrid controller with obstacle avoid	

Particle Filter Introduction

- A “particle” represents a <u>hypothesis</u>.
    - Cardinality: number of sources
    - Source locations
    - Source strengths



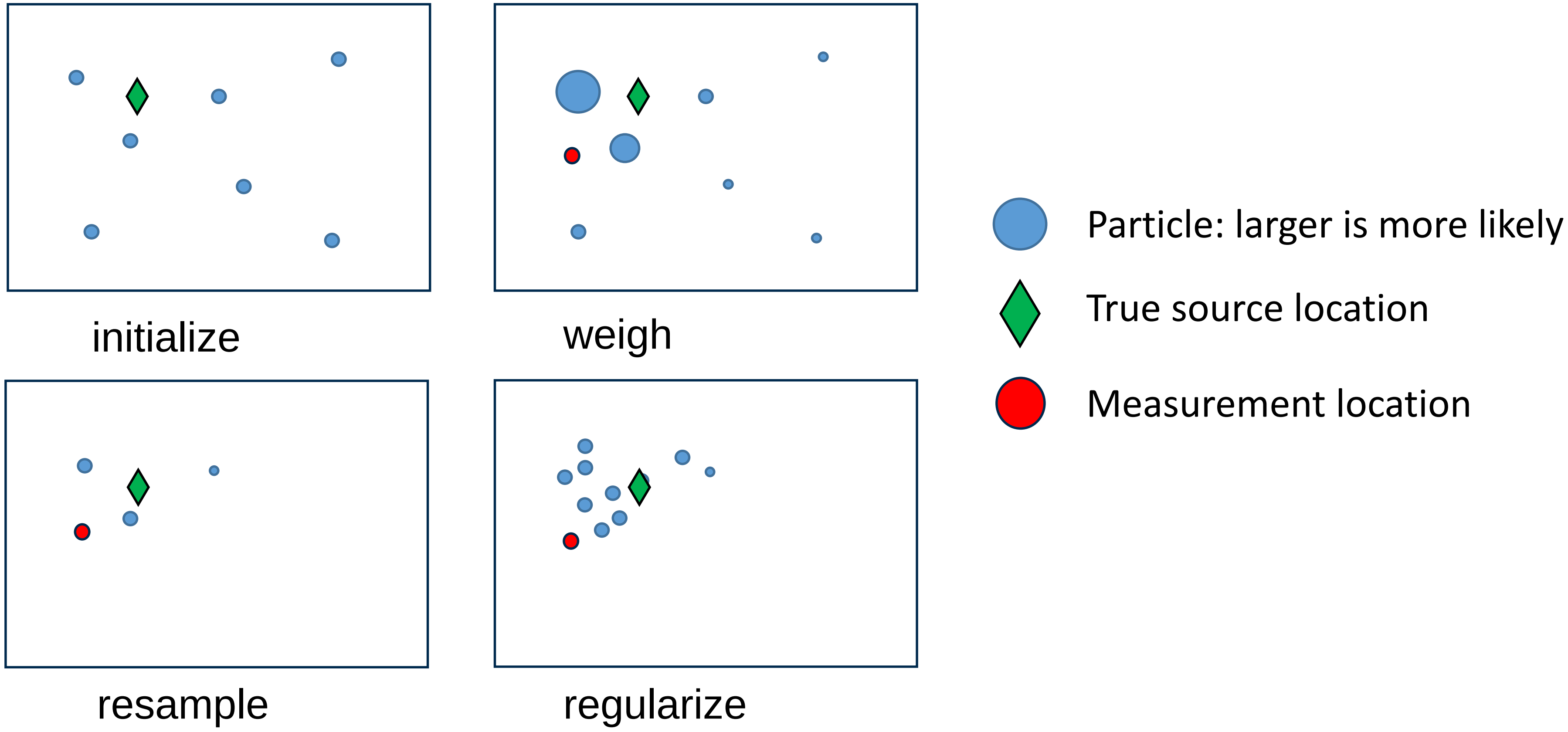
A “particle” is not a physical entity!

