Studies on a deep convolutional autoencoder for denoising pulses from a p-type point contact germanium detector

Mark Anderson

anderson.mark@queensu.ca

Queen's University, Kingston, Canada

XVIII International Conference on Topics in Astroparticle and Underground Physics 2023 | University of Vienna

Scan to see the paper [1] from our group this poster is based on!

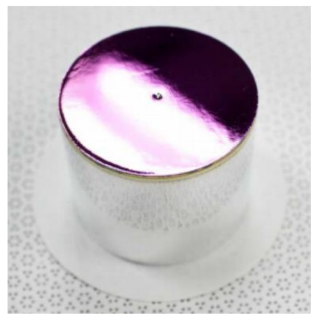
Introduction

- P-type point contact (PPC) high-purity germanium (HPGe) detectors are used for rare event searches, such as neutrinoless double-beta decay and other beyond Standard Model physics
- Detecting rare event interactions will ultimately help us to better understand the Universe
- Due to the infrequent nature of signal events, backgrounds dominate interactions of interest
- Electronic noise presents additional challenges in distinguishing/rejecting background events
- Further analytical techniques are required to extract information from modern experiments
  - We focus on using deep neural networks to remove noise from detector event traces

Background

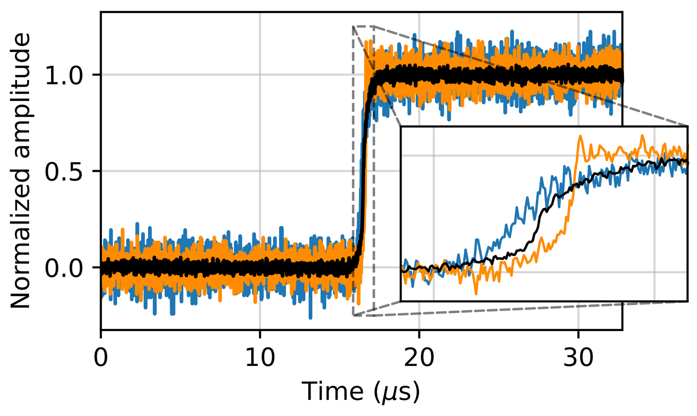
HPGe PPC Detector

- Signals are from a cylindrical 1kg PPC HPGe detector located at Queen's University



[2]

- Interactions disturb charge carriers in the detector medium
- These charge carriers are collected and converted to a voltage
- Voltage sampled at a fixed interval
- Result is a short 1D pulse of order ~30μs (4096 samples at 8ns)

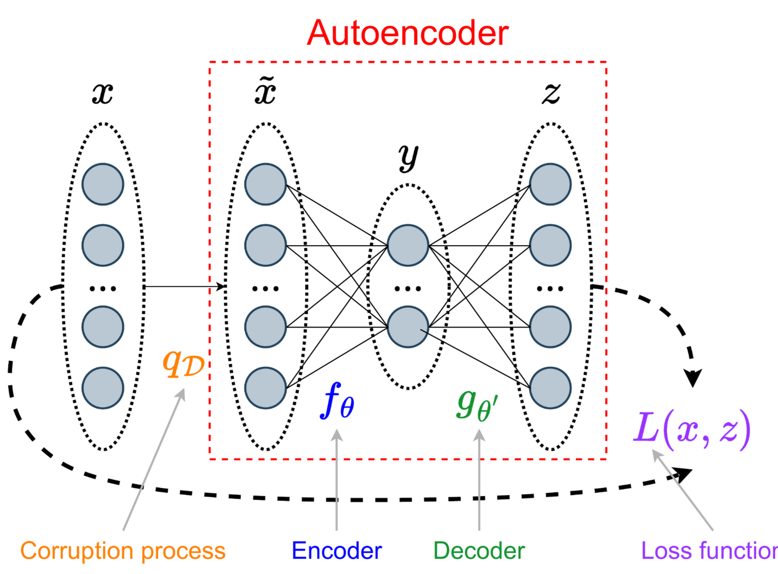


- Shape (rise time, single-/multi-site) is dependent on type of event and position in the detector
- Observed noise levels after preprocessing reflect energy of pulse; signal-to-noise ratio (SNR)
- Data collected continuously at 125MHz with a 16-bit digitizer

