ROBUST DETECTION OF RADIATION THREAT BY SIMULTANEOUS ESTIMATION OF SOURCE INTENSITY AND BACKGROUND

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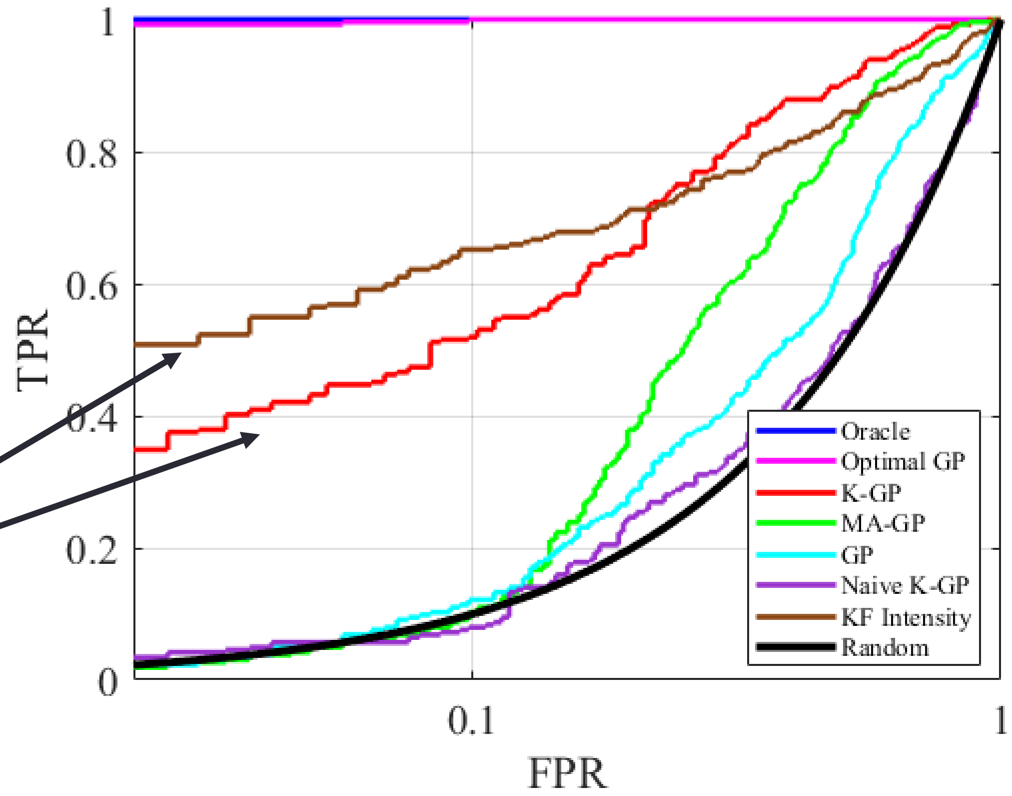
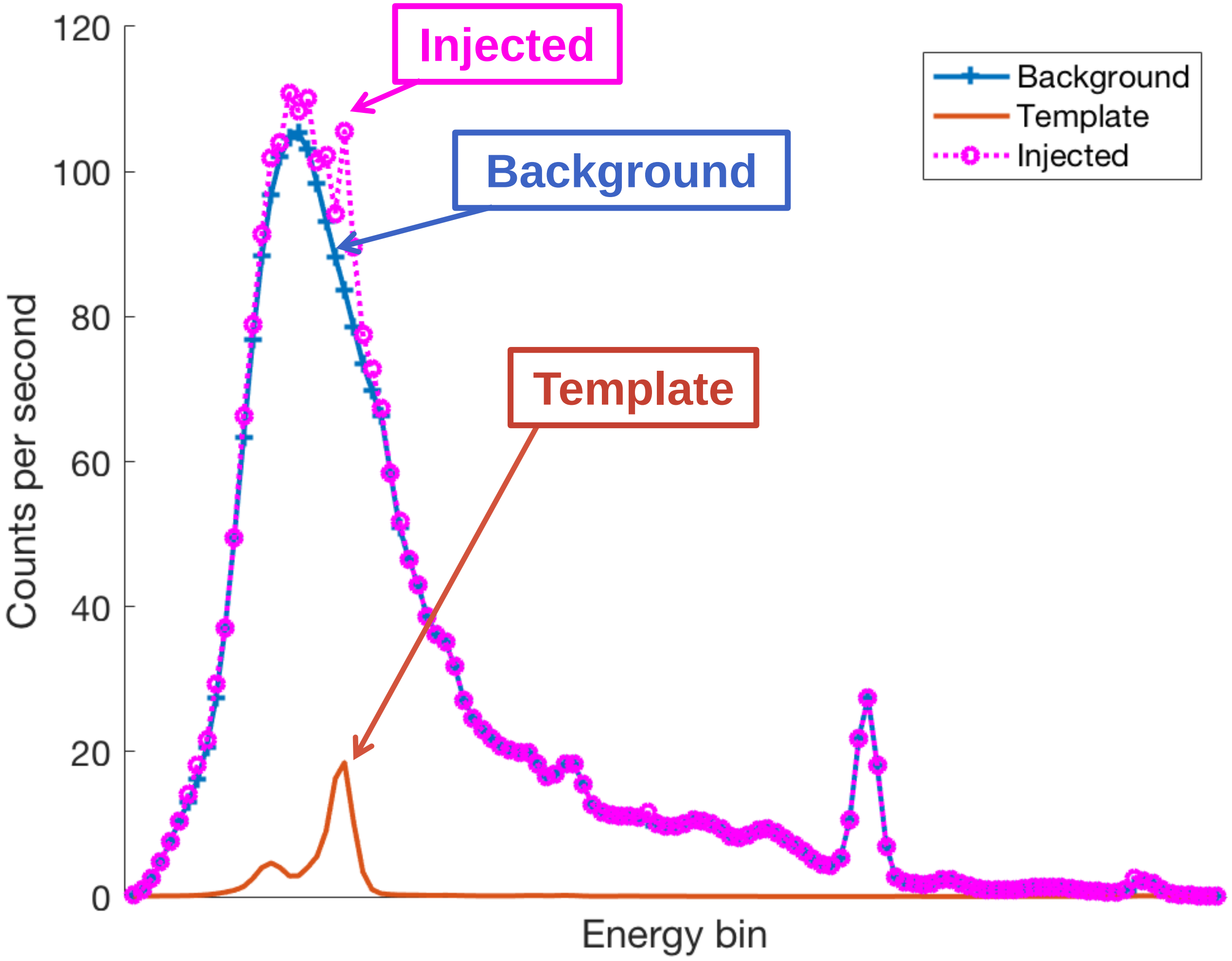
Overview