Simple Particle Filter Explanation

initialize

for each measurement

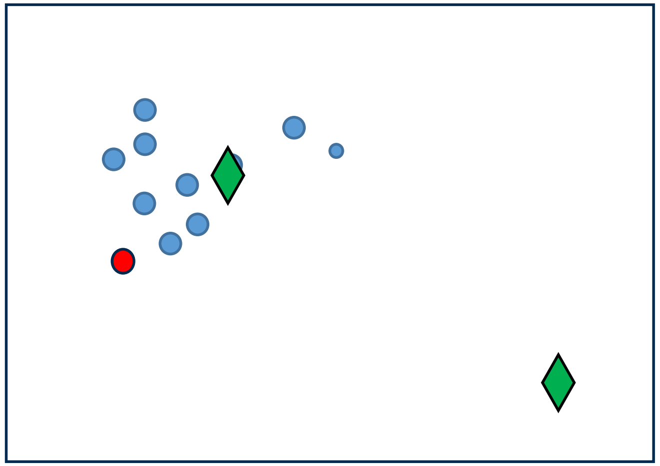
- weigh
- resample
- regularize



Particle Filter Challenges

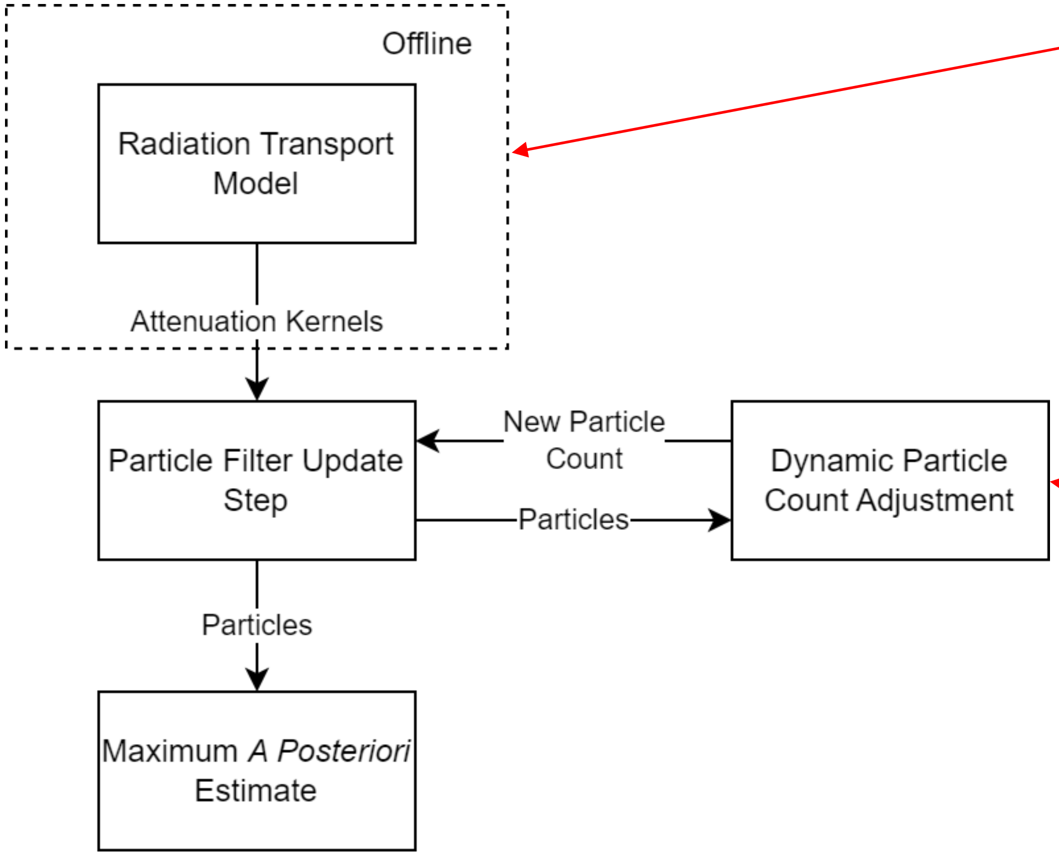
Challenges:

1. **Degeneracy**



2. **Underdetermination**
3. **Computation vs particle set size**

Contributions



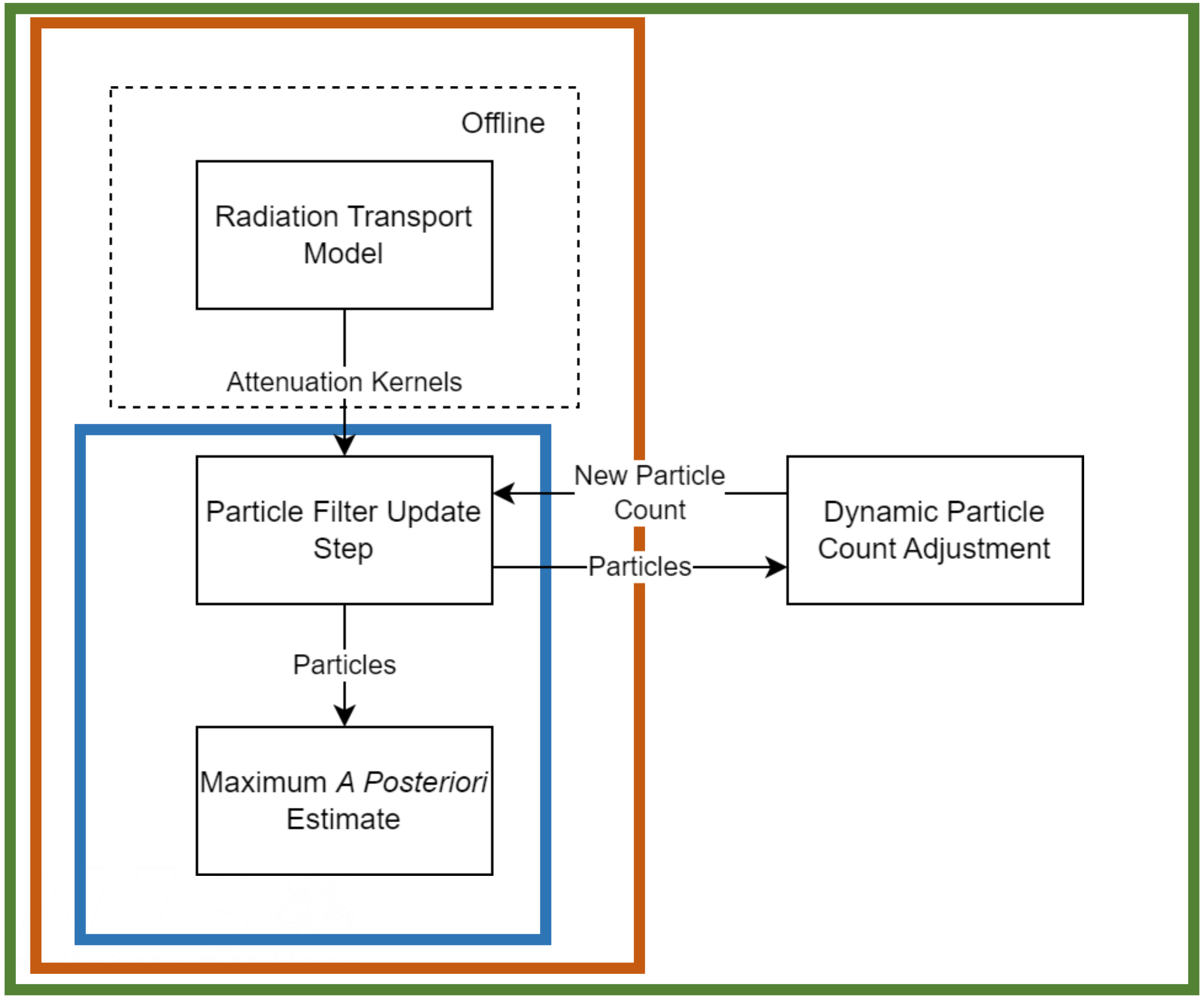
Attenuation Kernels (Transport Kernels)

- Quantify how count rate will be attenuated from a discretized set of possible source locations to a discretized set of measurement locations.
- Preserves accuracy, improves speed

Dynamic Particle Count Adjustment

- Monitor likelihood of particle set and increase or decrease the number of particles.
- Combats degeneracy, balances computation speed and accuracy