Deep Learning on Particle Detector Signals

- Denoising using machine learning offers numerous potential benefits
  - Reduction in the energy resolution
  - Identification of low-energy signal events masked by electronic noise
  - Improved background rejection techniques based on signal characteristics
  - Fast processing once model is trained; scalable to constant influx of detector data
- Technique can be extended to other experiments and beyond denoising
  - Utilization of latent representation of pulses for other classification tasks
  - Extendable to other problems including generating "fake" data
  - Applicable to a broad range of detector technologies and 1D electronic signals

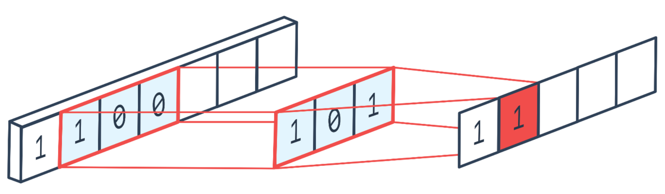
The Convolutional Autoencoder



- Developed a flexible convolutional autoencoder to remove electronic noise [1]
  - An autoencoder maps its input back to its input
  - Internal constraint is used to ensure only the most important parts of the data are encoded
  - Objective to remove noise is made explicit by forcing it to reconstruct the clean signal from the noisy input
- Applied it to signals from the PPC HPGe detector

x	simulated clean pulse
$\tilde{x}$	simulated pulse with added detector noise
y	encoded/latent representation
z	reconstructed output

- Architecture is fully convolutional
  - Weight sharing provides consistent noise removal
  - Emphasizes feature locality and shift equivariance
  - Significant reduction in trainable parameters
  - Allows for a ***variable input shape*** (subject to certain restrictions)

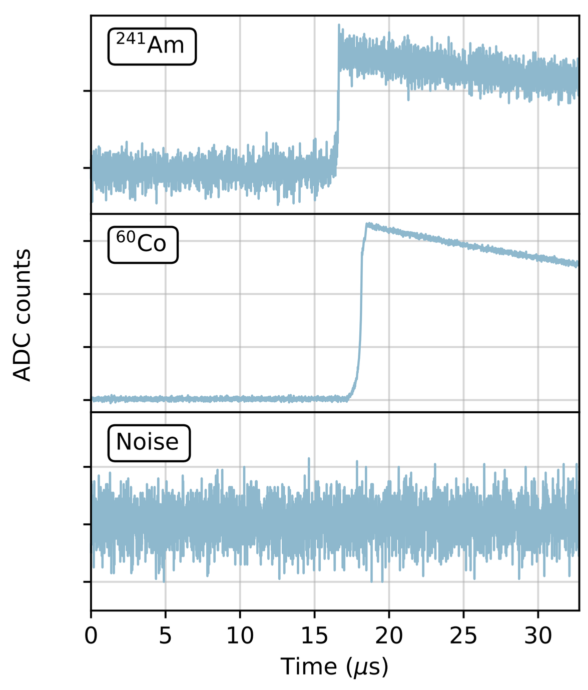


[3]

Procedure

Sources of data for training and validation

- Simulated clean pulses corresponding to points in detector
- Calibration sources with known energy distributions
  - ^{241}Am (60 keV; low energy/high noise)
  - ^{60}Co (1173 keV and 1332 keV; high energy/low noise)
- Pure detector noise (for data augmentation)

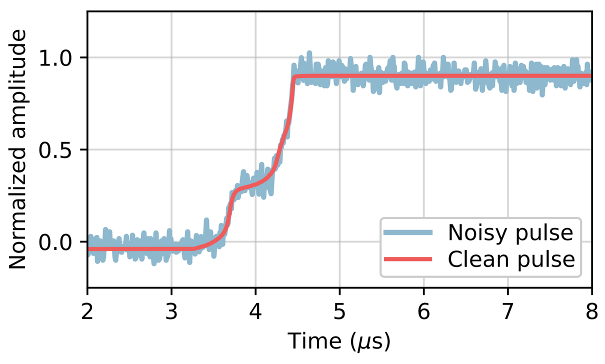


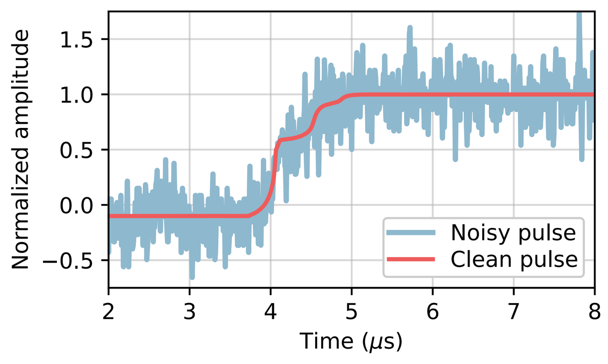
Data preprocessing procedure (*real detector data*)

