

Assessing List-Mode Observer Performance in Classification Tasks when Imaging Nuclear Inspection Objects



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Introduction

This project leverages advanced nuclear-medicine techniques to perform tasks useful for arms-control treaty applications. We developed and studied observer models that avoid aggregating sensitive information by classifying sources using list-mode data. The long term goals of this project are:

- Effectively classify objects using observer models that account for nuisance parameters such as variable object position, orientation, and radioactivity.
- Develop a range of observer models that store a variety of information about the object. The end goal is to develop observer models that avoid the need for sensitive-information barriers.

Theory

Ideal Observer

The recorded detector data consists of the counts N hitting a detector and list-mode data A_n for the n^{th} detection event. Under signal-known-exactly (SKE) conditions, where the count rate and spectra are known, the ideal observer is

$$A_n = \{\text{pixel, energy, particle type}\}$$

$$\gamma_j = \{\text{orientation, location, material age for source } j, \text{ etc}\}$$

$$\Lambda_{SKE}(\{A_n\}, N | \gamma_1, \gamma_2) = \frac{\text{pr}(\{A_n\}, N | \gamma_2, H_2)}{\text{pr}(\{A_n\}, N | \gamma_1, H_1)}$$

$$= \frac{\text{Pr}(N | \bar{N}_2) \prod_{n=1}^N \text{pr}(A_n | h_2)}{\text{Pr}(N | \bar{N}_1) \prod_{n=1}^N \text{pr}(A_n | h_1)}$$

The first set of terms is the ratio of the Poisson pdf values for the sample counts N given the known count rates in H_2 and H_1 . On the right is the ratio of the spectra pdf values for each observed energy. Data for each detection event is read/acquired, processed, and forgotten.

Generalizing the ideal observer with nuisance parameters improves performance:

$$\Lambda(\{A_n\}, N) = \frac{\int \text{pr}(\{A_n\}, N | \gamma_2, H_2) \text{pr}(\gamma_2) d\gamma_2}{\int \text{pr}(\{A_n\}, N | \gamma_1, H_1) \text{pr}(\gamma_1) d\gamma_1}$$

This expression can be calculated via Monte Carlo methods in some circumstances. In others [see future J.O.S.A. paper], we derive a form that is an integral over the SKE ideal observer.

$$\Lambda(\{A_n\}, N) = \int \Lambda_{SKE}(\{A_n\}, N | \gamma_1, \gamma_2) \text{pr}(\gamma_1 | \{A_n\}, N, H_1) d\gamma_1 \dots \text{pr}(\gamma_2 - \gamma_1) d(\gamma_2 - \gamma_1)$$

Two examples:

- Ideal observer averaging over two orientations

$$\Lambda_{\theta}(\{A_n\}, N) = \frac{\text{pr}(\{A_n\}, N | H_2, \theta = 0^\circ) + \text{pr}(\{A_n\}, N | H_2, \theta = 45^\circ)}{\text{pr}(\{A_n\}, N | H_1, \theta = 0^\circ) + \text{pr}(\{A_n\}, N | H_1, \theta = 45^\circ)}$$

- Ideal observer averaging over activity distribution

$$\Lambda_{\bar{N}_1, \bar{N}_2, \bar{N}_e}(\{A_n\}, N) = \int \Lambda_{SKE}(\{A_n\}, N | \bar{N}_1, \bar{N}_2) \text{pr}(\bar{N}_2) d\bar{N}_2 \dots \text{pr}(\bar{N}_1, \bar{N}_B | \{A_n\}, N, H_1) d\bar{N}_B d\bar{N}_1$$

Hotelling Observer

Defining a data vector \mathbf{g} in terms of an operator acting on list-mode data $\{A_n\}$

$$\mathbf{g}_m = \sum_{n=1}^N T_m(A_n)$$

The Hotelling observer uses only the mean $\bar{\mathbf{g}}$ and covariance $K_{\mathbf{g}}$ of the imaging data vectors. It is the linear discriminant \mathbf{w} that maximizes the SNR for the test-statistic distributions under H_2 and H_1 .

$$\mathbf{w} = K_{\mathbf{g}}^{-1} \Delta \bar{\mathbf{g}}$$

$$t = \mathbf{w}^t \mathbf{g} = \sum_{n=1}^N \sum_{m=1}^M w_m T_m(A_n)$$

We examined two forms of \mathbf{g} :

- g_m is the detected counts in a given energy-pixel bin
- g_m is the sum of energies in a given pixel

Imaging System

Object

Classification tasks were performed on inspection objects developed by Idaho National Lab (INL). Object 8 is plutonium shielded by depleted uranium while object 9 is plutonium shielded by highly enriched uranium. Both assemblies are supported by an aluminum framework inside an 8" by 8" aluminum box.