Contributions



Continuous Particle Filter (CPF):

- Baseline from literature [1]

Discrete Particle Filter (DPF):

- Attenuation Kernels

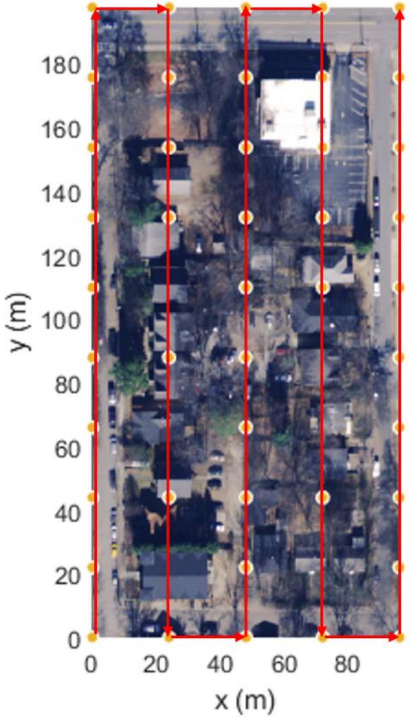
Dynamic Discrete Particle Filter (DDPF):

- Attenuation Kernels
- Dynamic Particle Count Adjustment

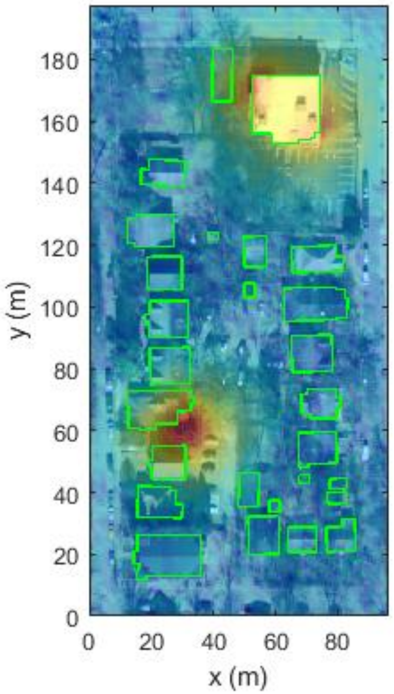
[1] Ristic, B., Morelande, M., & Gunatilaka, A. (2010). Information driven search for point sources of gamma radiation. *Signal Processing*, *90*(4), 1225-1239.

Monte Carlo Simulation Setup

Open Street Maps (OSM) Data



Boustrophedon Search Pattern



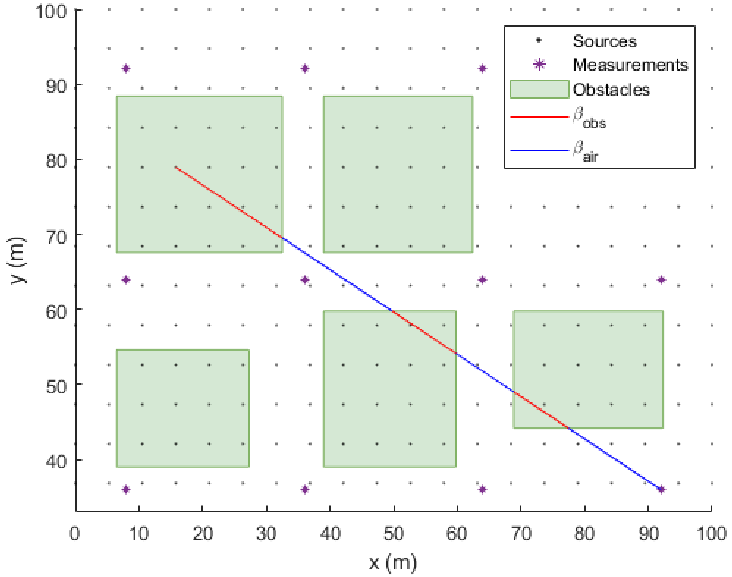
Visualization of expected count rate

- 100m x 200m search area
- Building data from Open Street Maps
- Buildings modelled as solid prisms with arbitrary absorption coefficients.
- Measurements taken with 1 minute dwell time.

Radiation Model

$$\mu = \underbrace{\mu_b}_{\text{Expected Background}} + \underbrace{\sum_{s=1}^{r}}_{\text{Sum over sources}} \underbrace{\frac{\phi_s}{d_s^2}}_{\text{Inverse Square Law}} \underbrace{e^{-\beta_{md} d_s}}_{\text{Exponential Absorption Law}}$$

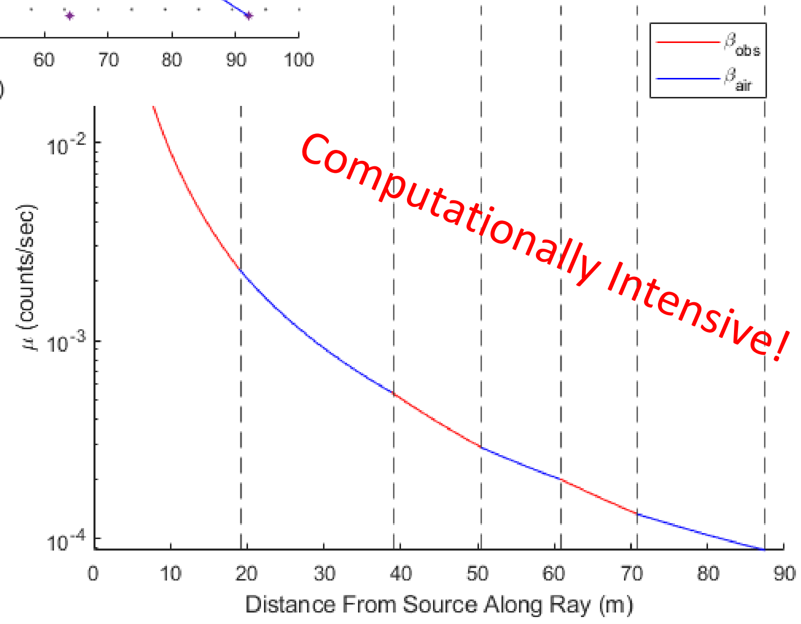
- Count measurements, z, are Poisson distributed with parameter $\lambda = \mu * \tau$
- $z \sim P(\lambda)$
- $\mu =$ Expected count rate (counts/s)
- $\tau =$ Duration of measurement



(Left) 2D overview of ray traced path

(Down) Absorption coefficient effect on count rate w/ distance

For CPF, this is computed for every particle at every likelihood calculation.
For DPF, this is computed once.



