Denoising Electronic Signals from Particle Detectors using a Flexible Deep Convolutional Autoencoder

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

Introduction

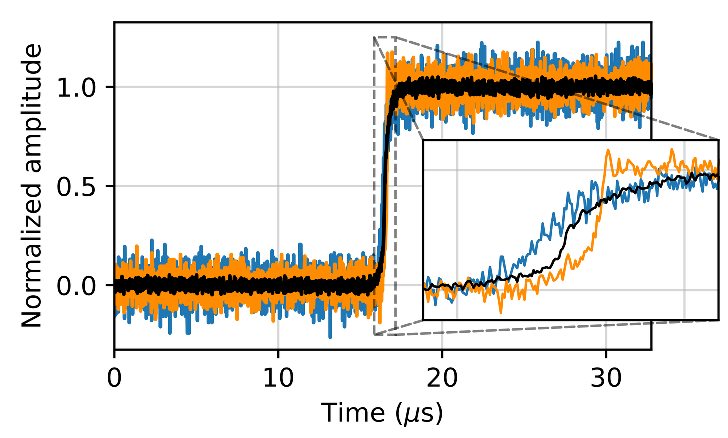
- High-purity germanium (HPGe) p-type point contact (PPC) detectors are used for rare event searches, such as neutrinoless double-beta decay and other beyond Standard Model physics
- Spherical proportional counter (SPC) detectors are another technology for low-energy physics experiments, primarily used for dark matter searches
- Detecting rare event interactions will ultimately help us to better understand the Universe
- Due to the infrequent nature of signal events, backgrounds dominate over interactions of interest
- Electronic noise presents further challenges in distinguishing and rejecting background events
- Further analytical techniques are required to extract information from modern experiments
  - We primarily explore deep neural networks to remove noise from detector signals

Background

HPGe PPC Detector

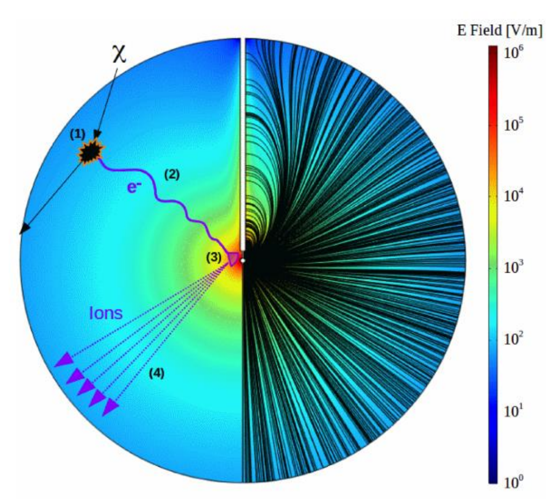
[2]

- Interactions disturb charge carriers in the detector medium
- These charge carriers are collected and converted to a voltage
- Result is a short 1D pulse (~30μs)
- Shape is dependent on type of event and its position in the detector
  - Multiple interactions from same particle produce multiple "bumps"
- Data collected continuously at 125MHz with a 16-bit digitizer



SPC Detector

- SPC detectors use spherically contained noble gasses as detector medium for low-energy physics
- Particles interact and deposit energy within the gas
- Ionized electrons drift through the detector's electric field towards the central sensor (primary ionization)
  - Electrons gain enough energy to trigger secondary ionizations, severely amplifying the signal
- Voltage sampled frequently to produce a ~4ms 1D pulse
- Data collected continuously at 1MHz with a 16-bit digitizer