- Remove baseline
- Remove exponential decay with pole zero correction
- Scale to have amplitude of unity (trapezoidal filter)

Data augmentation procedure (*simulations*)

- Combine simulated pulses to create artificial events
- Apply random horizontal and vertical shifts, amplitude scales
- Add detector noise with random standard deviation



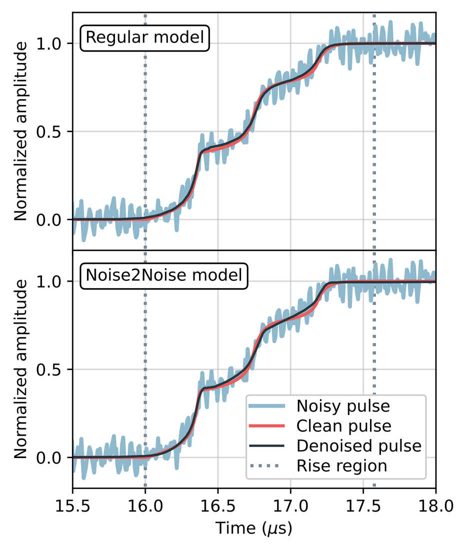


Training procedures

- Regular procedure maps noisy pulse to its clean progenitor (as described above)
- Also developed/applied two methods that ***do not require detailed detector simulations*** [1]
  - One method, an extension of Noise2Noise [4], maps a noisy pulse to another noisy pulse using the same underlying trace; learns to predict the mean
  - Very similar performance to regular training procedure on simulations and data

Results

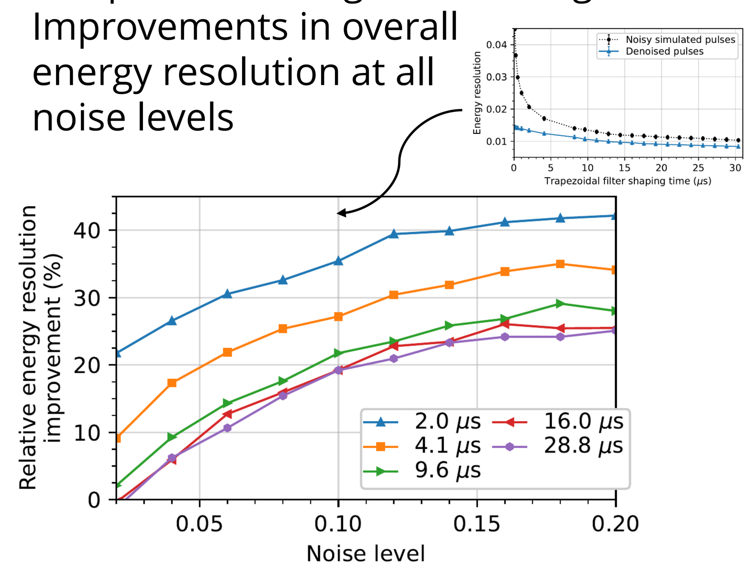
HPGe PPC Detector

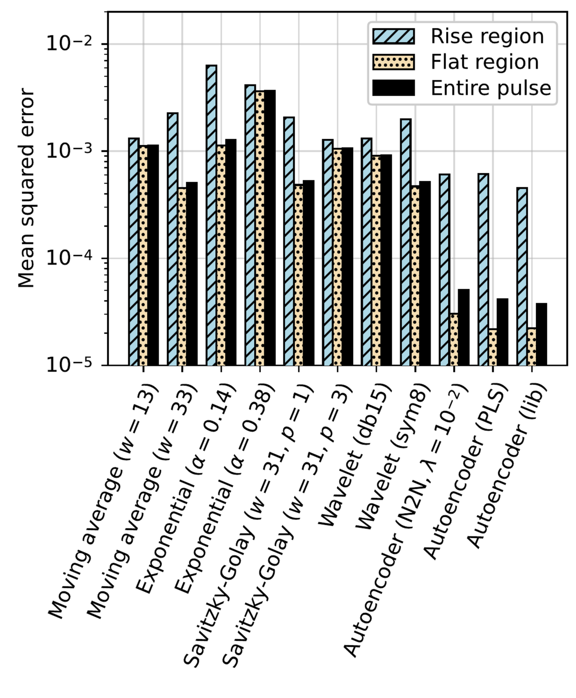


Qualitatively, the autoencoder does well on simulated data with detector noise

Results on simulated data:

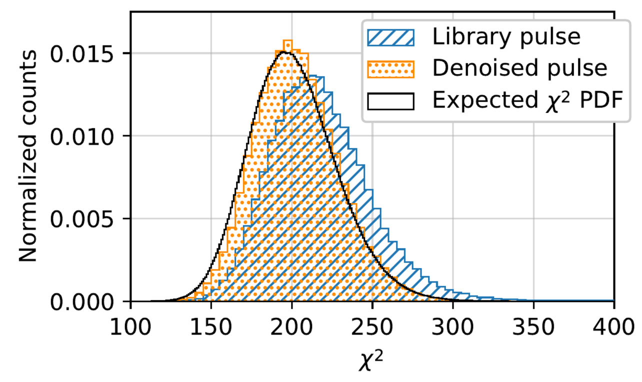
- Superior denoising over traditional methods from mean squared error comparisons using different regions
- Improvements in overall energy resolution at all noise levels





Results on real detector data:

- Better statistical agreement between noisy and denoised pulses than best fit simulated "library" pulse via χ^2 fit
- Improvements in energy resolution under some circumstances (*not shown*)
  - Less substantial than expected from simulations due to unmodelled effects in real data

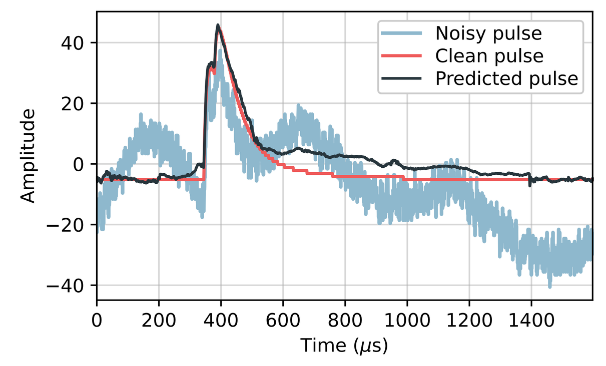


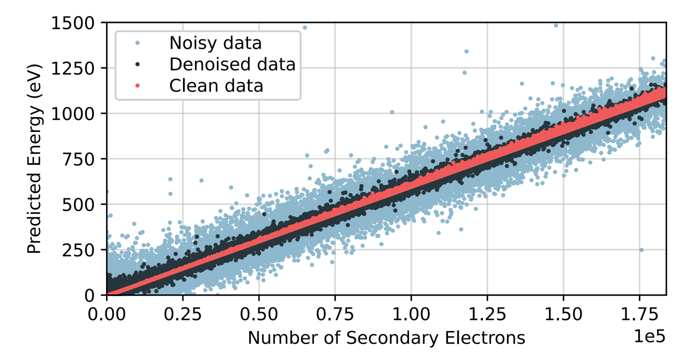
Extended Applications and Future Work

- Results presented here are focused on HPGe detector data
  - However, noise removal is obviously beneficial in many contexts
  - Work is broadly applicable to the particle astrophysics community and is easily expanded on
- Our group is now exploring various extensions of this research

Additional Detector Technologies

- Now applying these methods to signals from other detector technologies including spherical proportional counters (SPCs) and bubble chambers (*results here focused on SPCs*)
- Comparison to traditional noise removal methods (same ones as for the PPC HPGe detector) demonstrates that the autoencoder denoises SPC pulses well; outperforms traditional denoising methods by ~2 orders of magnitude (*not shown*)