National Nuclear Security Administration

ETI

Online Calculation Using Precomputed Kernels

$$\mu_m = \phi_s * \overset{O(1)}{\overbrace{K_{s,m}}}$$

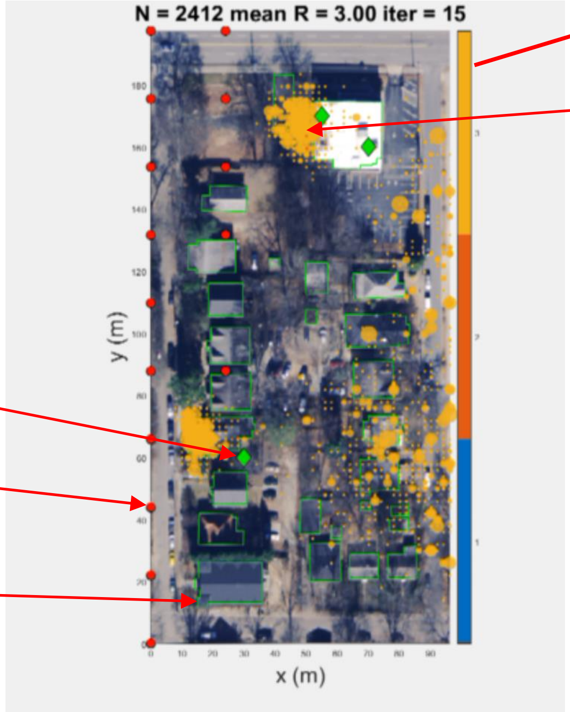
Result Notation and Terms

N = Number of particles
R = Particle source cardinality
iter = Current measurement

True source location

Measurement location

Building outline



Source cardinality hypothesis (how many sources does a particle represent)

Particle: larger is more likely

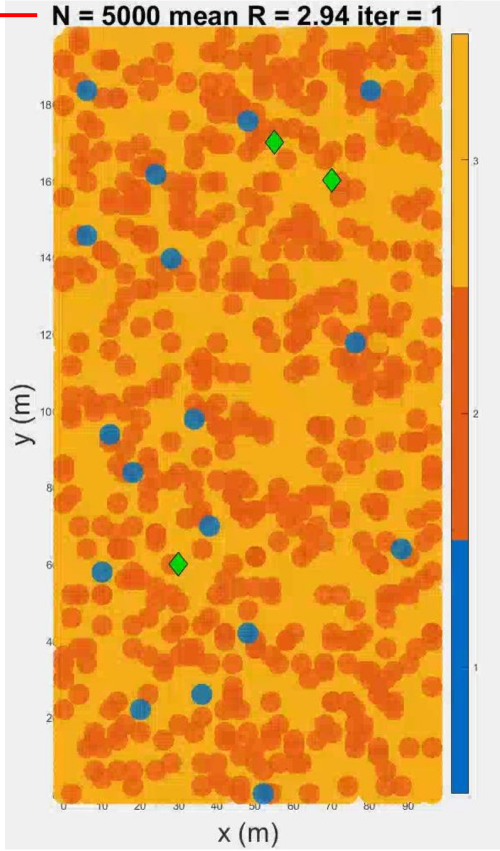
- 1 source
- 2 source
- 3 source

National Nuclear Security Administration

Example Sim Run- Dynamic Particle Count

Note the changing particle count

- As "confidence" in predictions build, particle count goes down
- Particles are removed at random uniformly



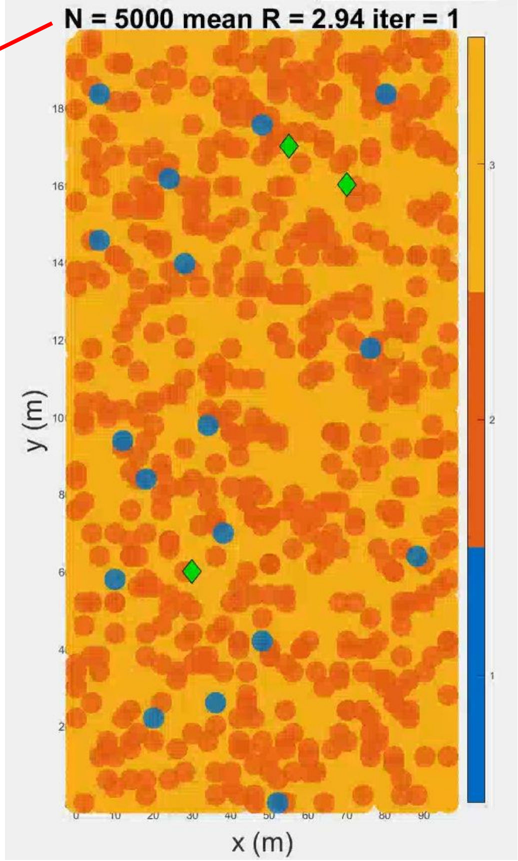
- When the model suspects all its <u>hypotheses are bad</u> (i.e., likelihood is low), the <u>particle count increases</u>.
- In this case, the count jumps to a large maximum value of 25,000 particles.
- We have tuned for accuracy over speed in this case.