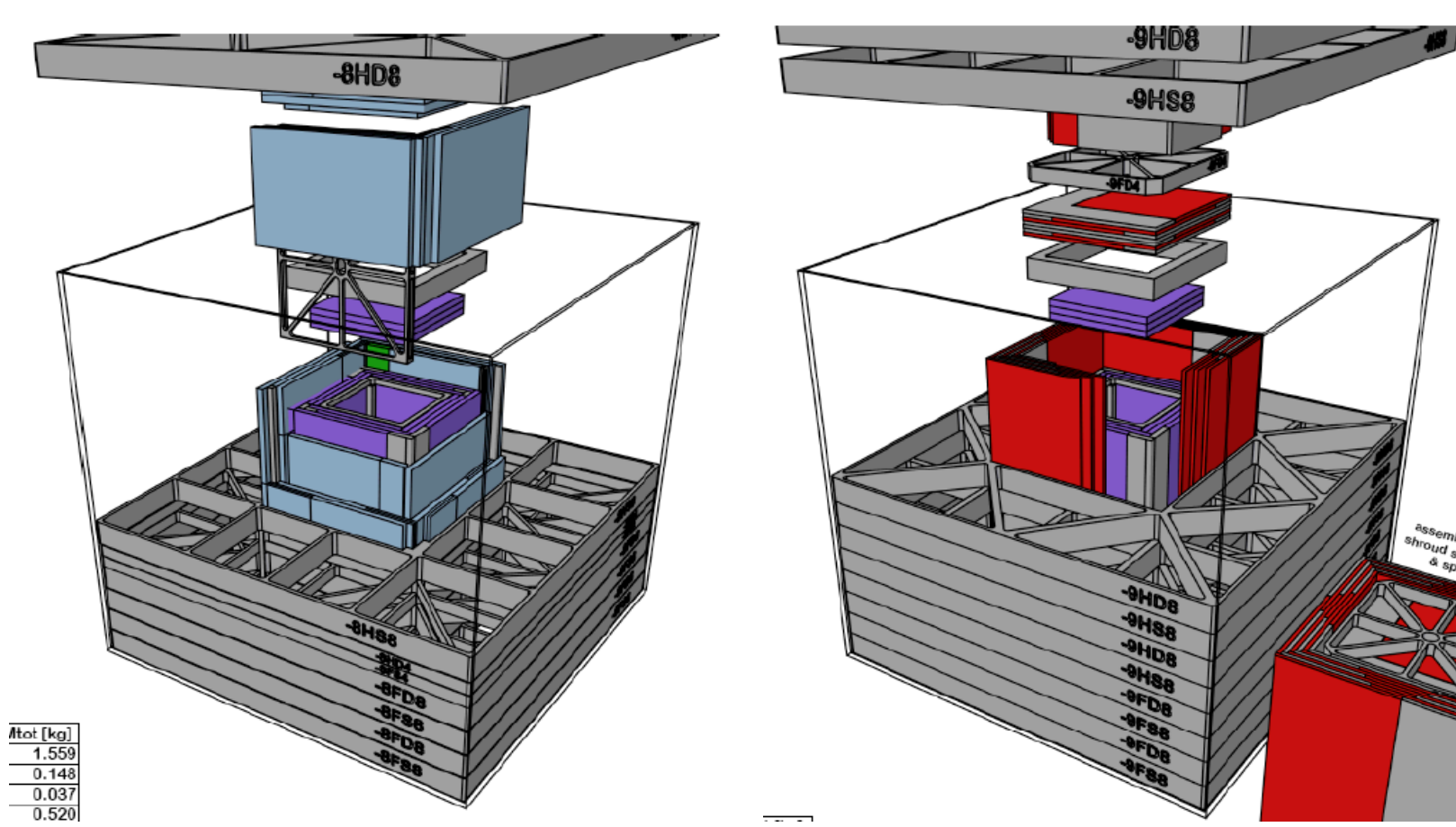


Figure 1 Inspection objects 8 (IO8) and 9 (IO9) developed by INL [INL/EXT-11-20876]

Detector

The detector used in these studies is a fast-neutron coded-aperture imager, developed by Sandia National Labs and Oak Ridge National Lab. The imager uses a polyethylene coded aperture and a 4x4 array of liquid-scintillator detectors, each consisting of 10x10 1cm² pixels.



