



Trigger proposal

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Analysis & reconstruction meeting

1.

Introduction

Introduction

- ▷ Motivation: reduce data to manageable levels by selecting only events of interest, saving storage and processing resources.
 - Each run may need up to 2 Gb to be stored after the compression.
 - ~1 Tb per day considering the current frequency.

Proposal

- ▷ Develop algorithms to be tested as online trigger to decide whether to save or not images taken by the detector.

on going → ○ Convolution of the image with several kernels: look for high correlation points. [Link of the last presentation](#)

- Explore Machine Learning methods

- ▷ Redo the analysis considering various energies below 1 keV.

2.

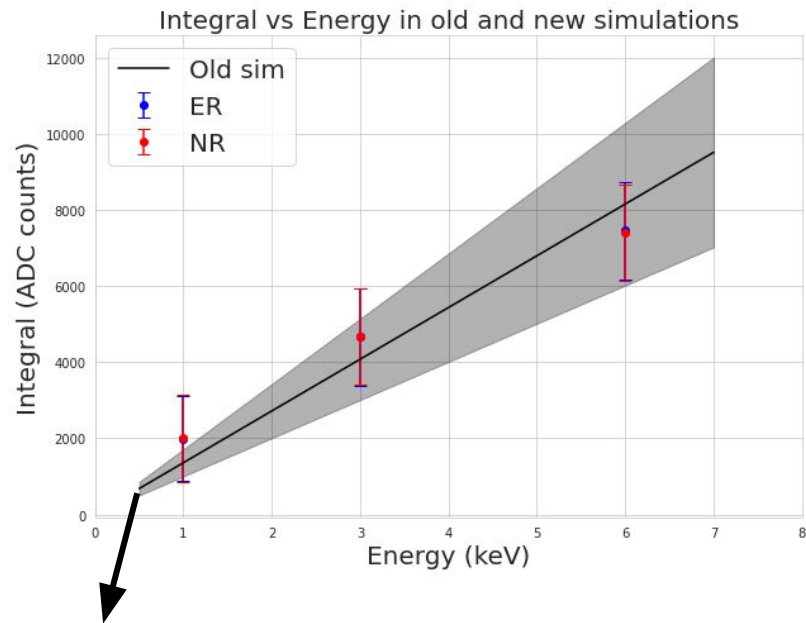
Dataset

Simulation

- ▶ We started using Pietro's simulation, which contains:
 - ER events with 1, 3, 6, 10, 30 and 60 keV (1k each)
 - NR events with 1, 3, 6, 10, 30 and 60 keV (1k each)
- ▶ The smaller energies were compared to the simulation used on the previous work.
 - The old simulation had 300 events with 5.9 keV ER signals.

Simulation

- ▷ It's possible to observe that the linearity supposed in the previous dataset underestimates the smaller energies.
 - The performance of both reconstruction and trigger tends to be higher than the results shown before.
- ▷ This imprecision may be reduced if we use the 1 keV dataset to estimate the smaller energies.



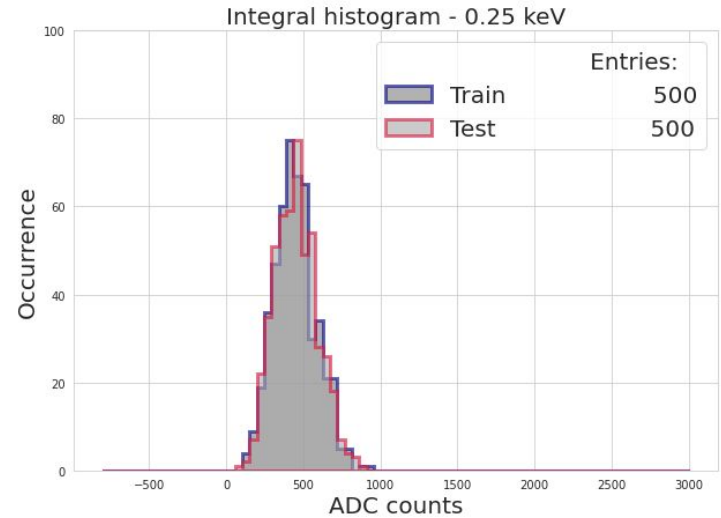
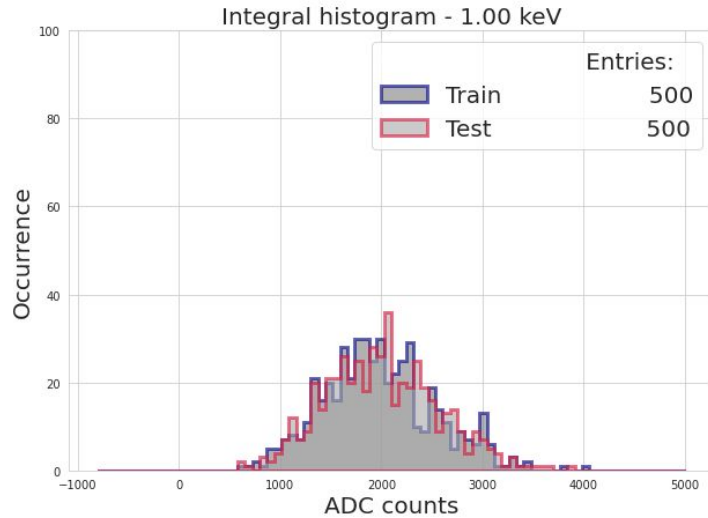
Last results

Datasets

▷ Datasets

- **Training (reconstruction was also used for comparison):**
 - Noise dataset: 500 images from pedestal runs (Run 4 underground).
 - ER signal simulation: 500 images containing 0.25, 0.5, 0.75 and 1 keV signals added to pedestal runs.
 - NR signal simulation: 500 images containing 0.25, 0.5, 0.75 and 1 keV signals added to pedestal runs.
- **Test (reconstruction was also used for comparison):**
 - Same numbers of training, but different signals and noise.