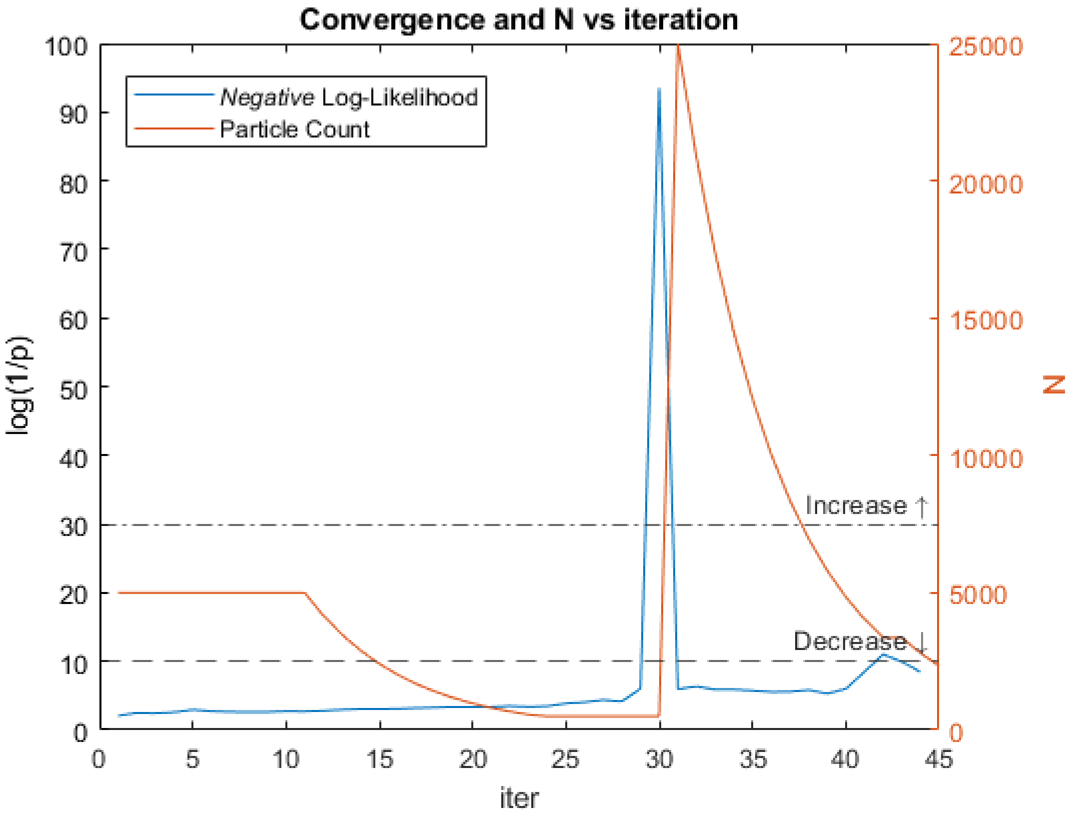
Note the regular grid the particles appear on! Those are the kernel locations

Example Sim Run- Dynamic Particle Count

The particle count decreases by a factor of 1.2 as confidence builds again.

- When particle count increases, new particles are initialized with the same rules as when first initialized.





Monte Carlo Results
Attenuation Kernel Study

Particle Filter	CPF		DPF	
Obstacles	No	Yes	No	Yes
$\hat{r}$ Correct (%)	84	83.33	87.33	86
$\mu(\epsilon_{\text{pos}})$ (m)	4.736	4.494	5.592	5.259
$\sigma(\epsilon_{\text{pos}})$ (m)	4.357	5.121	7.094	6.469
$\mu(\epsilon_{\varphi})$ (counts/s)	736.4	488.8	414.2	427.3
$\sigma(\epsilon_{\varphi})$ (counts/s)	2534	2392	2247	2653
Avg. Runtime (s)	1730	31,910	13.5	12.9
Std. Dev. Runtime (s)	51.08	5070	1.407	1.147

- On par accuracy (within 1% full scale)
- ~36x improvement in runtime without obstacles
- ~4,420x improvement in runtime for cases with obstacles

More complex models come with no runtime cost!!!

Monte Carlo Results
Dynamic Particle Count Study

- Reduced effect of degeneracy and low particle count (lower 95th percentile error) (P_{95})
- Improved runtime

Particle Filter	DPF ($N = 5,000$)						
$r_{\max}$	**2**	**3**	**4**	**5**	**6**	**7**	**8**
$\hat{r}$ Correct (%)	**98.67**	**92.67**	**85.33**	76	60.67	54.67	47.33
$\mu(\epsilon_{\text{pos}})$ (m)	**2.509**	**3.579**	4.492	5.514	6.45	6.593	8.373
$\sigma(\epsilon_{\text{pos}})$ (m)	**3.445**	3.87	3.465	4.069	4.943	5.049	5.774
$P_{95}(\epsilon_{\text{pos}})$ (m)	**5.44**	11.08	11.41	13.9	15.88	13.22	20.3
$\mu(\epsilon_{\varphi})$ (counts/s)	387.1	474.4	510.8	527.6	**616.4**	**491.4**	**1064**
$\sigma(\epsilon_{\varphi})$ (counts/s)	**1688**	**2139**	2462	**2628**	2770	3142	3875
Mean Runtime (s)	75.46	76.57	77.87	79.01	79.95	**82.82**	**83.05**
Median Runtime (s)	77.25	78	79.1	79.9	81.15	83.99	83.81

Particle Filter	DDPF ($N_0 = 5,000$)						
$r_{\max}$	**2**	**3**	**4**	**5**	**6**	**7**	**8**
$\hat{r}$ Correct (%)	**98.67**	**92.67**	84	**76.67**	**63.33**	**62.67**	**49.33**
$\mu(\epsilon_{\text{pos}})$ (m)	2.636	3.76	**4.454**	**5.33**	**5.92**	**6.091**	**7.471**
$\sigma(\epsilon_{\text{pos}})$ (m)	2.846	**3.064**	**3.035**	**3.484**	**3.576**	**3.519**	**4.038**
$P_{95}(\epsilon_{\text{pos}})$ (m)	6.115	**10.56**	**10.74**	**12.66**	**12.41**	**12.19**	**14.68**
$\mu(\epsilon_{\varphi})$ (counts/s)	**304.7**	**348**	**298.5**	**460.7**	833.2	814.8	1170
$\sigma(\epsilon_{\varphi})$ (counts/s)	2090	2229	**2264**	2632	**2648**	**3119**	**3539**
Mean Runtime (s)	**31.68**	**43.41**	**69.26**	**68.47**	**77.63**	110.3	134.1
Median Runtime (s)	**27.07**	**26.95**	**27.39**	**27.98**	**29.11**	**36.3**	**42.11**