Figure 2 Fast-Neutron Coded-Aperture Detector

Simulation

Forward model

The detector and INL sources were coded into GEANT4, which was used to track the photons and neutrons from these objects to the detector. Due to a very low detection probability, photons were emitted with a linear energy bias and an energy cutoff of 100 keV. A detector-response code collects the deposited energies and bins them into a mean pixel location. Perfect pulse-shape discrimination between gammas and neutrons is assumed.

Experimental outline

Two GEANT4 data sets were found for IO8 and IO9 under each orientation. The first is treated as calibration data and used to find the appropriate H_2 and H_1 parameters in the observer models. These observer models are then used to classify data sampled from the second set.

Performance metric

Observer models were evaluated using the area under the ROC curve (AUC), computed using the two-alternative forced-choice test, in which the observer is forced to choose which of the two sources is present. The fraction chosen correctly is equivalent to the AUC.

Results

Ideal-observer study with orientation variability

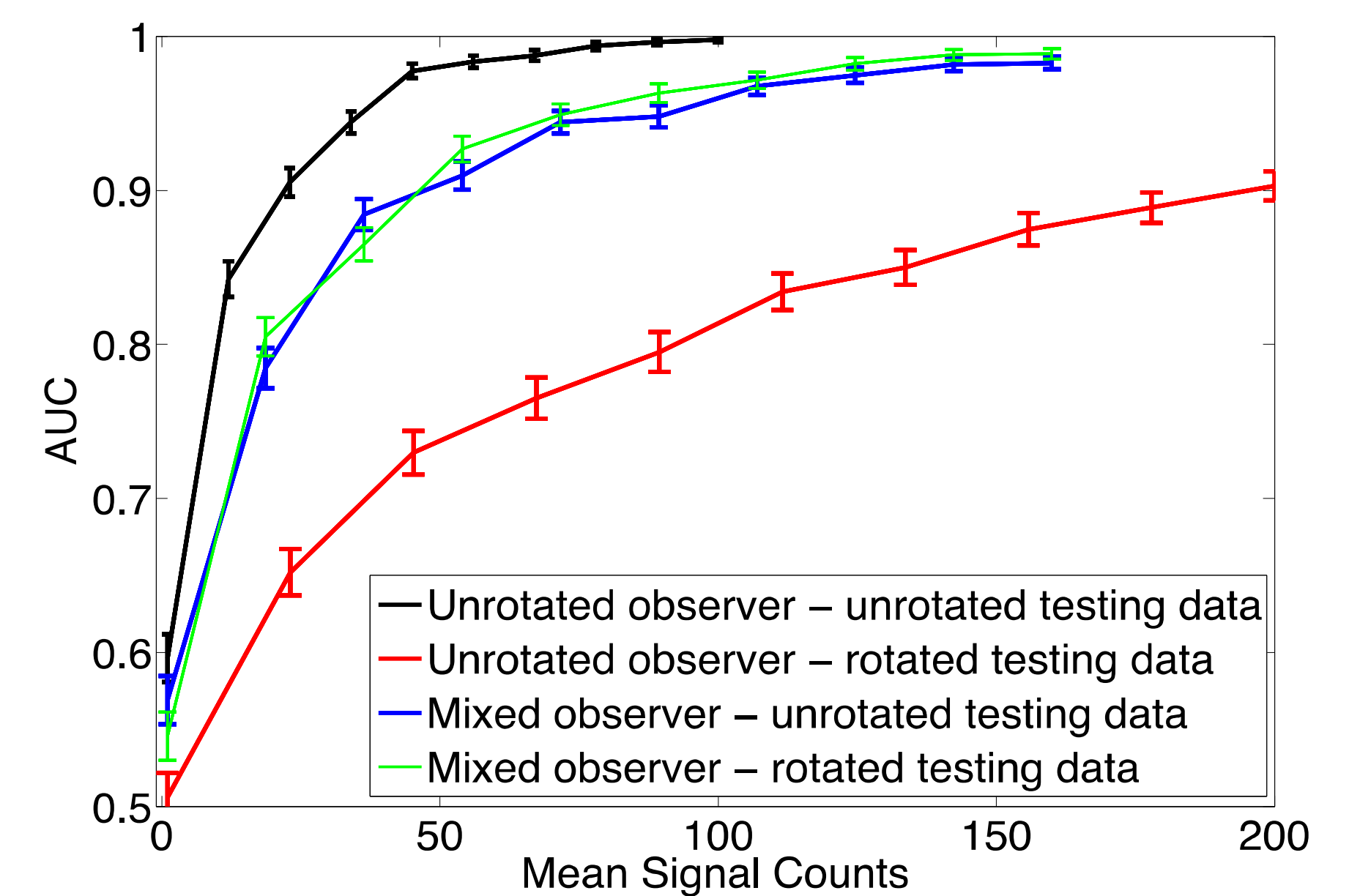


Figure 3 SKE ideal observer performs poorly when classifying object of different orientations. Overall performance improves when using the ideal observer that averages over these two orientations

