Reducing the background in X-ray imaging detectors via machine learning

D. R. Wilkins [a], S. W. Allen [a], E. D. Miller [b], M. Bautz [b], T. Chattopadhyay [a], C. E. Grant [b], S. Hermann [a], R. Kraft [c], P. Nulsen [c] and G. Schellenberger [c]

(a) Kavli Institute for Particle Astrophysics and Cosmology, Stanford University
(b) MIT Kavli Institute for Astrophysics and Space Research
(c) Harvard-Smithsonian Center for Astrophysics

E-mail: dan.wilkins@stanford.edu
www.danwilkins.net

The sensitivity of astronomical X-ray detectors is limited by the instrumental background. The background is especially important when observing low surface brightness sources that are critical for many of the science cases targeted by future X-ray observatories, including Athena and future US-led flagship or probe-class X-ray missions such as AXIS. Above 2keV, the background is dominated by signals induced by cosmic rays interacting with the spacecraft and detector. We develop novel machine learning algorithms to identify events in next-generation X-ray imaging detectors and to predict the probability that an event is induced by a cosmic ray vs. an astrophysical X-ray photon, enabling enhanced filtering of the cosmic ray-induced background. We find that by learning the typical correlations between the secondary events that arise from a single primary, machine learning algorithms are able to successfully identify cosmic ray induced background events that are missed by traditional filtering methods employed on current-generation X-ray missions, reducing the unrejected background by as much as 30%.

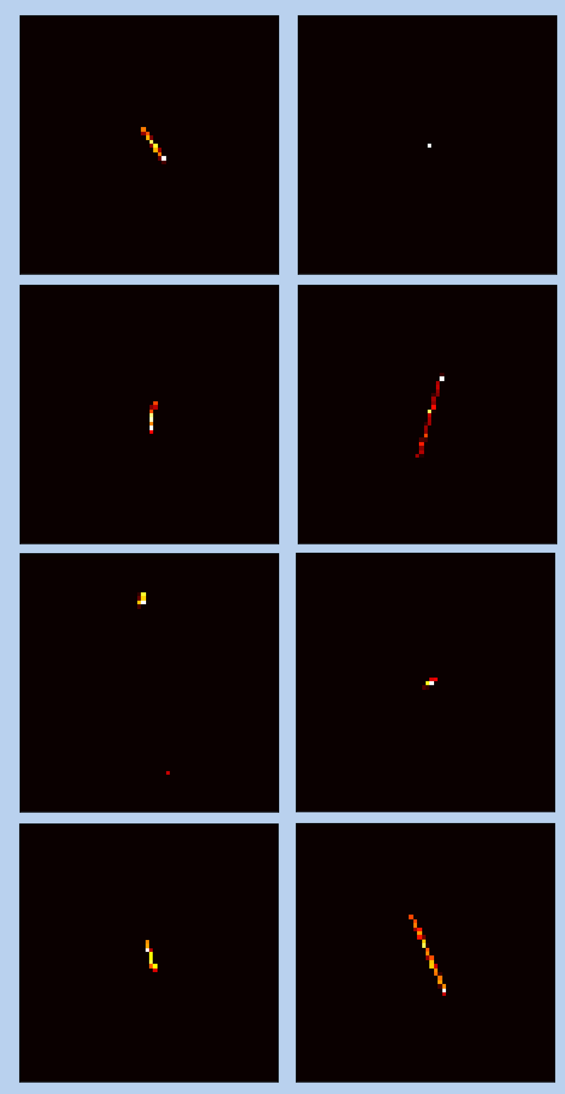
Simulating cosmic ray interactions with the detector