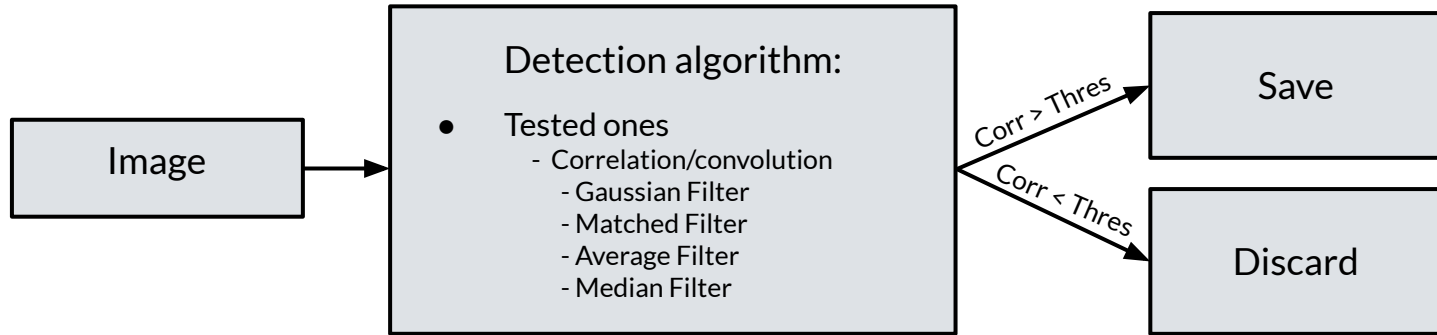
Simulation



The train and test datasets were split in a way that both have similar distributions

3. Analysis

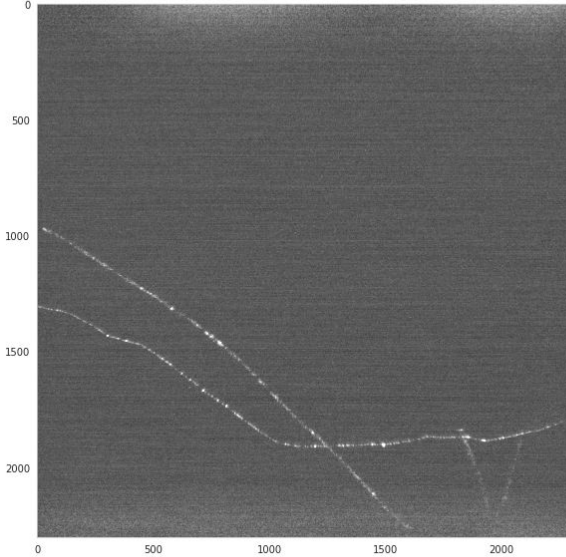
Methodology



- ▷ A large set of parameters was used during the training for each filter (window size and sigma if needed)
- ▷ The filters had a slightly better performance using pedestal subtraction method.

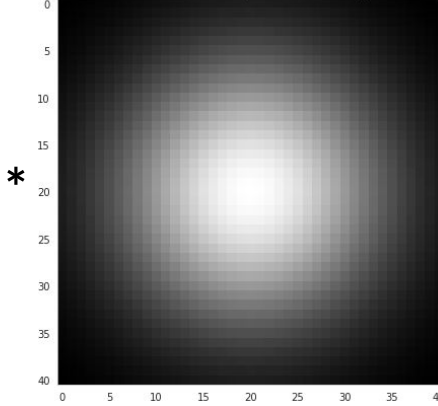
Correlation/Convolution

Run 12189 - Ev 25



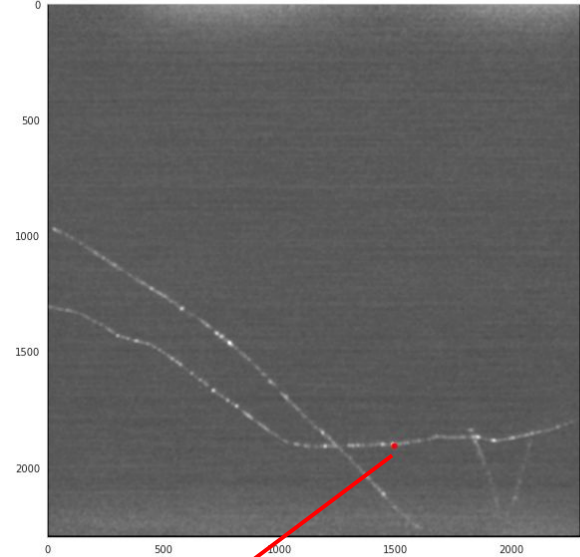
Raw image

Gaussian window (size: 41, sigma:10)



Normalized for area equal to 1.