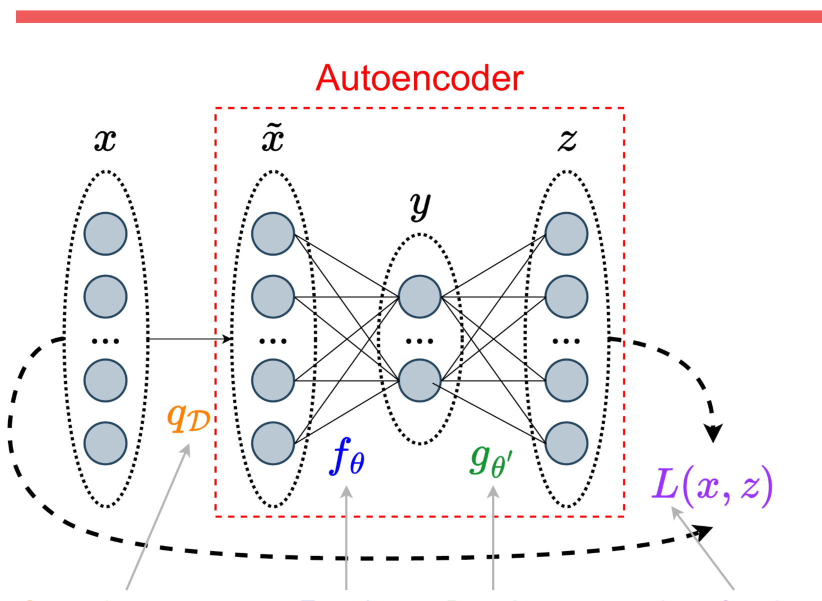


Deep Learning on Particle Detector Signals

- 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

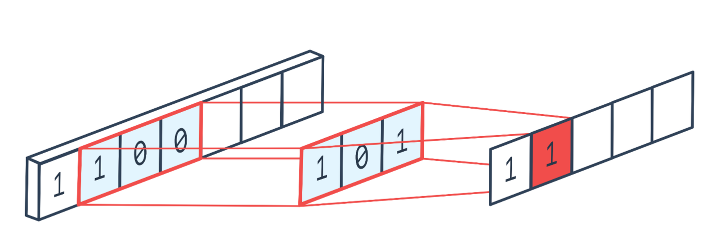
The Convolutional Autoencoder



- 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 clean signal from noisy input
- Applied it to signals from detectors described above

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*** (with some restrictions)



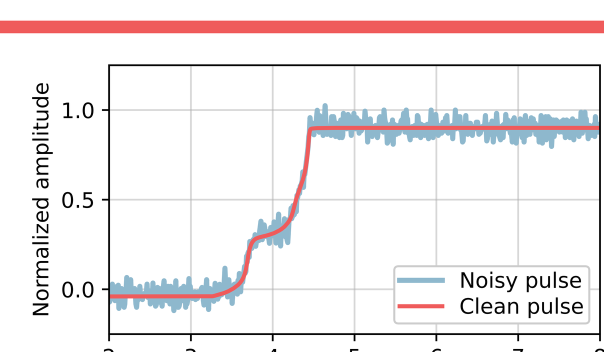
[3]

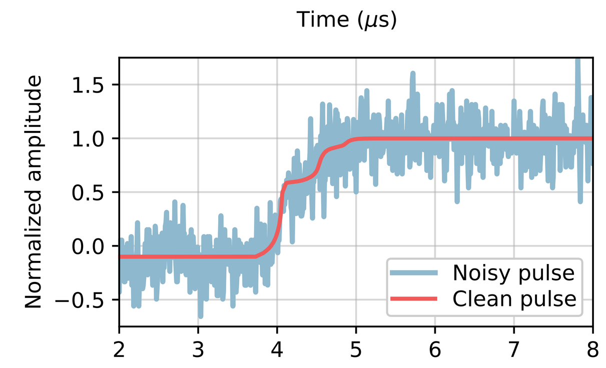
Procedure

Sources of data for training and validation
- Simulated clean pulses corresponding to points in detector
- Calibration sources with known energy distributions
- 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)

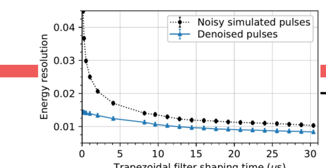
Data augmentation procedure (*simulations*)
- Combine simulated pulses to create artificial events
- Apply random horizontal and vertical shifts, amplitude scales
- Add detector noise with random standard deviation



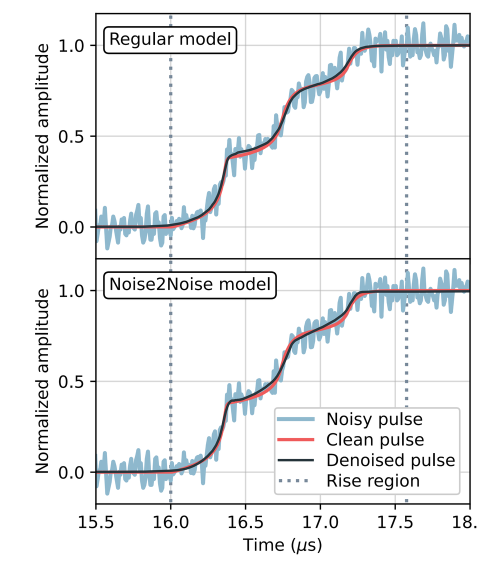


Training procedures
- Regular procedure maps noisy pulse to its clean progenitor
- Also developed/applied two methods that ***do not require detailed simulations of the detector*** [1]
  - One method, Noise2Noise [4], maps noisy pulse to another noisy pulse (same underlying trace)
  - Very similar performance to regular training procedure on simulations and data