National Nuclear Security Administration

Hardware Results

- **Search area:** 15m x 6m
- **17 obstacles**
    - 2 densities of concrete
- **45 measurements** taken using Kromek Sigma-50 CsI(Tl) scintillator with 2-minute dwell time.
    - Not all measurements were used in some cases
    - The entire dwell time was not used in some cases

Note the tape marking the locations of the obstacles

Ground vehicle search time-lapse with obstacles present

Hardware Results
Single source, no obstacles

- Cs-137 @ 24.69 mCi

Results:

Spatial error: 5.75 cm (.0113%)

Strength Error: 1.04%

Hardware Results
Single source, with obstacles

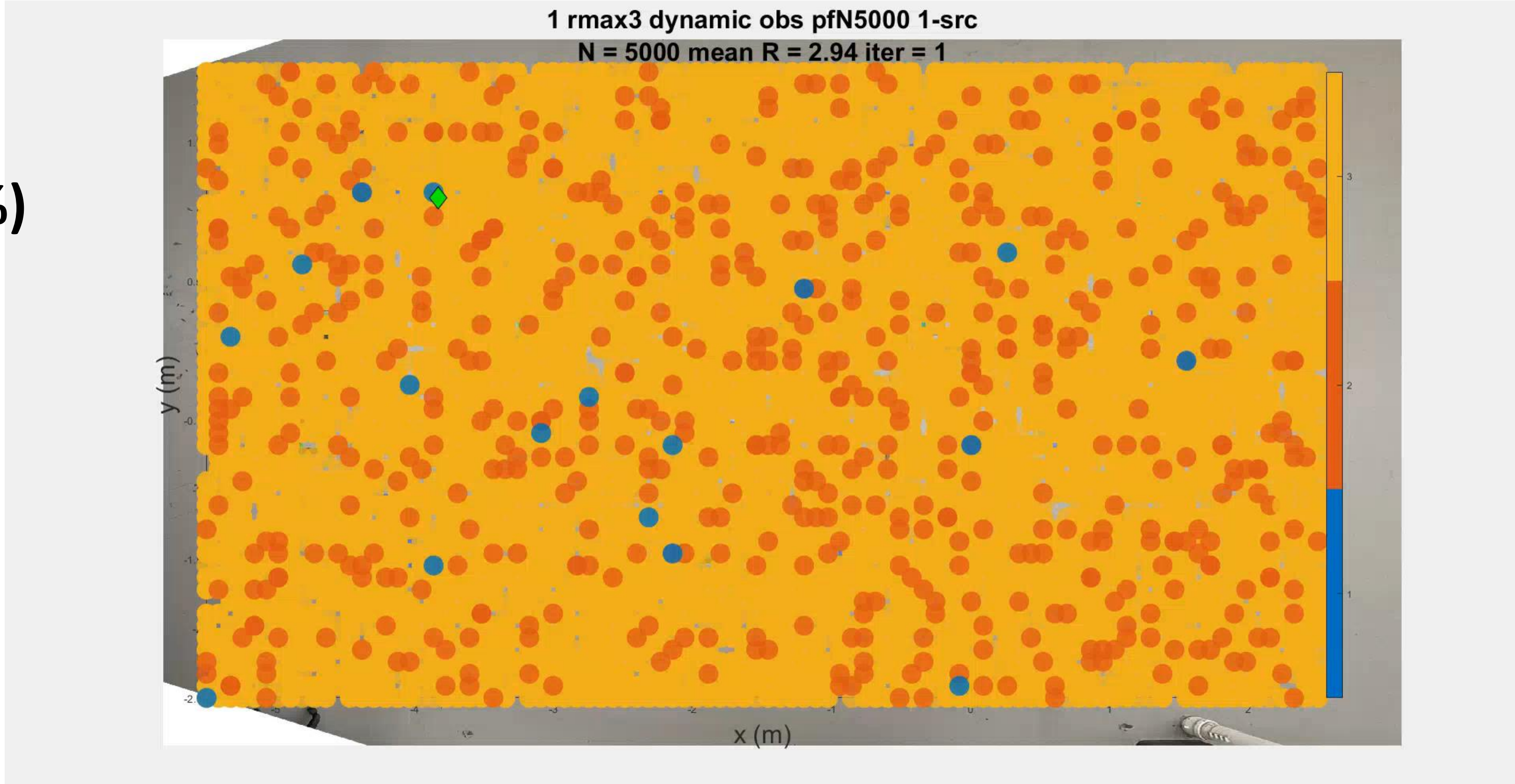
- Co-60 @ 4.76 mCi

Results:

Spatial error: 13 cm (.059%)

Strength Error: 16%

Accuracy is worse than with Cs-137 because of my spectrum processing algorithm. This will be discussed more in future work section