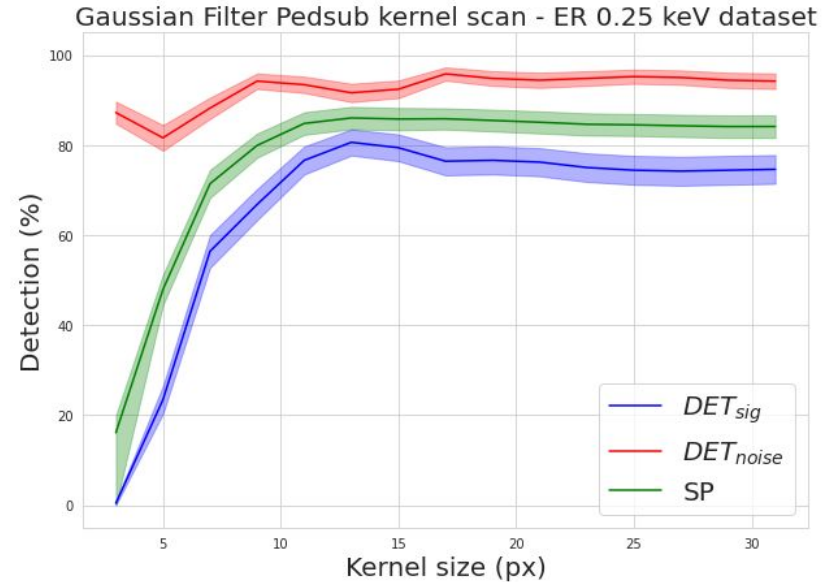
Convolution Run 12189 - Ev 25



Pixel with highest correlation

Training - ER

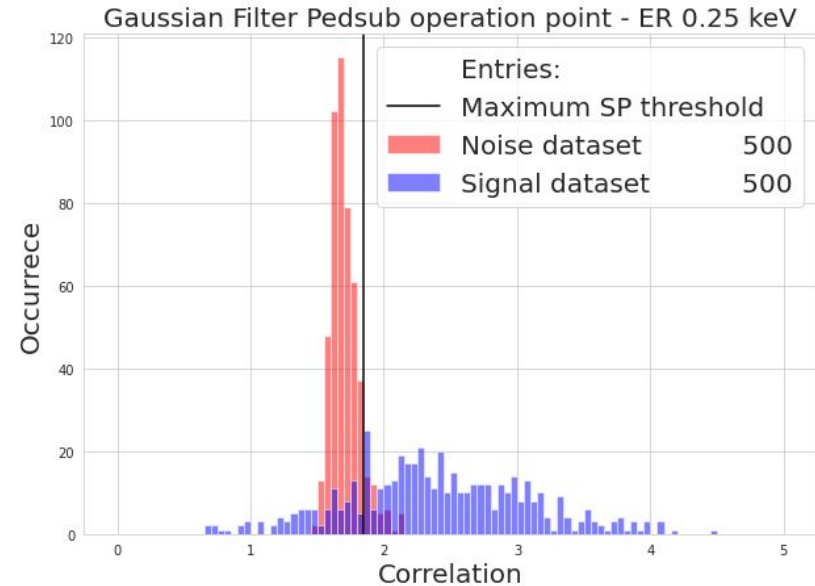
- ▷ The operation point is selected by testing the parameters aiming for the maximum SP.
- ▷ In this example, the gaussian filter on images after pedestal subtraction achieved the maximum SP with kernel size equal to 13.