Ideal-observer study with count-rate (CR) variability

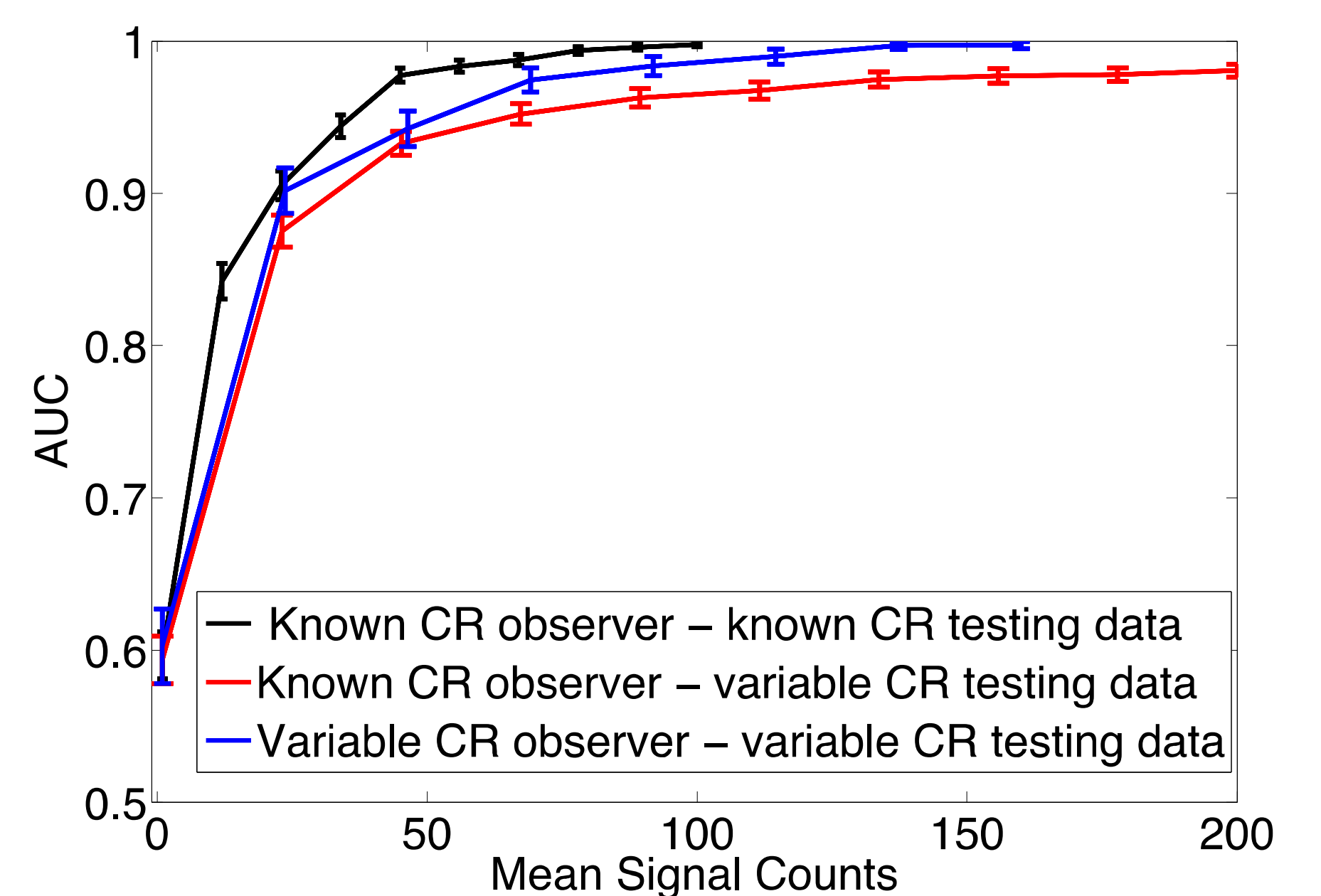


Figure 4 The known CR (SKE) ideal observer performs poorly when classifying sources with varying activity rates. Using the variable CR ideal observer discussed earlier, performance improves