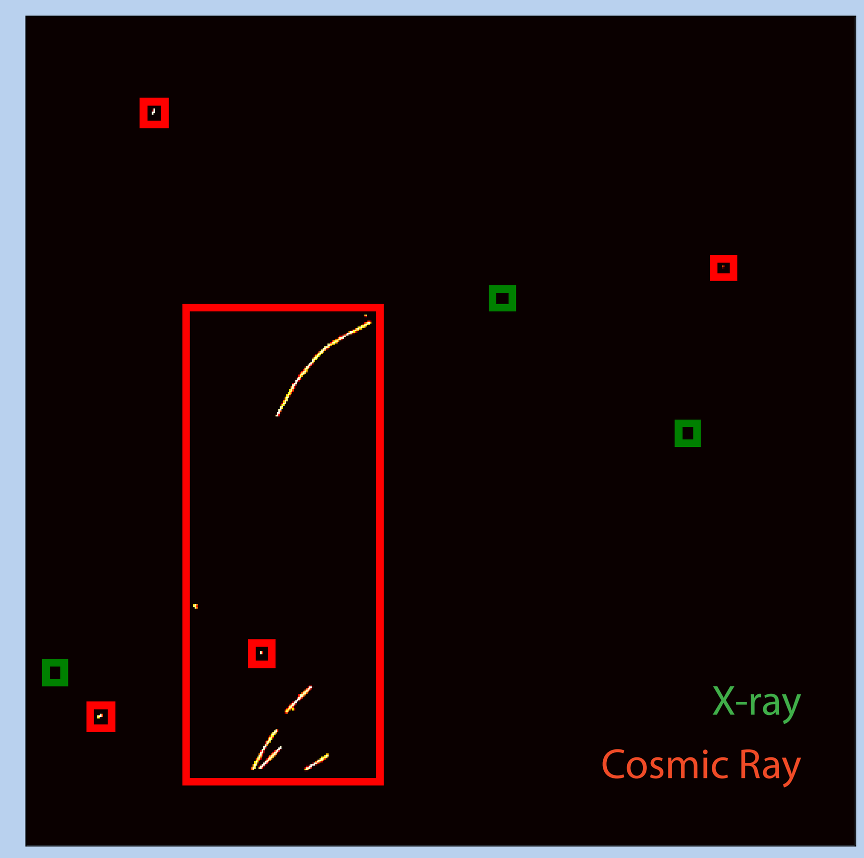
We use GEANT4 simulations of the interactions of cosmic ray protons and their secondaries to predict the background signals induced in pixelated silicon imaging detectors (e.g. CCD, DEPFET, CMOS). The Geant4 simulations are based upon the detector and mass model of the Athena Wide Field Imager, or WFI (Hall et al. 2018, Grant et al. 2020, Miller et al. 2022).

The protons may pass directly through detector, at which point the energy they deposit in each pixel is recorded. Alternatively, primary cosmic ray protons can interact with other elements of the spacecraft, producing a shower of secondary particles (including further protons, electrons/positrons, and X-ray fluorescence photons emitted by the material), any of which can go on to reach the detector, also depositing energy in the pixels (von Kienlin et al. 2018).

We simulate frames that would be read out from the detector, containing a random number cosmic ray events in addition to a random number of astrophysical X-ray events (which are the X-ray photons reaching the detector via the telescope optics). The numbers of X-ray and cosmic ray events in each frame are drawn from Poisson distributions corresponding to the anticipated mean event rate per frame (given the detector frame rate). The total signal recorded in each pixel is assumed to directly correspond to the energy deposited in that pixel.

At the nominal frame rate for the Athena WFI (5ms integration time), we expect ~1 cosmic ray event per detector quadrant, per frame (Miller et al. 2022). For low surface brightness sources, we can expect a mean photon rate of only around 1 per frame. The fast frame time and low photon rate are important factors in cleanly associating cosmic ray events with their secondaries, and separating these from the astrophysical photons.





▲ *Simulated frame read out from a quadrant of the Athena WFI detector, with an exaggerated event rate. X-ray and cosmic ray events are marked.*