Results



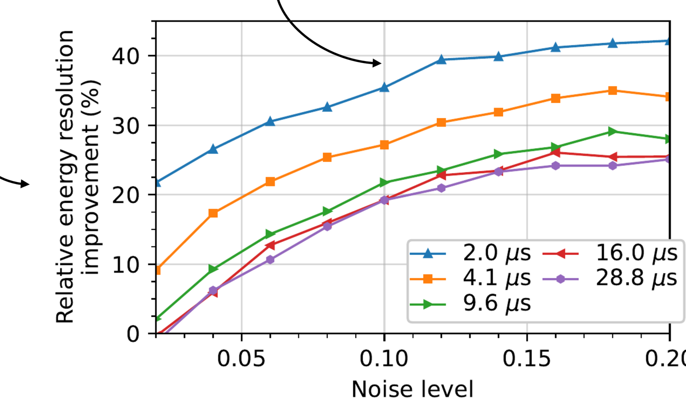
HPGe PPC Detector

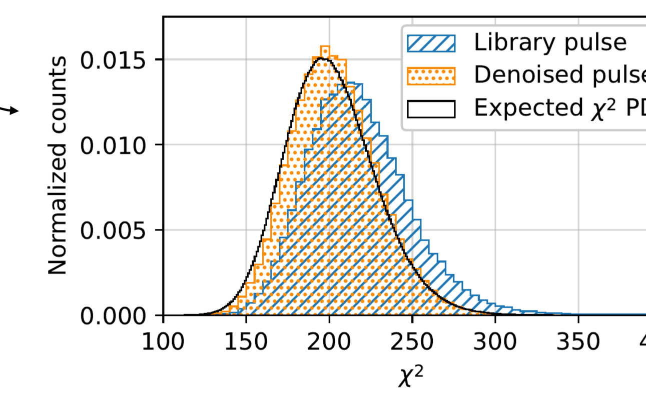


Qualitatively, the autoencoder does well on simulated data with detector noise

Results on simulated data:
- Improvements in the overall energy resolution at all noise levels
- Superior denoising over traditional methods from mean squared error and SSIM comparisons (*not shown*)

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 that are not present in training data

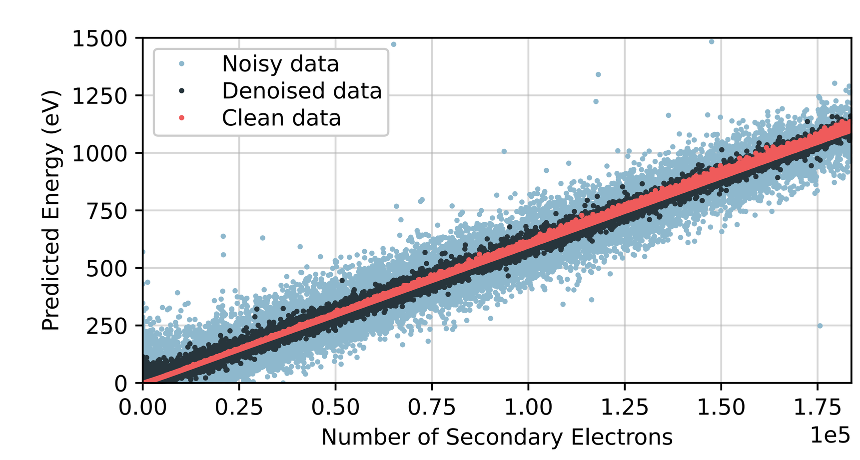


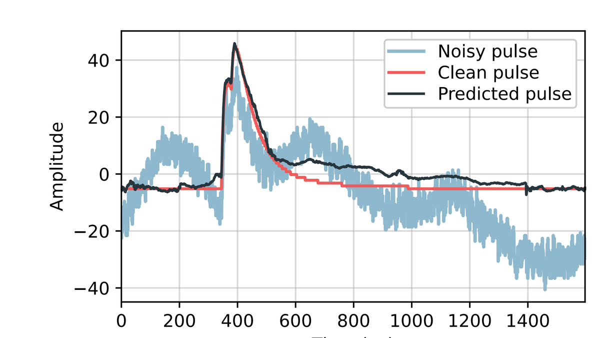


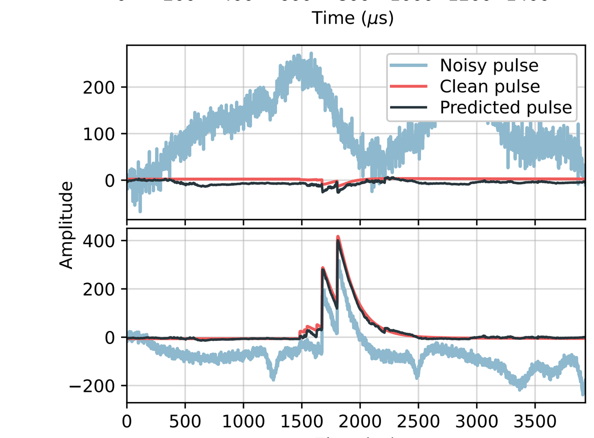
SPC Detector

Comparison to traditional noise removal methods:
- Tested 4 standard digital noise removal methods on SPC pulses
- Neural network denoising improves on traditional approaches by ~2 orders of magnitude