Hotelling observers

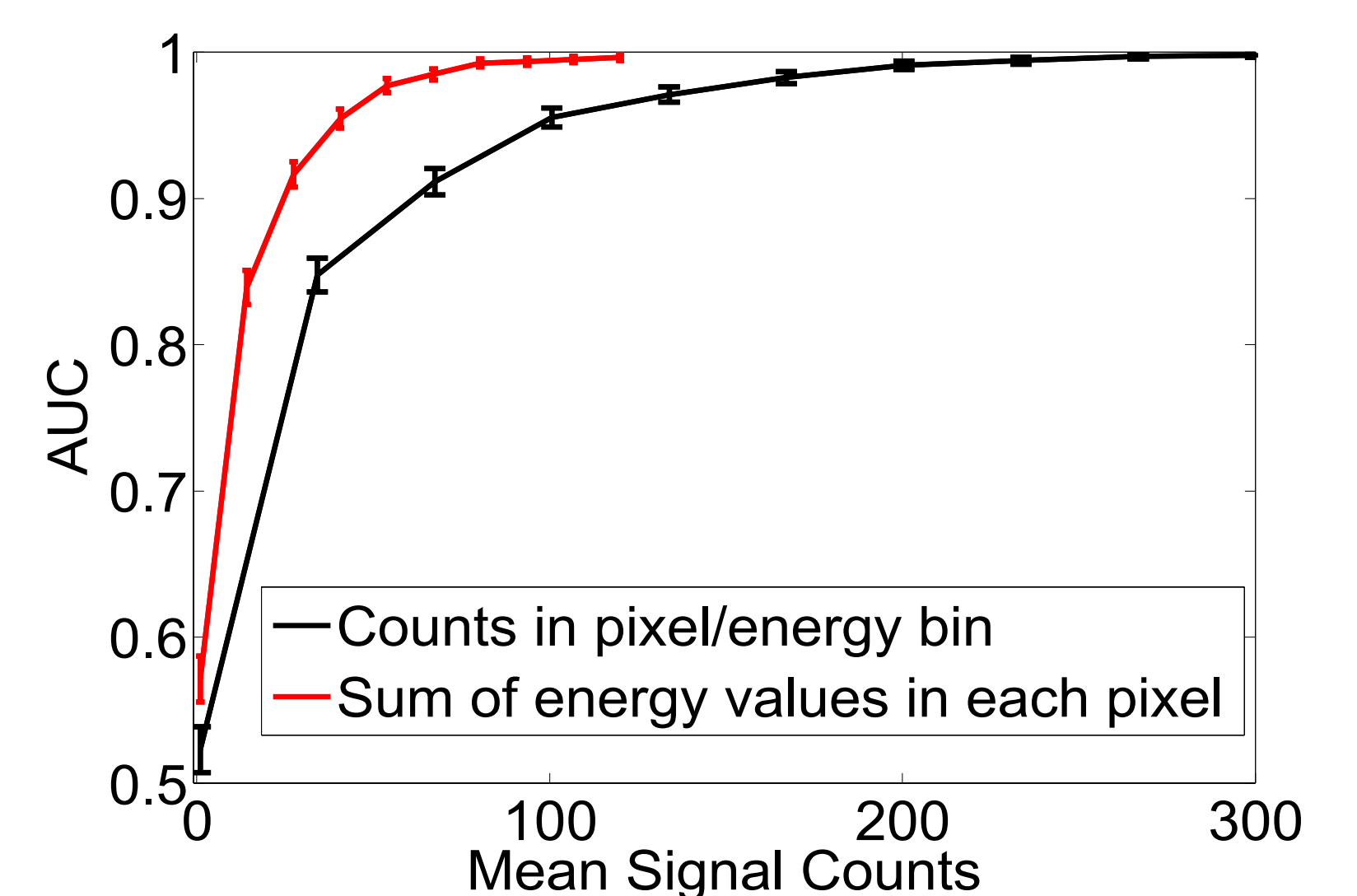


Figure 5 Performance of the two Hotelling observers classifying objects with known orientation and count rate. The observer utilizing all pixel and spectral information outperforms the observer only using sum of energies in each pixel.

Summary

This work emphasizes the tradeoffs between the various observer models. The ideal observer requires full knowledge of randomness in the imaging data, while the Hotelling observer can require far less knowledge but shows worse performance. Models that average over nuisance parameters are optimal but require the most calibration data.

Future work

- Compare simulated GEANT4 data to real data obtained at testing sites.
- Continue development of observer models that require less sensitive information to classify source.
- Begin localization studies. Develop interpolation methods between positions to reduce processing time