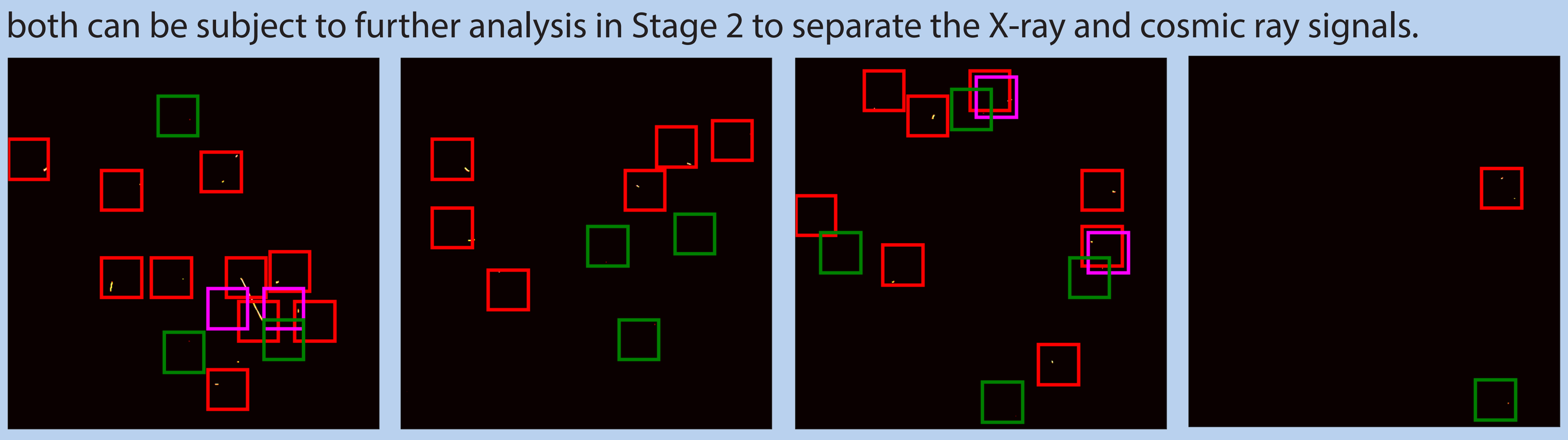
◀ *GEANT4 simulations of cosmic ray interactions with the Athena WFI detector. Cosmic ray protons and their secondaries deposit energy in the pixels of the detector, inducing signals.*

Step 1: Identifying regions of interest with a neural network image classifier

The first stage of the AI event classification and background filtering scheme is to identify regions of interest within the frame image. A region of interest is a 64x64 pixel subframe that is identified by a neural network as likely containing (1) only astrophysical X-rays, (2) only cosmic rays and their secondaries, or (3) a combination of both astrophysical X-rays and cosmic rays. A hierarchy of region sizes can be applied in series to identify tracks and showers of secondary particles on different scales.

A 64x64 pixel sliding window is run over the image to extract every possible region, and each of these subframe images is classified using a convolutional neural network (CNN) image classifier algorithm (Wilkins et al. 2020). For each subframe, the CNN returns three predictions, each a number between 0 and 1. These can be interpreted as the probability that the subframe contains (1) only X-rays, (2) only cosmic rays, or (3) both. The CNN is trained upon 10,000 simulated subframes, as described above, for which the true classification is known.

Where multiple possible regions of interest in each classification overlap, we employ non-maximal suppression. Only overlapping subframes with the highest prediction confidence in each category are kept. This produces the final list of regions of interest. Those predicted to contain only X-rays can go forward for X-ray event reconstruction. Those predicted to contain only cosmic rays can be flagged and events contained in these regions can be rejected from the analysis. Finally, those predicted to contain both can be subject to further analysis in Stage 2 to separate the X-ray and cosmic ray signals.