- Context of source detection
- Challenges in background variation and assumption of a training set
- Proposed solution of adaptive background estimation
- Experiments to compare proposed solution to alternatives



Radiation Threats in Spectral Data

- Our purpose is to detect compact sources of potentially harmful radiation in the presence of background noise.
- We analyze individual gamma-ray spectrometer measurements from a mobile sensor, some of which may reflect presence of the sources sought.
- A significant challenge is to filter the source from the background, as the signal-to-noise ratio is low.



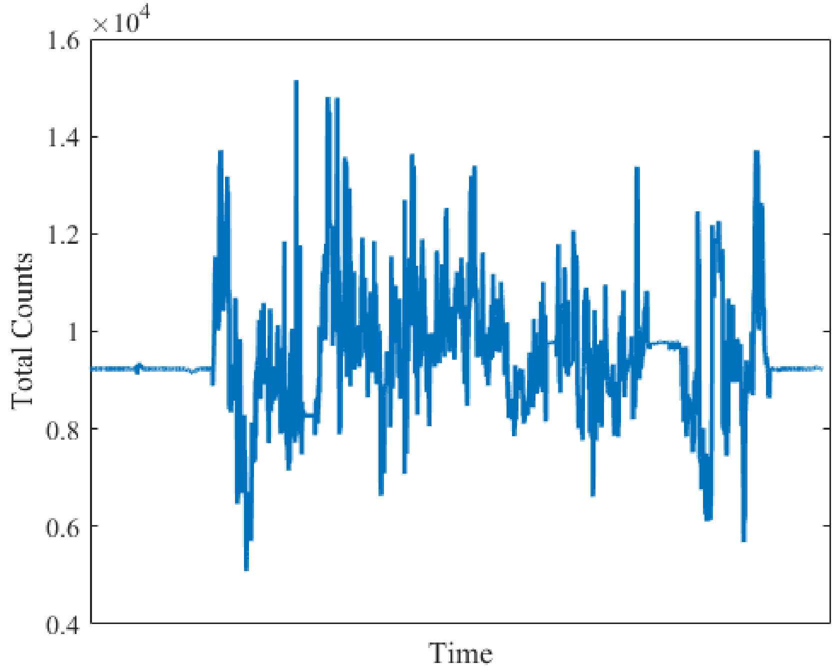
Existing Methods Use Stationary Representations