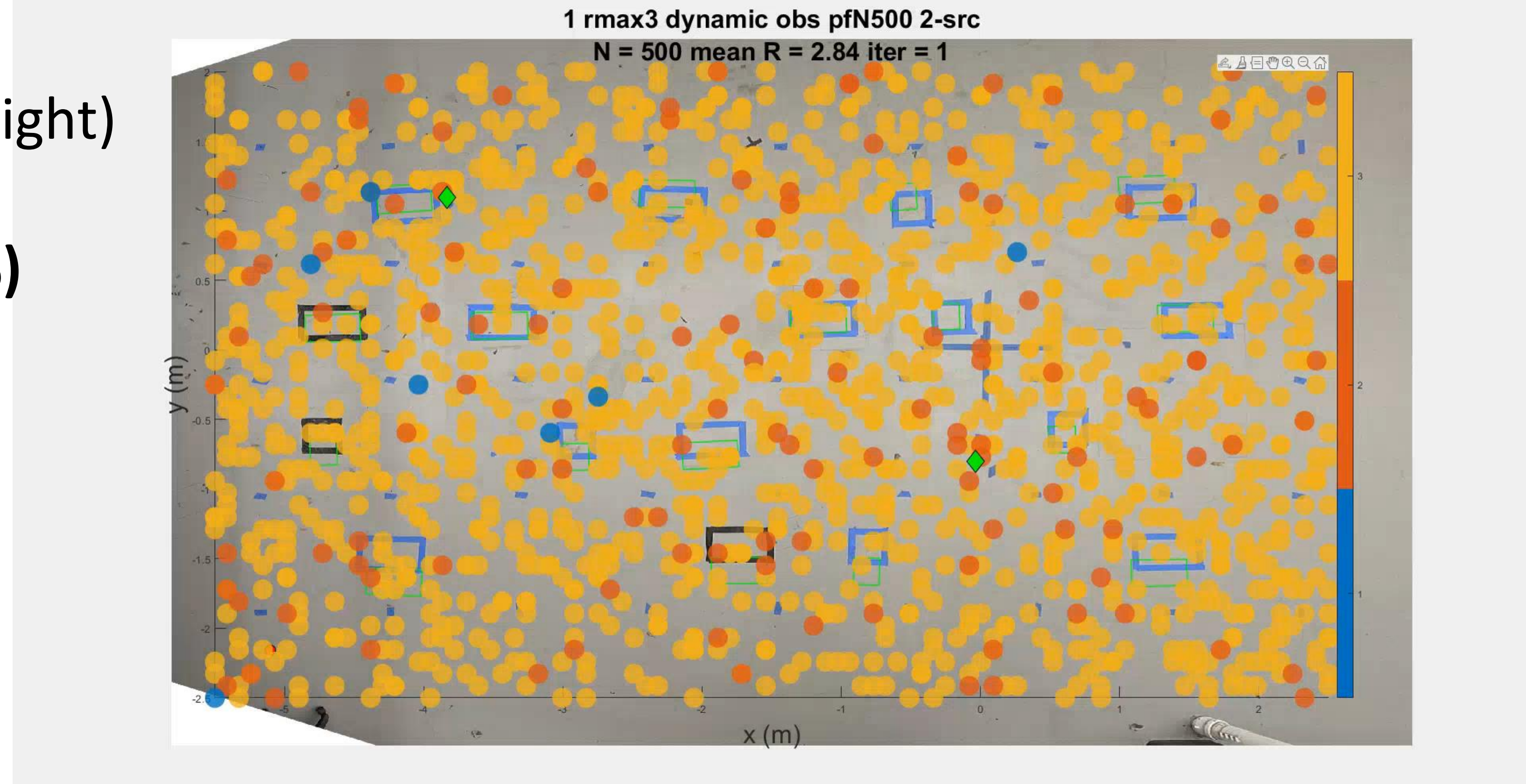
Hardware Results
2 source, with obstacles

- Cs-137 @ 24.69 mCi (Top Left)
- Cs-137 @ 0.152 mCi (Bottom Right)

Results:

Spatial error: 4.6 cm (.0074%)