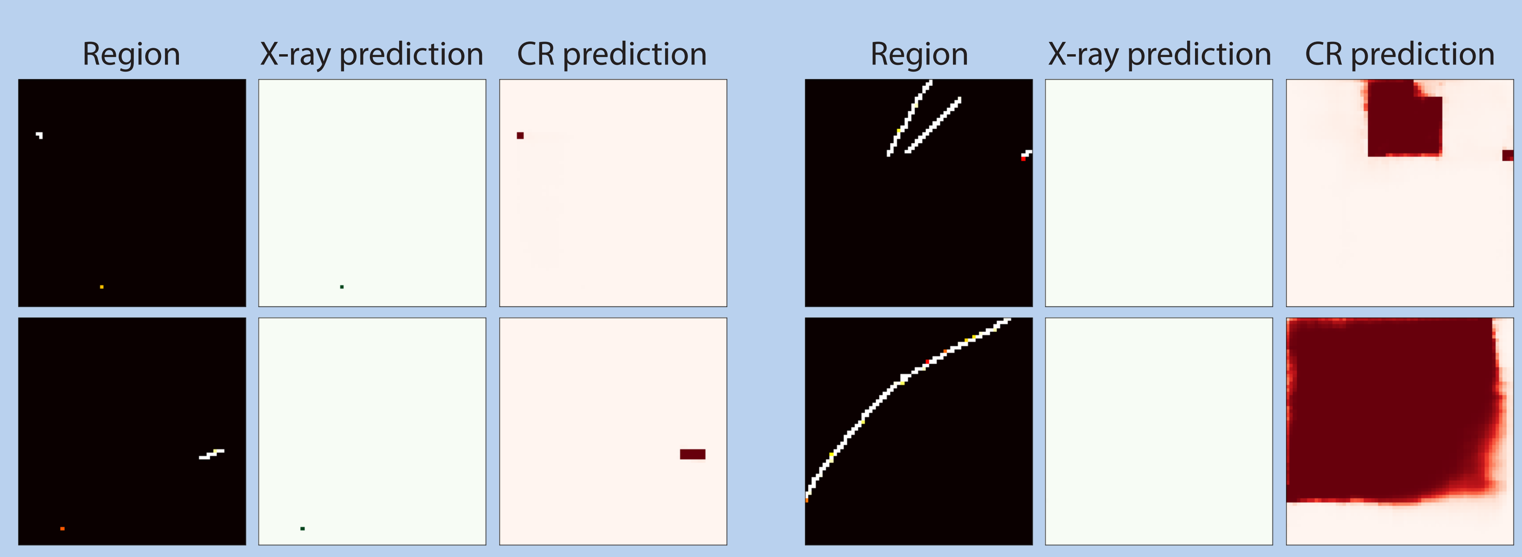
▲ *Regions of interest predicted by the CNN algorithm to contain just X-rays, just cosmic rays, or both X-rays and cosmic rays, in simulated frames from one quadrant of the Athena WFI.*
Colours indicate region predictions: X-ray regions ◆ Cosmic ray regions ◆ X-ray + cosmic ray regions

Step 2: Pixel-by-pixel classification within regions of interest

When regions of interest are identified as likely containing both astrophysical X-ray and cosmic ray signals, it is necessary to separate the signals within those regions such that the background signals can be filtered, but not at the expense of the astrophysical signals that are required for the scientific analysis.

These regions are input to a second machine learning algorithm that performs pixel-by-pixel classification and is based upon the Unet architecture (Ronneberger et al. 2015). This algorithm first uses a series of convolutional filters to downsample the image to a smaller number of predictions, similar to the CNN image classifier (referred to as the 'encoder' stage). A 'decoder' stage is then used to upsample and map those predictions onto the original pixels of the image. For each pixel, the Unet algorithm returns three predictions, which can be interpreted as the probability that (1) the pixel is empty, (2) the pixel contains a signal from an astrophysical X-ray, and (3) the pixel contains a cosmic ray-induced signal.

X-ray events reconstructed from the frame image can then be associated with the X-ray and cosmic ray probability values calculated for the pixels in which they are detected (where an event spans multiple pixels, we associate the reconstructed event with the highest probability), and events exceeding a threshold cosmic ray probability can be filtered from the data set.



▲ *Pixel-by-pixel classification of regions of interest by the Unet algorithm. Each pixel is assigned a probability of containing an X-ray or cosmic ray event, and the maps of those probabilities for each region are shown.*