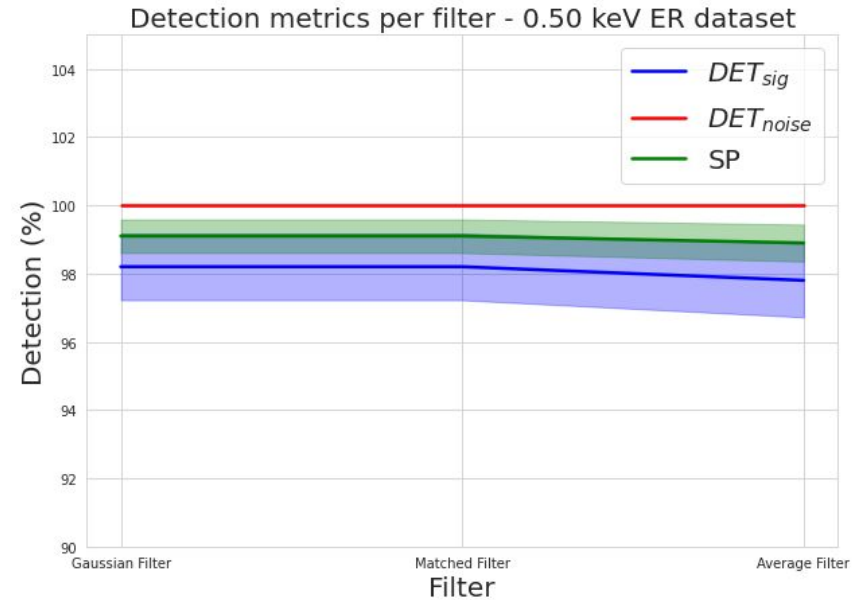
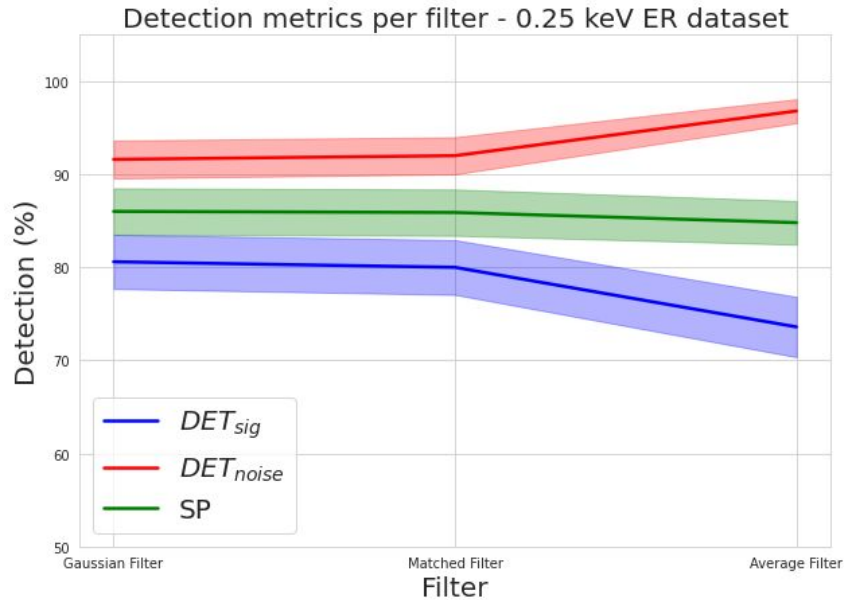
Sigma = 5

Training - ER

- ▶ The operation point is selected by testing the parameters aiming for the maximum SP.
- ▶ In this example, the gaussian filter on images after pedestal subtraction achieved the maximum SP with kernel size equal to 13.
 - $DET_{sig}: (80.6 \pm 2.9)\%$
 - $DET_{noise}: (91.6 \pm 2.0)\%$
 - $SP: (86.0 \pm 2.5)\%$

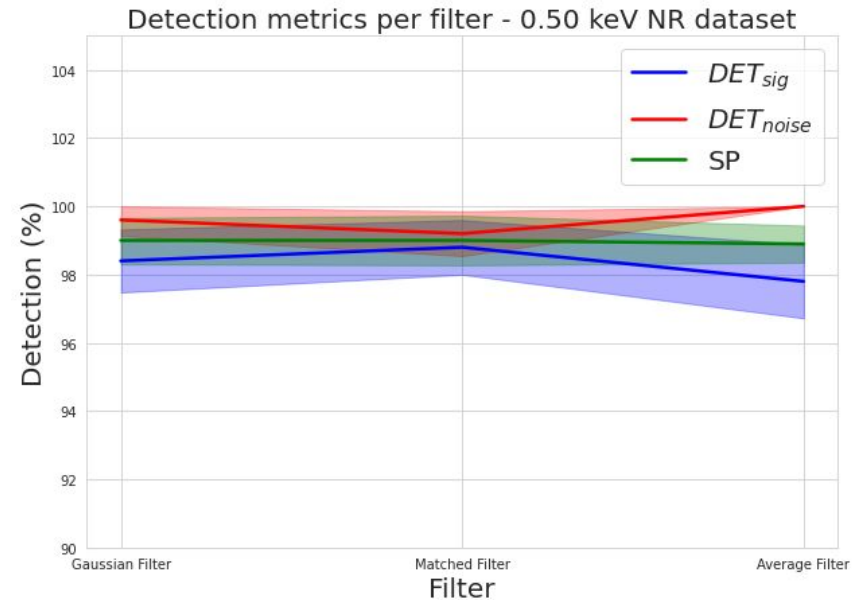
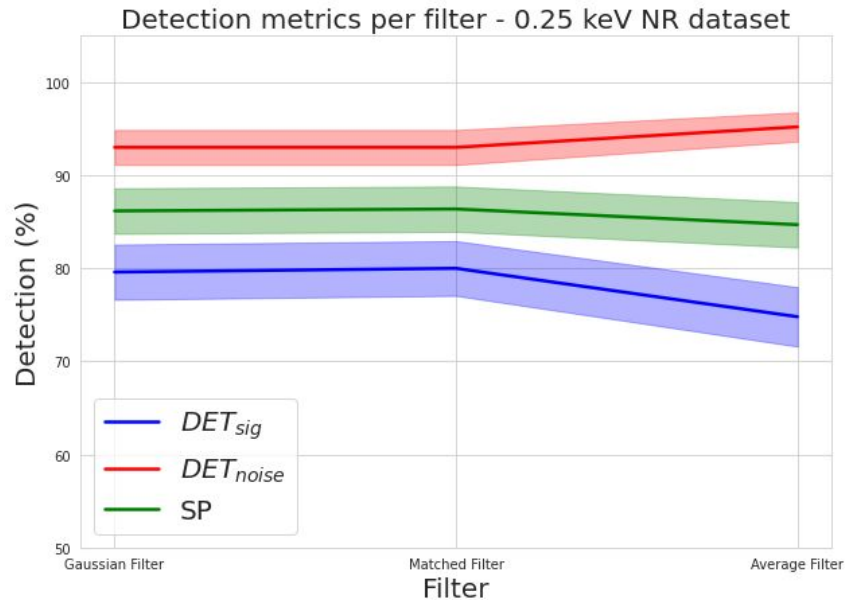