Energy measurement results:
- Compared energy measurements on standard and denoised events to energy measurements 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





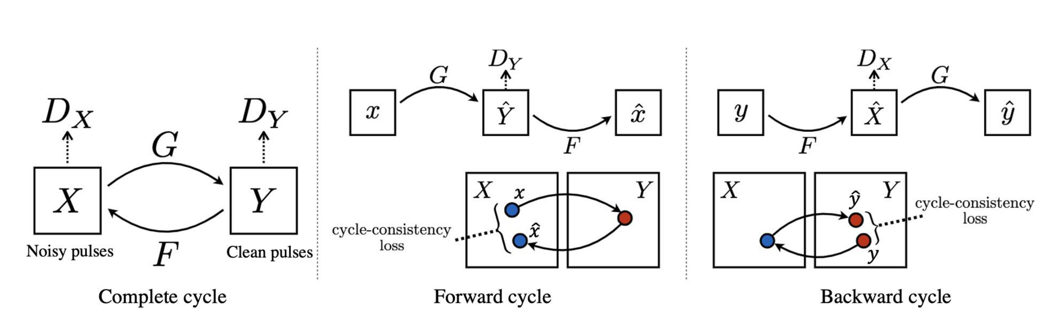


Future Work

Our studies have uncovered new avenues for advancing this research, with a focus on two key areas: CycleGAN-based denoising and inline detector denoising. Below is a summary of our initial investigations and an outline for future possibilities for research in these two directions.

CycleGAN

- CycleGAN architectures offer a unique way to train denoising neural networks
  - ***Does not require corresponding clean and noisy training pairs***, avoiding linear noise assumptions
- CycleGAN systems use two generative and discriminator models that learn adversarially and to fool one another
- Used to transfer elements between two corresponding domains, our CycleGAN learns to transfer physics events between the 'noisy' and 'clean' domains



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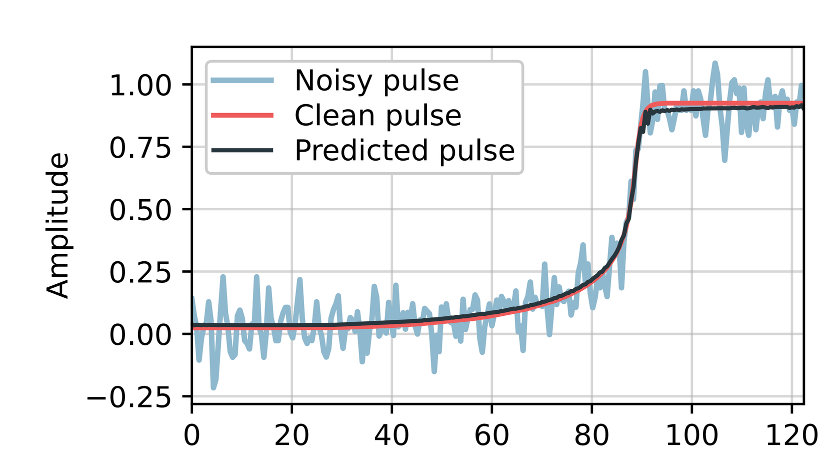
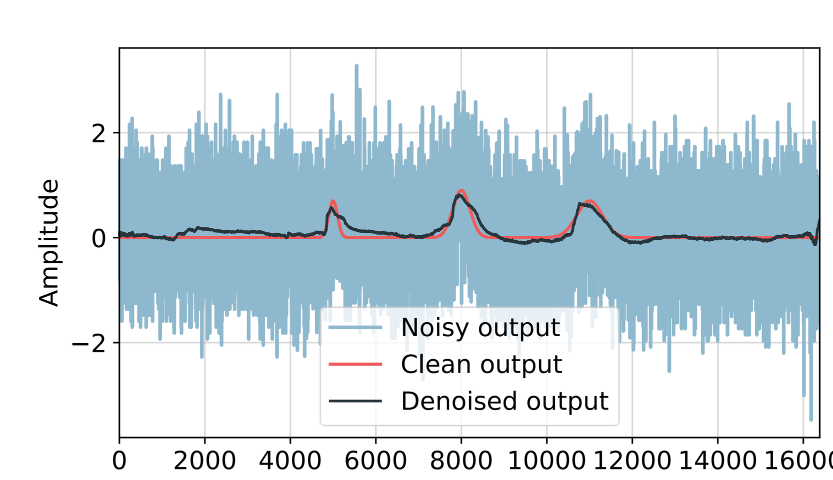


Inline Detector Denoising

- 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
  - ~16Mb/s for SPC detectors
- This system could be extended to actively learn, allowing for a denoising system that could be transferred to different detectors/applications



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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