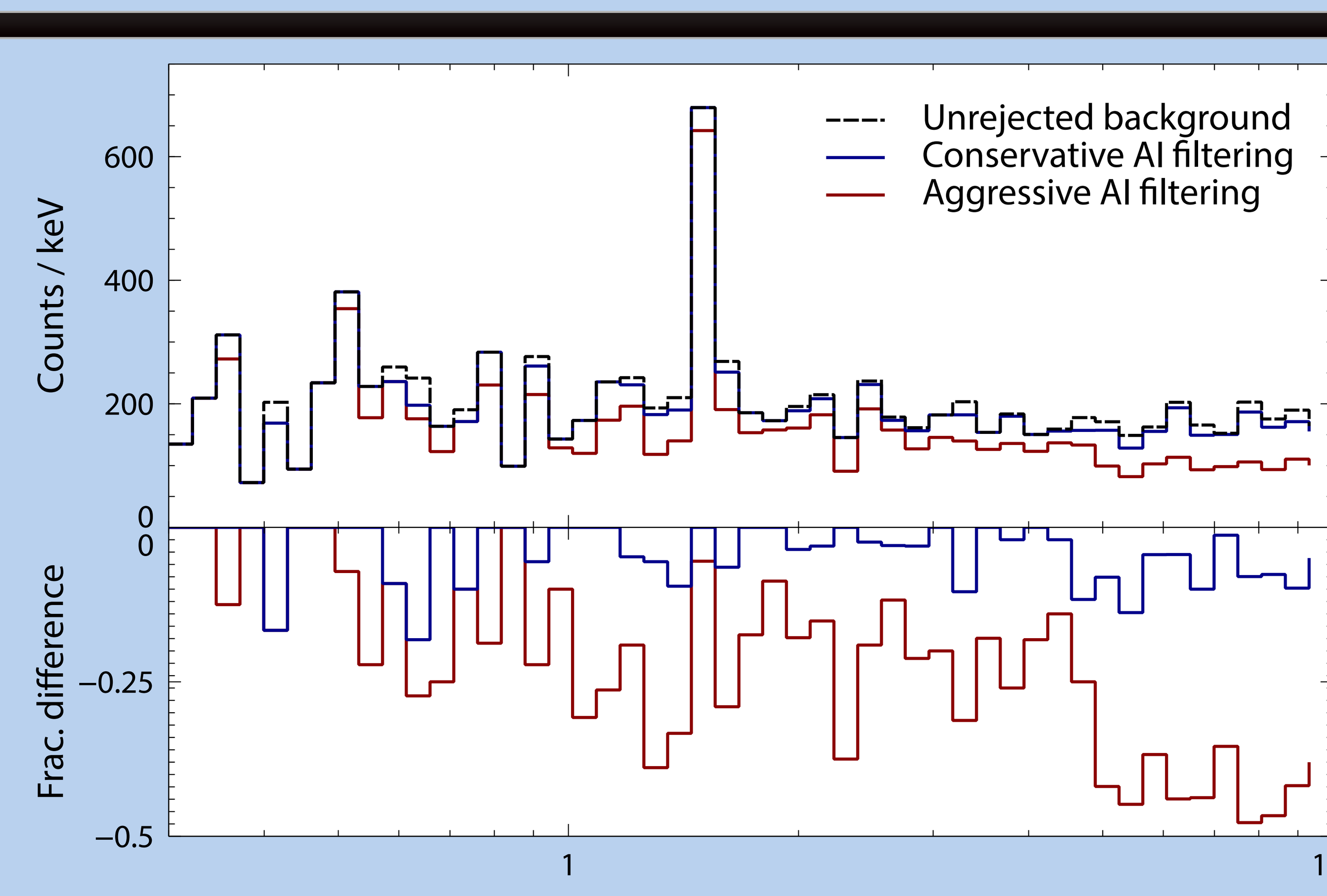
A hybrid AI algorithm to reduce the cosmic ray background

The above stages are combined into a hybrid event classification algorithm. We test the performance of the hybrid algorithm on a set of simulated frames, constructed using GEANT4 events that were not part of the training sets. We compare the performance of the algorithm to just the filtering cosmic rays based upon the total event energy and event PATTERN or GRADE (i.e. number and shape of illuminated pixels), employed on present-day X-ray instruments.

We find that when employing the most aggressive mode of filtering, rejecting all events in regions identified to contain either cosmic rays or cosmic rays and X-rays, the AI algorithm provides a reduction in the unfiltered particle background by 30% compared to the present-day method. This aggressive filtering, however, comes at the expense of reducing the effective area of the detector during each frame. For reasonable X-ray event rates for low surface brightness sources, this translates to a loss of 5% of valid X-ray events.

More conservative filtering, separating the pixels in regions identified to contain both cosmic rays and X-rays produces only a 6% reduction in the background at the current time. However, the architecture of the pixel classification algorithm has not yet been optimised, and there is a feasible path to improving this performance.

Machine learning algorithms are able to provide enhanced background filtering by learning the spatial correlations between the valid, unfiltered events caused by secondaries. These events can be associated with either the primary tracks or with other nearby valid events that result from the same primary. High frame rates, resulting in a small number of events per frame, facilitate the separation of cosmic ray and X-ray events by machine learning algorithms.



▲ *Simulation of the unfiltered particle background in the Athena WFI, compared to the background that remains after filtering by the AI algorithm with conservative (pixel-level filtering) and aggressive (by region only) filtering.*

Stanford University

References
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