Training - ER



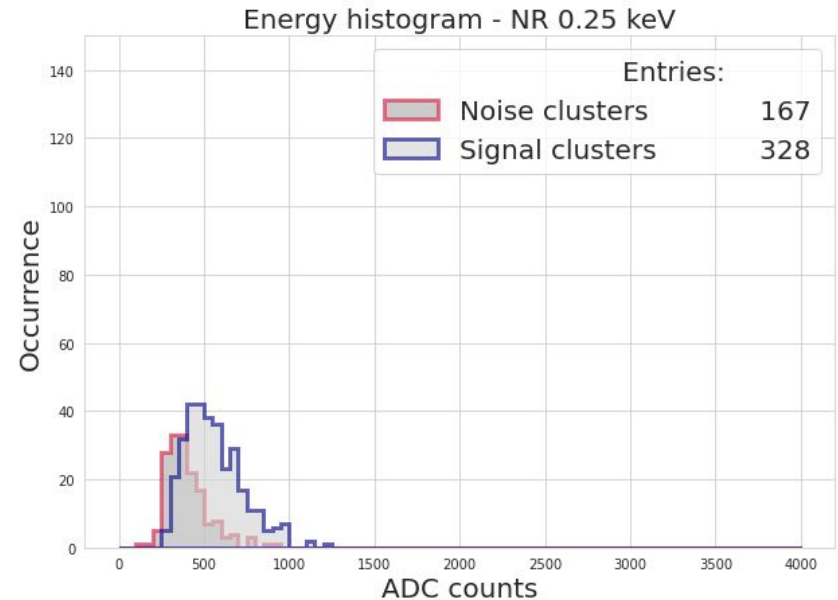
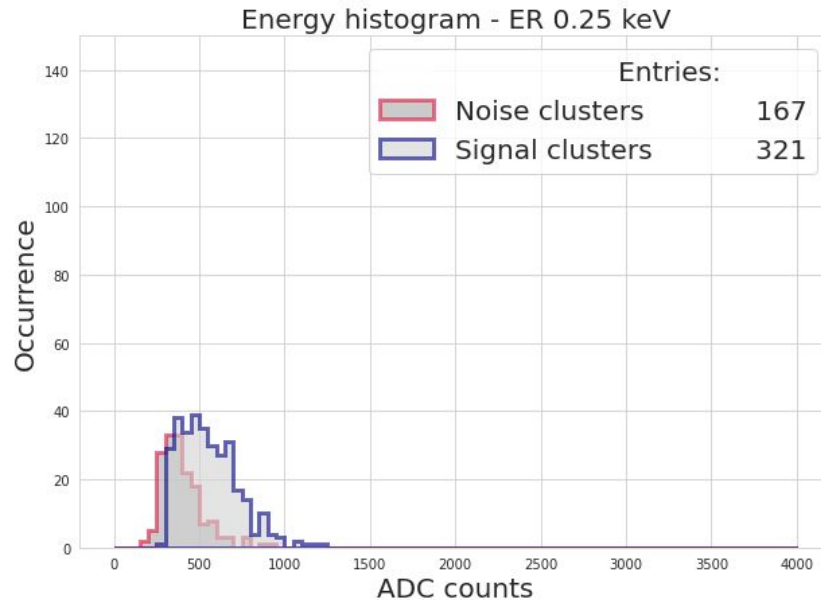
The 0.5 keV ER signal is almost fully separable

