Robust Detection of Radiation Threat by Simultaneous Estimation of Source Intensity and Background

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Introduction. In nuclear physics, an important problem is the detection of radiation threats. We consider a mobile detector used for search, such as a vehicle that travels through an urban environment to locate dangerous radioactive materials. The primary challenge is a low signal-to-noise ratio in observed radiation caused by background radiation. Urban environments contain large numbers of nuisance (benign) sources—potentially every material present—which can heavily obfuscate the signal from the target source. These nuisance sources may include ordinary objects like concrete or bananas as well as shielding materials that intentionally hide the source. Moreover, since the environment changes as the detector moves, the background radiation fluctuates widely, further compounding this problem.

This work explores detection of a compact source in a single pass of the detector. Existing methods for this problem commonly assume that a training set of background radiation measurements is given and that the average spectrum of background radiation is the same between the training set and test set. Relaxing these assumptions, we investigate a scenario in which a discrepancy exists between background radiation in training and test sets or in which there is no training set at all. There are multiple practical situations in which this a scenario could arise, such as different environments for training and testing, environments with non-stationary background, a lack of time to collect training data for new sensors, and gain drift. A new method is proposed that is robust to these situations by adapting to the local distribution of background radiation in real-time. In particular, a Kalman filter is employed to simultaneously estimate source intensity and background. It is demonstrated to greatly advance the state-of-the-art when the training set is uninformative, using an authentic radiation dataset collected in a noisy urban environment.

Objective. We introduce a method for detection of a single source in the presence of background noise that is robust to uninformative or unavailable background training data.

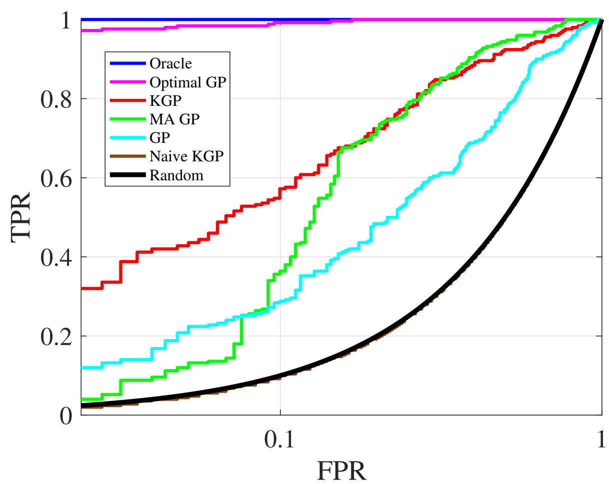
Background. There are many existing methods for source detection, and in this work we focus on those that assume knowledge of a source template. One class of state-of-the-art methods are Matched Filters [1], which essentially compute the similarity between a source template and the part of observed radiation that is not expected from background. Another recent development is Gaussian-Poisson MAP estimation [2], a Bayesian method that computes a likelihood ratio between the hypotheses of source and no source by modeling radiation as Poisson variates under a Gaussian prior. These methods are trained on background radiation observations, which are implicitly assumed to be similar to the observations at test time. After training, they can be given new radiation observations for which they output a score according to how likely a source is present.

Method. In the Gaussian-Poisson (GP) method, the Gaussian prior on the background rates has a time-invariant mean and covariance. The method can be improved by dynamically estimating the background rates at each step to better estimate the parameters of the prior. To do so we apply the Kalman filter, a widely used method for estimating an unobserved signal underlying an observed noisy discrete time series. In plain terms, it filters out statistical noise to obtain more precise estimates of a signal. Consequently, it is a natural candidate to model radiation. The state space $x_t \in \mathbb{R}^{d+1}$ contains the background rates in each of d energy bins in the first d elements. Furthermore, the source intensity must be modeled in order to decouple its effect on the measured spectra from the background radiation. Source intensity can vary with distance and obfuscation. Accordingly, we model source intensity in the last element $x_t^{(d+1)}$. Next, the observation $y_t \in \mathbb{R}^d$ contains the measured counts at time t. We propose a dynamical system given by $x_{t+1} = x_t + w_t$ and $y_t = x_t^{(1:d)} + x_t^{(d+1)} s + v_t$ where $s \in \mathbb{R}^d$ is the target source template. Given $y_1, \ldots, 1_t$, the Kalman filter estimates the background rates $x_t^{(1:d)}$, which are used as the mean μ of the Gaussian prior in the GP method. In addition, the covariance of the prior is estimated as the covariance of the estimated background rates up to time t. The covariances of w_t and v_t are estimated adaptively by a simple method, omitted here for brevity.

Data and procedure. Our experiment tested detection of a roadside source in a single pass. The dataset was a collection of over 11,000 gamma-ray measurements recorded in one-second intervals by a sodium-iodide detector mounted on a vehicle moving around an urban area in downtown Berkeley, CA, USA. On average there were 10,000 photon counts per second. Each measurement contained $d = 116$ quadratically spaced energy bins. The measurements were assumed to be background data. The background rates were estimated by applying the GP method over observations within 10 meters of the current measurement being estimated. These were regarded as the true rates for simulation and comparison purposes.

To create positive measurements, we selected a single threat template with a Pearson correlation of only 7% with the mean background. A location for the source was randomly sampled from the set of points at most 20 meters from the path of the sensor. The test set was taken to include all data points where the sensor was at most 100 meters away from the source, along with all data points in between, forming a contiguous window. The training set was taken to be the remaining data points. To simulate different distributions between the training and test sets, we applied a shifting algorithm to each measurement in the training set. The counts in any particular energy bin were shifted to higher energy bins. This shift induced a Pearson correlation of roughly 50% between the mean training background spectrum and the test background spectra. Every observation in the test set was injected with a sample from the source distribution with intensity based on distance. The maximum intensity was set to a given value. Then the methods were applied to score each test point. The maximum score for each method was recorded as the output of the run. Next, all runs were repeated identically except with no source injection. By this procedure we created multiple runs with positive or negative ground truth.

Results. [Currently running fresh experiments to compare to MF.] We compared performance between six methods. The figure shows the ROCs computed over XXX positive and negative runs with maximum intensity of 125 counts per second. The best methods are Oracle and Optimal GP, which leverage information not realistically available and are hence expected to perform better. The next best is our proposed method, KGP, which beats a variant of GP called MA GP by a large margin in the low false positive rate range: about 20% in true positive rate and 5% in false positive rate. Standard GP and Matched Filter (MF) do poorly.



Receiver operating characteristics of different methods.

Conclusion. We characterized photon counts distributions in gamma-ray spectra using a Kalman filter and Gaussian-Poisson model to adaptively predict source presence. This approach produced a classifier that when tested on an authentic radiation dataset was substantially more sensitive and threat-specific than other methods when the training set of background radiation was uninformative. This work advances the state-of-the-art in a variety of practical use cases, such as such as different environments for training and testing, environments with non-stationary background, a lack of time to collect training data for new sensors, and gain drift.

References.

[1] Nelson, Karl, and Simon Labov. "Aggregation of mobile data." Lawrence Livermore National Lab Technical Report 1.2.2 (2012): 2-3.

[2] Jin, Jay. "Detection of sources of harmful radiation using portable sensors." Unpublished master's thesis, Robotics Institute, Carnegie Mellon University (2016).

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