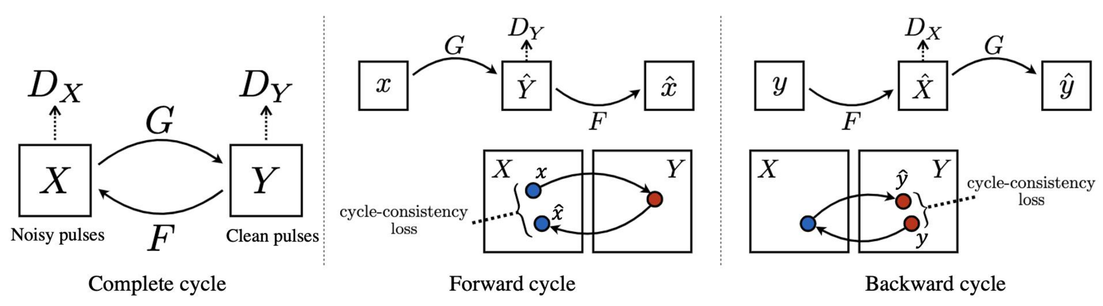




- Also compared energy measurements on both noisy and denoised events to those on clean events
- Energy measurements on denoised events are more consistent and better model energy measurements on clean events
  - Supports argument that noise removal tends to create an event more like a clean pulse

CycleGAN

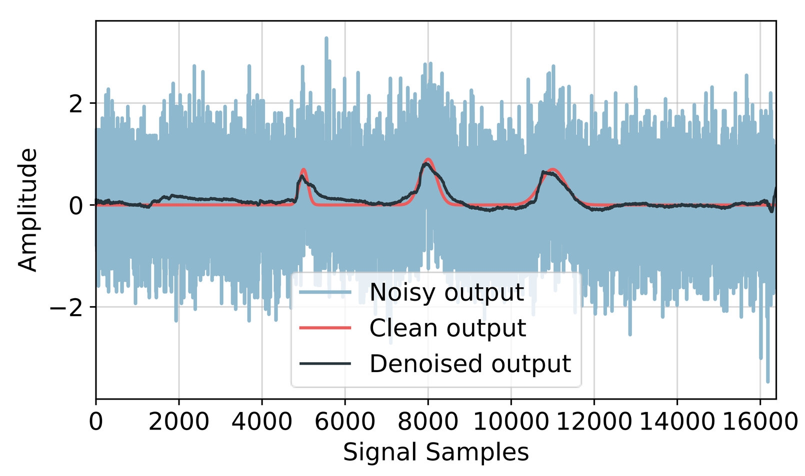
- CycleGAN architectures offer a unique way to train denoising neural networks
  - ***Does not require corresponding clean and noisy training pairs***
- CycleGAN systems use two generative and discriminator models that learn adversarially and to fool one another
- Transfers elements between two corresponding domains
  - Our CycleGAN learns to transfer physics event signals between the "noisy" and "clean" domains
- See poster by Tianai Ye for more details on the procedure and corresponding results



[5]

Inline Detector Denoising

- By implementing the denoising model prior to the event triggering system, the triggering threshold can be lowered (as electronic noise is reduced)
  - Signals dominated by noise can be identified/recorded, improving sensitivity to low-energy rare event searches
- Will need to denoise considerable amounts of data
  - ~2Gb/s for HPGe PPC detectors
- This system could be extended to actively learn, allowing for a denoising system that could be transferred to different detectors/applications



Acknowledgements

- Thank you to my supervisor Prof. R. D. Martin and to all other authors of the denoising paper: V. Basu, C. Z. Reed, N. J. Rowe, M. Shafiee, T. Ye
- This work was supported by the Natural Sciences and Engineering Research Council of Canada, the Arthur B. McDonald Canadian Astroparticle Physics Research Institute, the Canada Foundation for Innovation, the Walter C. Sumner Memorial Fellowship, and the NVIDIA corporation through their academic hardware grant program

References

[1] Anderson, M. R. *et al.*, "Performance of a convolutional autoencoder designed to remove electronic noise from p-type point contact germanium detector signals," Eur. Phys. J. C 82, 1084 (2022). arXiv:2204.06655; doi:10.1140/epjc/s10052-022-11000-w
[2] "P-Type Point-Contact (PPC) Germanium Detectors," https://www.npl.washington.edu/majorana/design-technologies
[3] "1D convolution," https://peltarion.com/knowledge-center/documentation/modeling-view/build-an-ai-model/blocks/1d-convolution
[4] Lehtinen, J. *et al.*, "Noise2Noise: Learning image restoration without clean data," Proc. Int. Conf. Mach. Learn., vol. 80, pp. 2965–2974 (2018). arXiv:1803.04189
[5] Zhu, J. Y. *et al.*, "Unpaired image-to-image translation using cycle-consistent adversarial networks." Proc. IEEE Int. Conf. Comput. Vis. (2017). arXiv:1703.10593