Training - NR



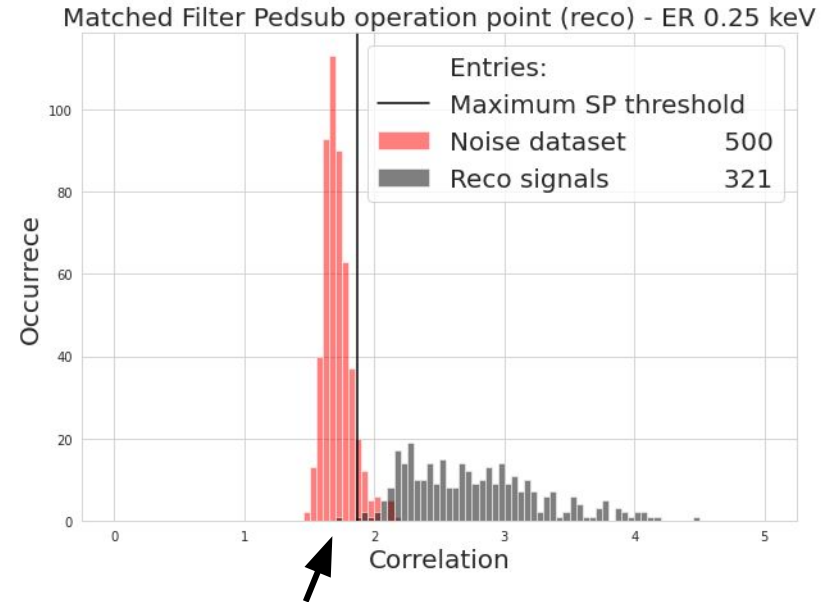
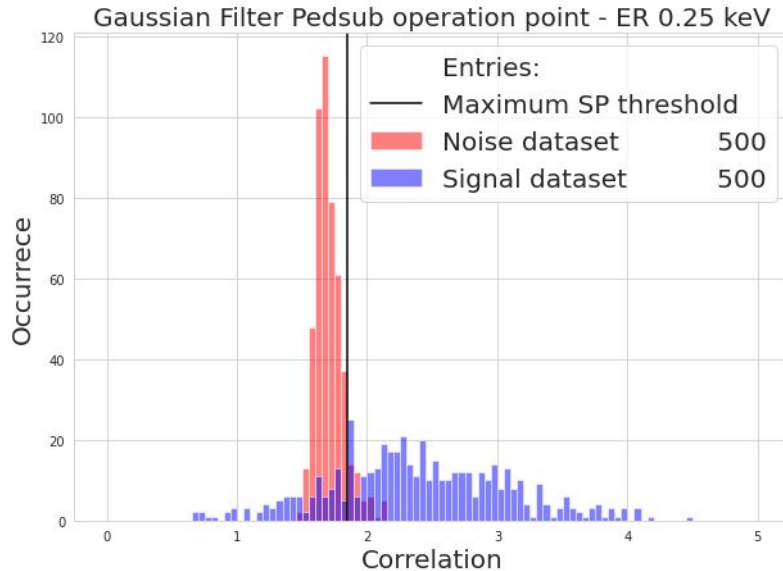
The NR simulation had almost the same results of ER (operation points were equal).

Reconstruction



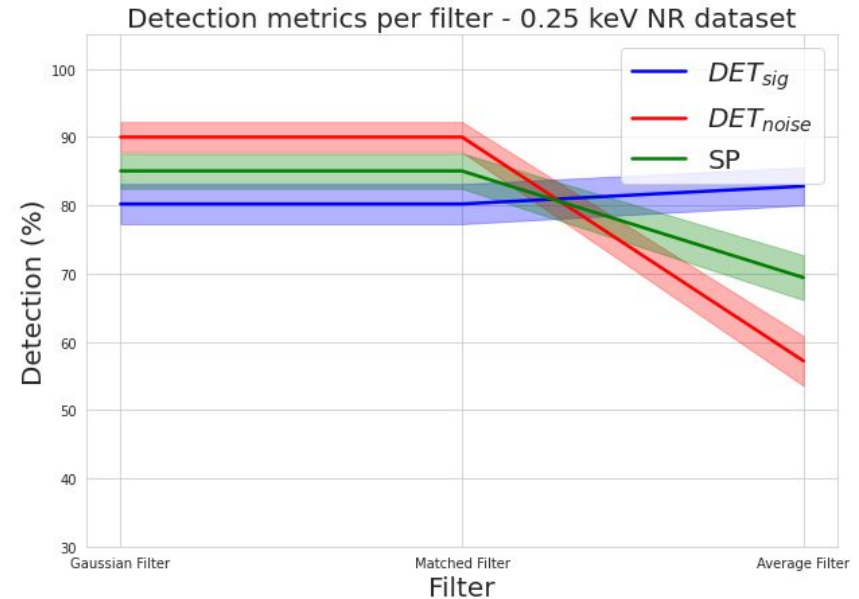
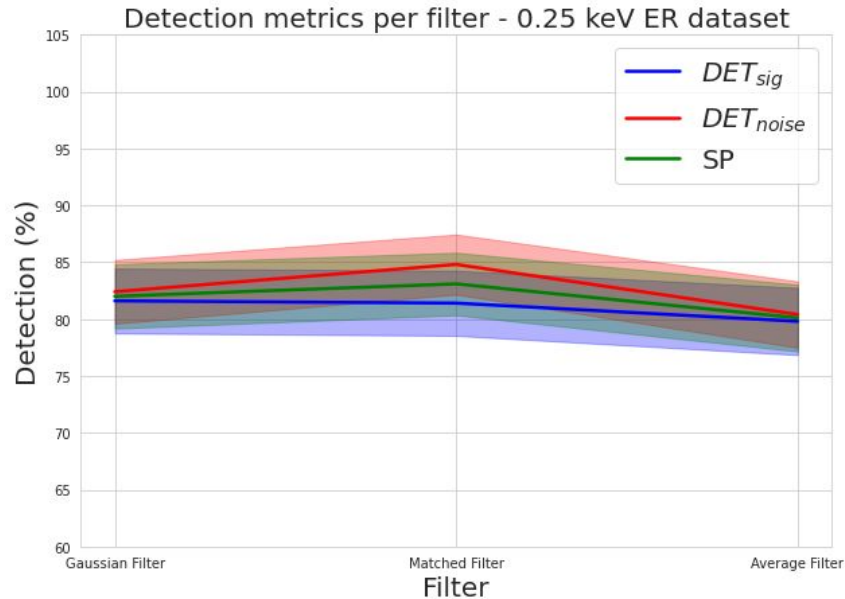
The reconstruction was able to detect 64.2% and 65.6% of the ER and NR signals respectively, while having a 66.6% noise rejection.