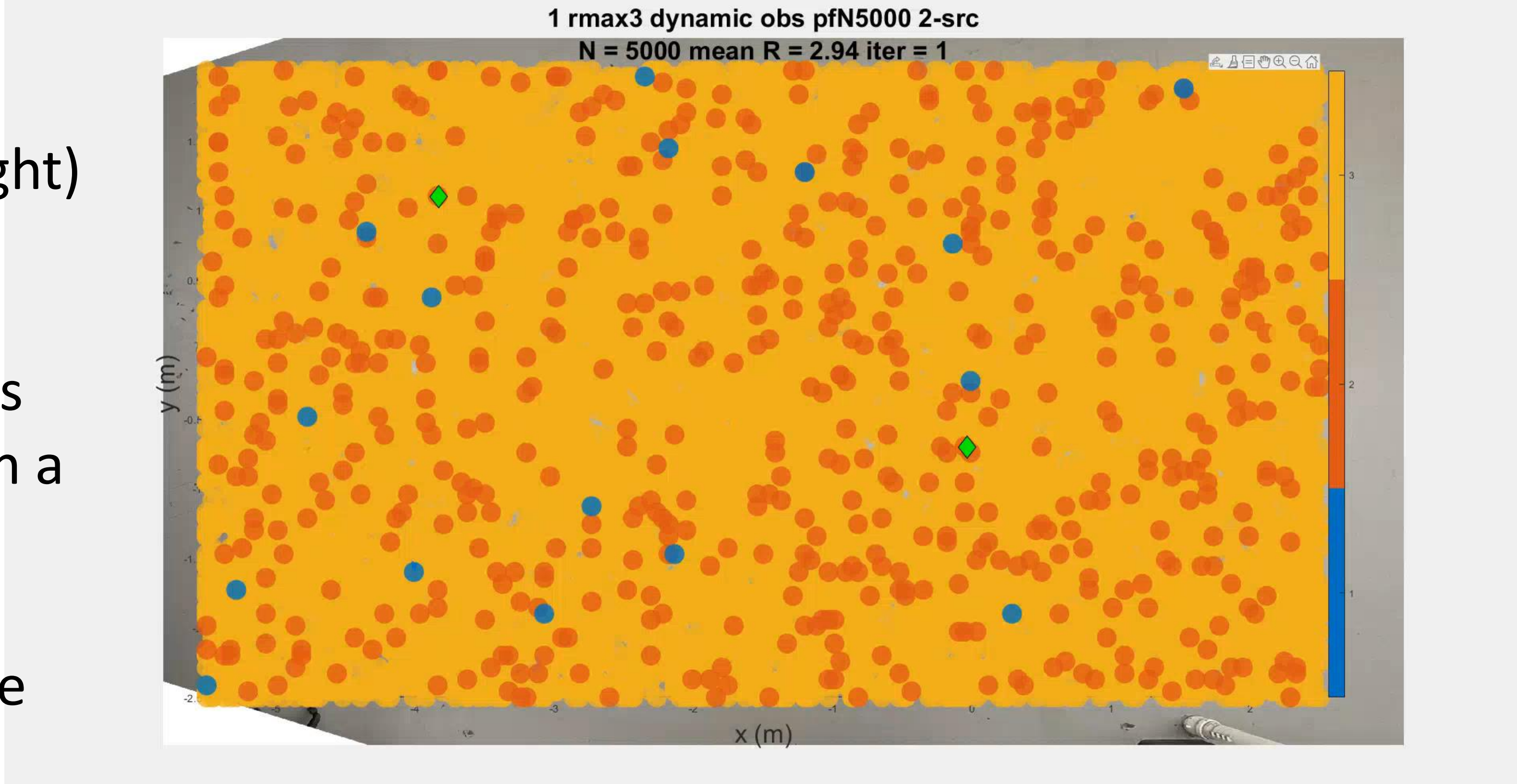
Strength Error: <1%



Particle Filter Limitations

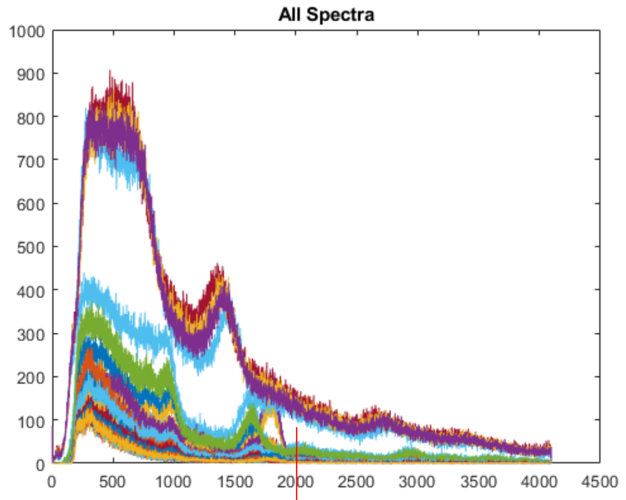
- Cs-137 @ 24.69 mCi (Top Left)
- Cs-137 @ 0.152 mCi (Bottom Right)

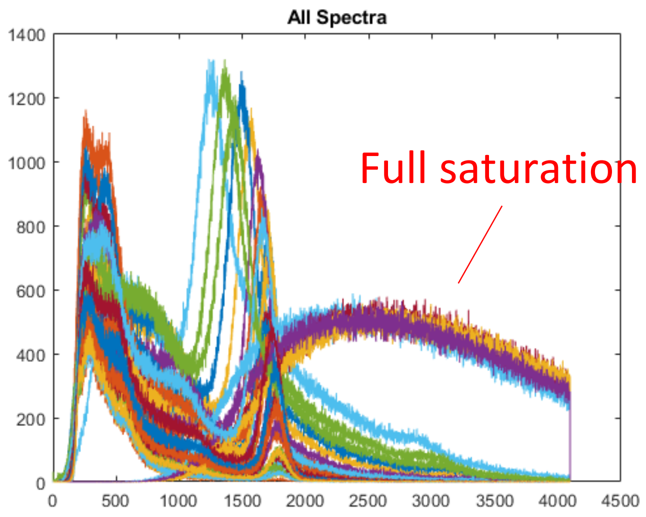
- 162x difference in strengths:
  - Like trying to hear someone's indoor voice while they're on a lawnmower.
- Stochastic method:
  - For small particle sets, can be dependent on luck

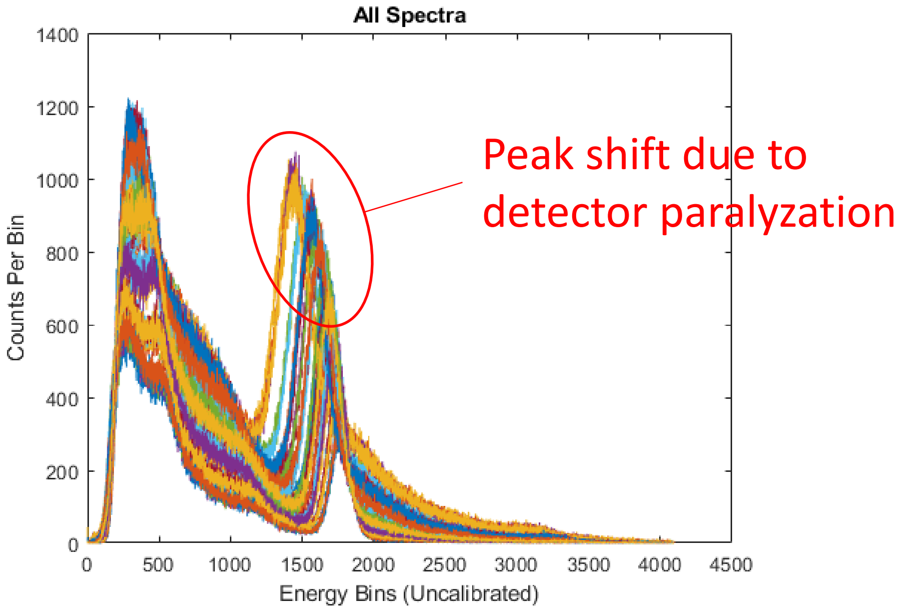


Hardware Results Challenges

- Can we extract the relative contributions of each isotope as a scalar?
- How do we deal with shifting photopeaks and saturation?
- Currently using rudimentary peak detection tuned for Cs-137







What isotopes are there? How strong are they relative to one another?

National Nuclear Security Administration

Conclusion

- **Runtime and accuracy consistently outperform state of the art.**
  - ~.0125% Area Ratio (Error in localization area relative to search area)
  - ~36x improvement in runtime for simplest inverse-square model
  - ~4,420x improvement in runtime for 1st order ray-tracing model

- Future work
  - Isotopic identification and improved spectrum analysis
  - Run multiple filters in parallel for different isotopes
  - Full scale hardware experiments

ETI Impact

- Hoping to do an internship this summer (hit me up national labs)
- Presented at IEEE SSRR 2021
  - Kemp, S., & Rogers, J. (2021, October). UAV-UGV Teaming for Rapid Radiological Mapping. In *2021 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)* (pp. 92-97). IEEE.
- Pending journal publication in IEEE Transactions on Nuclear Science
- Currently collaborating with Craig Bakker at PNNL

Connections, mentors, collaborators, etc.

- Jonathan Rogers and Satvik Kumar at Georgia Tech
- Craig Bakker and Amoret Bunn at PNNL
- David Chichester at INL
- Brian Quiter at LBNL
- Paul Wilson at UW
- Yuguo Tao, Anna Erickson, and Mackenzie Duce at Georgia Tech
- Andrew Torgesen, Andrew Fishberg, and Jonathan How at MIT

ACKNOWLEDGEMENTS

This material is based upon work supported by the Department of Energy / National Nuclear Security Administration under Award Number(s) DE-NA0003921.