- Some methods are based on principal components such as Spectral Anomaly Detection and Matched Filter.
- Other methods may be based on the mean background spectrum such as Gaussian-Poisson MAP Estimation.
- In general, most methods utilize a stationary representation of background extracted from a training set of background.

Stationary Parameters (Mean, PCA)

Challenge 1: Variation in Background

- The background spectrum depends on many factors such as materials and atmosphere.
- Therefore, the background may be a non-stationary process that varies temporally and spatially.
- By reducing background to a stationary representation, most methods ignore the sequential nature of the data and are thus insensitive to local variations.



Challenge 2: Informative Training Data

- The assumption of informative training data may not be safe.
- Background characteristics at deployment could differ from when the data were recorded. At worst, data might be totally uninformative.
- There might not even be training data from the location being checked. If so, the methods probably cannot be trained satisfactorily.
- When the training data are less informative, the performance of many methods can suffer drastically.

Proposed Solution: Adaptive Estimation of Background

- Both challenges can be solved by estimating the local background in real-time during deployment.
- The estimated background can then be given as input to other methods, which makes them
  - (+) More sensitive to background variation.
  - (+) Feasible when no informative training data exist.
  - (-) Less robust to noise because of fewer data points.
- The primary obstacle is that if a source exists, its radiation might get mixed in with background by an estimator.

Kalman Filter for Linear Dynamical Systems

- The Kalman Filter (KF) estimates an unobserved process x_t given an observed process y_t by filtering out stochastic noise.
- A linear dynamical system is assumed where

$$x_{t+1} = Ax_t + w_t$$
$$y_t = Cx_t + v_t$$

- KF recursively estimates a Bayesian prior mean and covariance on state x_t.
- If noise terms w_t and v_t are normally distributed and uncorrelated, then KF is the linear minimum mean-squared error estimator.
- Hyperparameters to be set are A, C, $Cov(w_t)$, $Cov(v_t)$, and mean and covariance of the initial prior.

Simultaneous Estimation of Source Intensity and Background

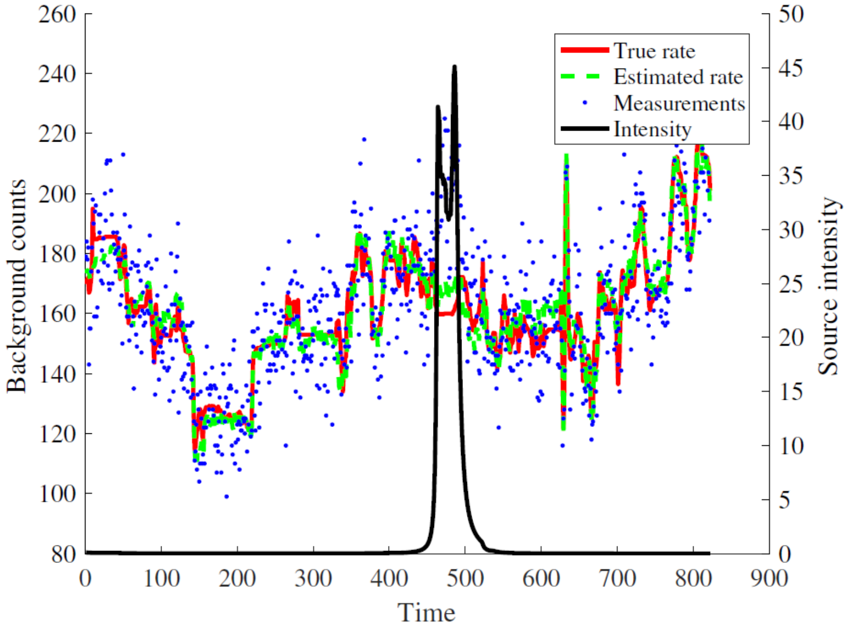
- Let the state x_t be the multivariate background spectrum Poisson rates λ_t appended by source intensity γ_t.
- Let y_t be the observed counts.
- Transition model: no change *a priori*.

$$x_{t+1} = x_t + w_t$$

- **Assumption**: The source template s is known.
- Emission model: sum of background and source.

$$y_t = \lambda_t + \gamma_t\, s + v_t$$

- Noise is not Gaussian, but if rates are high, Poisson approximates Gaussian.