Reconstruction correlations ER



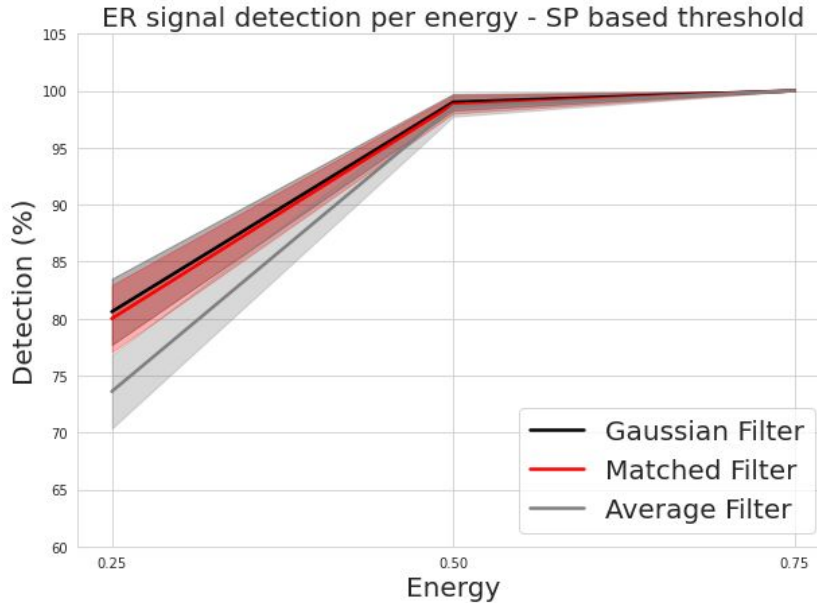
- If we compare the correlations in all events detected by the reconstruction, some of them may not be detected by this method, although the overall signal detection is higher.

Training Reco Threshold

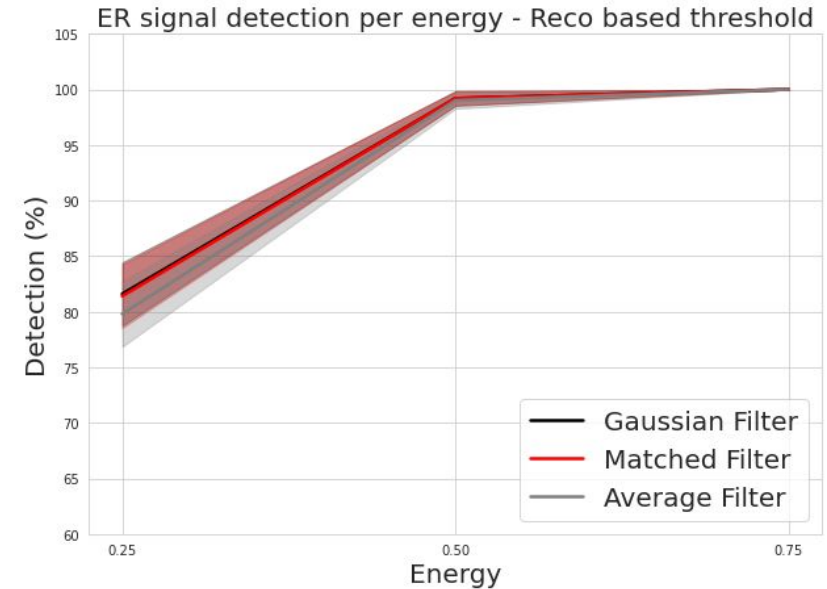


- ▶ Another way to select an operation point would be to select a threshold capable of triggering all events detected by the reconstruction while also maximizing the SP.

Energy performance - ER

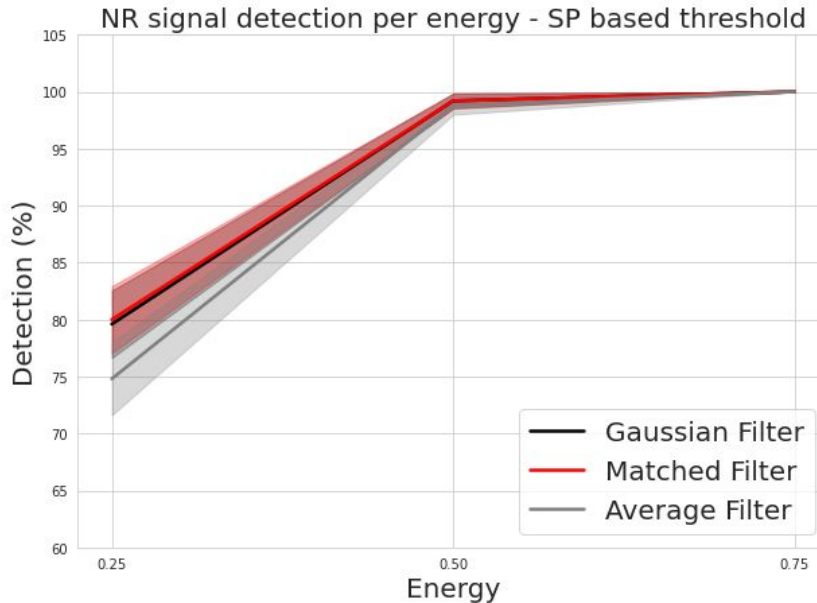


Gaussian Filter noise rejection = 91.6%
Matched Filter noise rejection = 92.0%
Average Filter noise rejection = 96.8%