Adaptive Filtering to Set Up Kalman Filter

- KF is very sensitive to the hyperparameters $Cov(w_t)$ and $Cov(v_t)$.
- An adaptive KF assumes they are non-stationary and estimates them in real-time.
  - Bayesian, MLE, covariance matching, correlation
  - Often computationally expensive
- We propose a simple method that functions well for this problem.

$$Cov(\lambda_t) = K_{L,\sigma}(\widehat{Cov}(\hat{x}_i - \hat{x}_{i-1}))$$
$$Cov(\gamma_t) = \gamma_0$$
$$Cov(v_t) = diag(\hat{x}_{t-1})$$

where $K_{L,\sigma}$ is a Gaussian filter with length L and variance σ^2

- Disadvantage 1: Introduces additional uncertainty.
- Disadvantage 2: Requires a short burn-in period ($B < 120$ measurements).

Making Predictions from the Kalman Filter

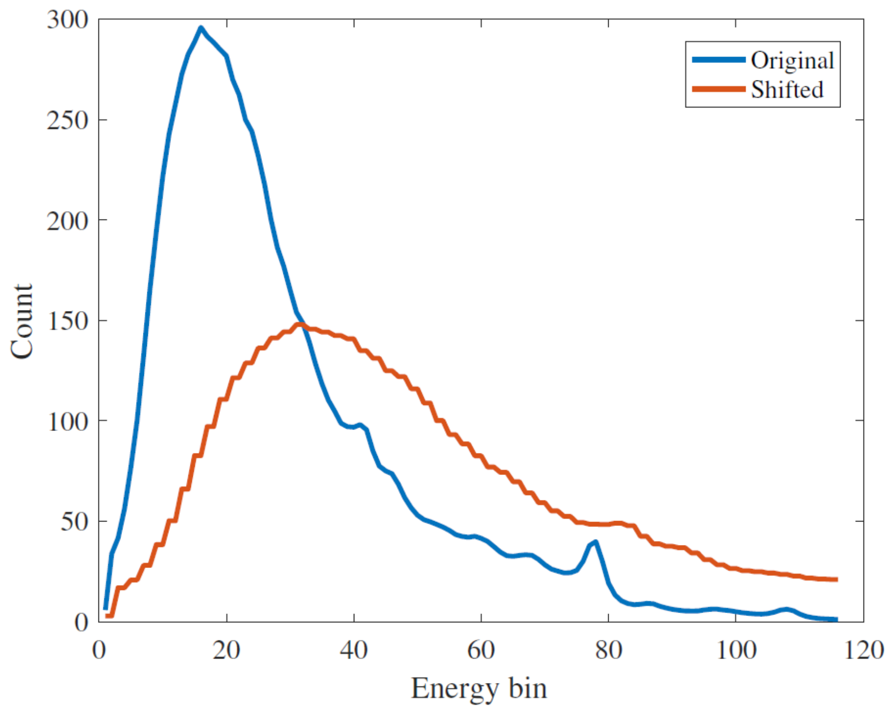
- **The first approach** is to insert background estimates x_t into non-sequential methods.
  - For example, Gaussian-Poisson (GP) MAP estimation takes mean background and background covariance as stationary input.
  - GP: Compute MAP likelihood ratio of source versus no source using a Gaussian prior over the Poisson rates.
  - GP can be made locally adaptive by inserting $\hat{x}_t$ as the prior mean μ and sample covariance $\widehat{Cov}(\hat{x}_t)$ as prior covariance Σ, which are both inputs.
- **The second approach** is to use the intensity estimates γ_t as a score.

Dataset and Experimental Design

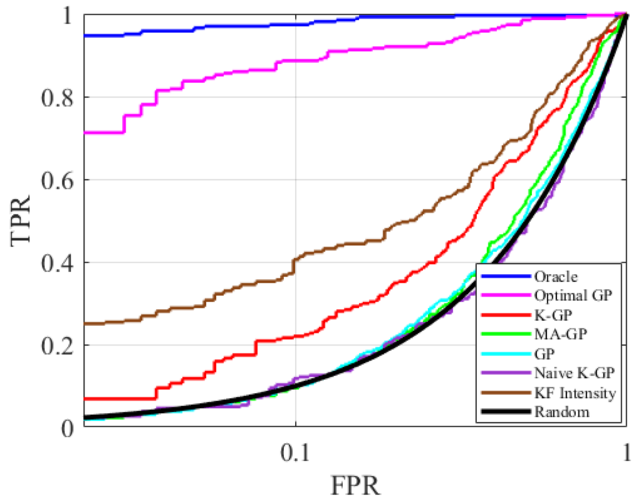
- The dataset was a collection of 11,000 gamma-ray measurements recorded in one-second intervals by a NaI detector on a vehicle moving around downtown Berkeley, CA.
  - Photons were partitioned into 116 quadratically spaced energy bins.
  - Contained about 10,000 counts per second on average.
- The original measurements were taken as background. A generative model was fitted to the background so that background counts were resampled in each trial.
- Synthetic positive measurements were created by injecting Poisson samples from a source template for Americium-241, a nuclear waste isotope.
- The experiment tested detection of a roadside source in a single pass. In each trial, the source location was randomized.
- Half the trials did not include a source.

Evaluating the Kalman Filter with Training-Test Mismatch

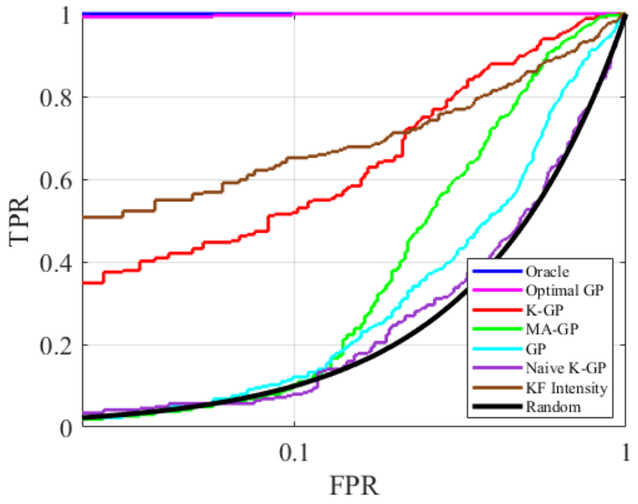
- The Kalman filter does not require training data, but other methods usually do.
- It may be naïve to assume that training data match test data.
- To induce mismatch between training and test background, test spectra were shifted to higher energy bins, similar to an extreme form of gain drift.
- We compared several methods:
  - Oracle: Likelihood ratio using exact background rates and intensity.
  - Optimal GP: GP with perfect prior.
  - **Kalman GP** (KGP): GP with prior set by KF.
  - Moving Average GP (MA GP): Like KGP but with simple moving average.
  - GP: GP method with prior set by training data.
  - Naïve KGP: KGP with non-adaptive covariance hyperparameters estimated from training data.
  - **Intensity**: Intensity estimated by KF.



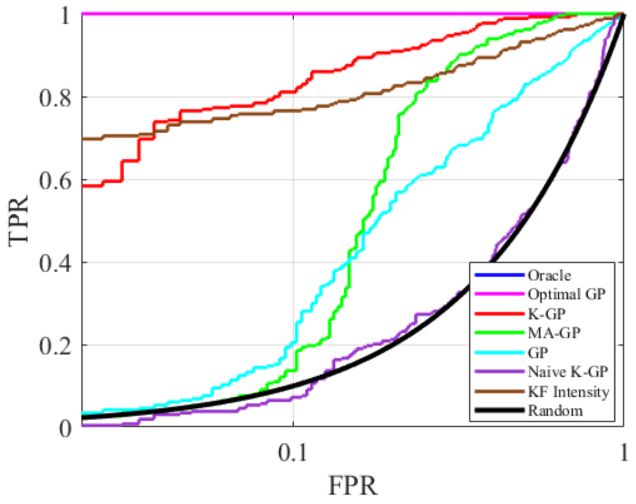
Adaptive Approaches Perform Better



ROCs with intensity of 75.