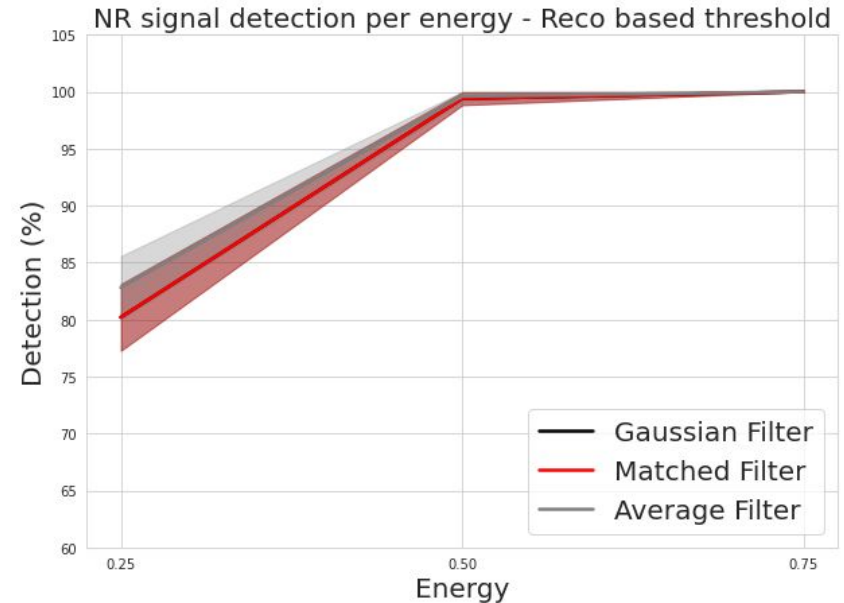


Gaussian Filter Noise rejection = 82.4%
Matched Filter Noise rejection = 84.8%
Average Filter noise rejection = 80.4%

Energy performance -NR



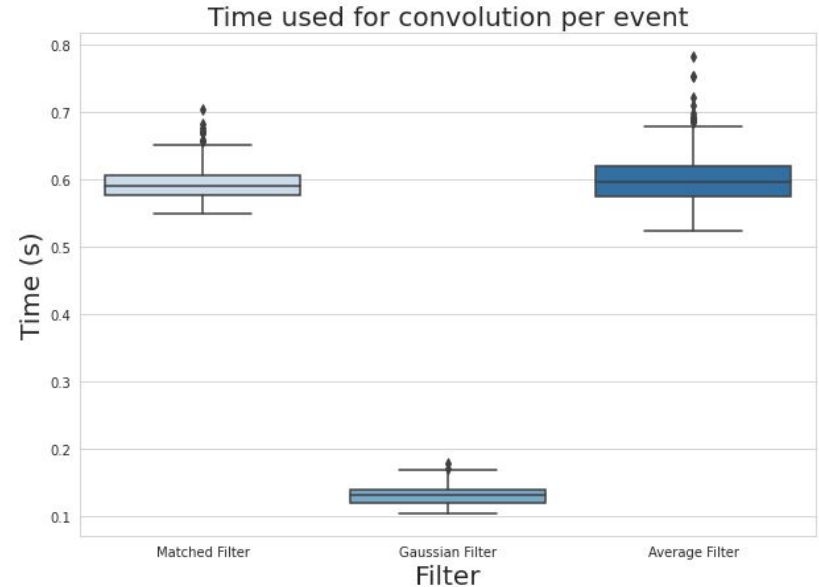
Gaussian Filter noise rejection = 93.0%
Matched Filter noise rejection = 93.0%
Average Filter noise rejection = 95.2%



Gaussian Filter Noise rejection = 90.0%
Matched Filter Noise rejection = 90.0%
Average Filter noise rejection = 57.2%

Time analysis

- ▷ The Gaussian Filter outperforms by far the other filters in speed.
 - Gaussian filter has a dedicated function that uses its symmetry characteristic to speed up the convolution.
 - Average and Matched filters were applied via FFT and IFFT.



Conclusions

- ▷ The proposed method was able to reach a high noise rejection and signal detection at 0.25 keV (over 80% depending on the operation point).
 - Old simulation had 90% detection on 0.5 keV whereas the new has almost 100%.
 - ER and NR with very similar results at the low energy region.
- ▷ It has a processing time smaller than 1 second. (independent of the number of tracks present on the image)

Next steps

- ▷ Finish the analysis on the Test dataset.
- ▷ Compare the method with a CNN. (Guilherme's work)
- ▷ Check if the actual simulation of energies below 1 keV follow a linear behavior as it was assumed.
- ▷ Test the method on low vgem runs.

Thanks!