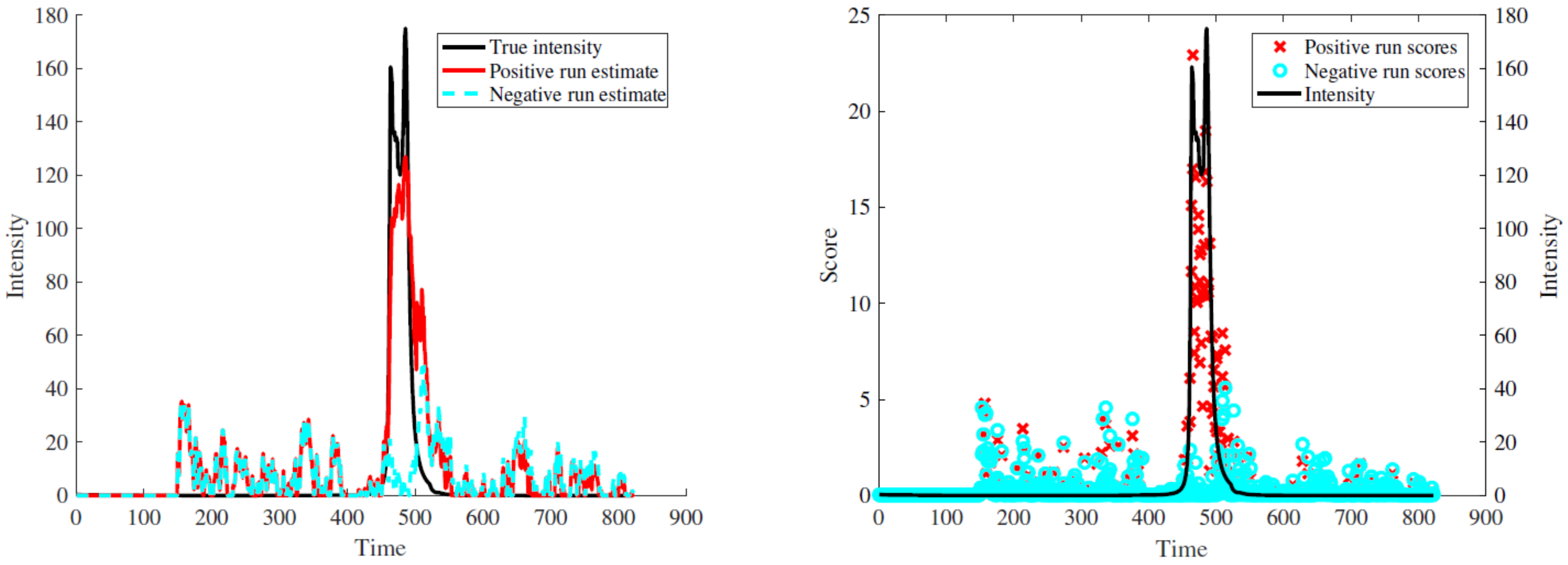
ROCs with intensity of 125.



ROCs with intensity of 175.

- Oracle and Optimal GP give upper bounds on performance of realistic methods.
- Proposed methods KF Intensity and KGP are significantly better than every alternative except Oracle and Optimal GP.
- In low FPR ranges at 125 counts per second, KF Intensity TPR can be 0.5 higher than the next best.
- Plain GP does not adapt to local variations in background.
- MA GP does not separate source and background.
- Naïve KGP demonstrates the importance of adaptive filtering.

Examining Estimated Intensity and Scores



(a) Kalman filter intensity estimates. (b) KGP scores.

- Estimates of intensity were compared to the true intensity, which spiked when the detector moved near the source.
- Intensity and KGP scores tracked the true intensity well with low lag.
- There were not large spikes when there was no source.

Conclusion

- The main contribution was to propose a method for source detection that greatly reduces the dependence on a training set, which can be useful when:
  - A training set is not available for a new location.
  - Background has shifted over time.
  - The background has heavy local variation.
  - The training set is inaccurate because of miscalibration, e.g. gain drift.
- We modeled radiation as a linear dynamical system and applied a Kalman filter to simultaneously estimate source intensity and background.
- The method was demonstrated to perform well when the training set was uninformative on a modified RadMAP dataset.
- Future work includes investigating how the method performs on a dataset with naturally high background variation, and how the Kalman filter can be inserted into other methods such as the Matched Filter.

References

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