# Denoising Signals from a High-Purity Germanium Detector using Generative Adversarial Networks with Convolutional Autoencoders

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## Introduction

- High-purity Germanium (HPGe) p-type point contact (PPC) detectors are used for rare event searches, such as Neutrinoless double beta decay (0νββ), dark matter and other beyond the Standard Model physics
- They have low energy threshold, excellent energy resolution and ultra-low background
- This work of signal denoising is developed based on PPC detectors, but is applicable to other Ge detector geometries as well as a broad range of other detector technologies and one-dimensional electronic signals

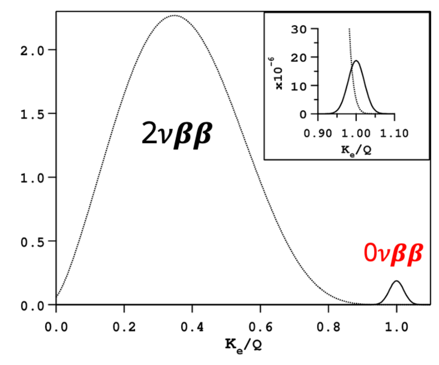



Fig. 1: Energy spectrum of double beta decay [1]

## HPGe PPC Detectors

A PPC detector is a semiconductor diode with a "p-i-n" (p+ point contact - intrinsic region - n+ layer) structure. The intrinsic region is made of high purity germanium crystal (can be enriched in $^{76}$Ge) that is sensitive to ionization. A reverse bias voltage is applied across the detector to deplete the intrinsic region and to create an internal electric field that sweeps the charge carriers to the contacts. The detector measures the total energy deposited in an interaction by collecting charges at the point contact readout electrode.

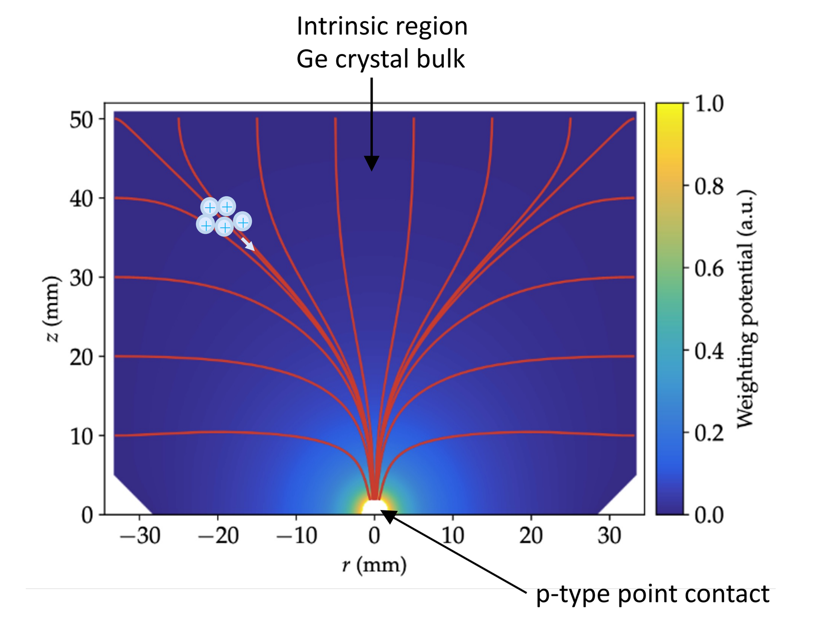



Fig. 2: Side view schematic of a PPC detector [2]. Weighting potential is indicated by the color pattern. Red lines show the drift paths of charge carriers.

The PPC geometry creates a localized "weighting potential" pattern (colored in Fig. 2). This creates pulse shapes that rise slowly at the start then followed by a rapid increase (Fig. 3). The start of the rise is often difficult to measure due to noise.

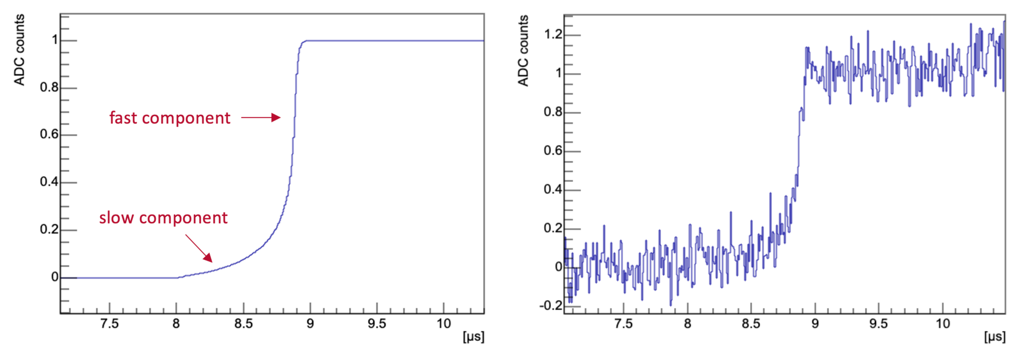



Fig. 3: Simulated charge pulse (left) and the same pulse with detector noise added (right).

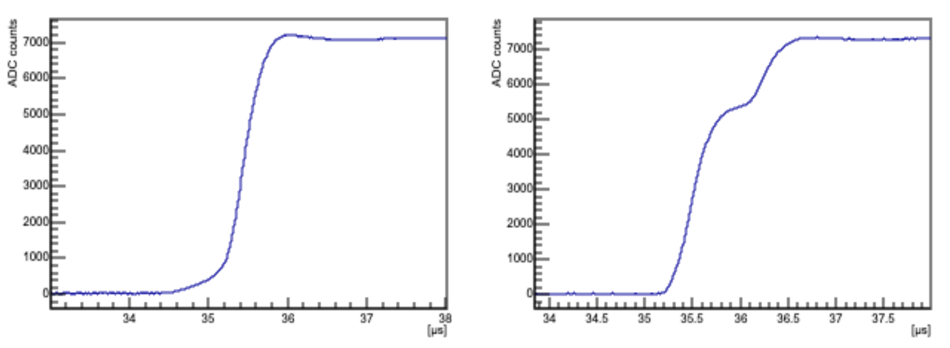


Fig. 4: Simulated clean detector pulses for a single-site event (left) and a multiple-site event (right).

The weighting potential also results in characteristically different pulse shapes for single-site and multiple-site events (Fig. 4). This provides background discrimination power between single-site 0νββ events and multi-site gamma backgrounds, such as Compton scattering.

## Denoising Ge Detector Signals using Deep Learning

**Removing electronic noise from signals can:**

- Improve measurements of pulse shape characteristics → better energy resolution and background rejection power
- Help identify low-energy signal events that are masked by electronic noise

**Advantages of deep-learning based methods:**

- Effective at denoising one-dimensional electronic signals from PPC detector, and often outperforms traditional denoising methods (e.g. moving average, exponential, Savitzky-Golay)
  - ➢ Shown in our work using autoencoder [3] : *Anderson et. al. Eur. Phys. J. C 82, 1084*
- Can simulate detector pulses without the need to include complex detector physics
- Applicable to a broad range of detector technologies and one-dimensional electronic signals

See Mark Anderson's poster for more details

Built upon our previous work, we investigate generative adversarial networks applied on autoencoders to further improve denoising and enable training without the need of simulation.

## GAN - Generative Adversarial Network

A GAN consists of two models, a generative model and a discriminative model, learning adversarially in a zero-sum game [4].

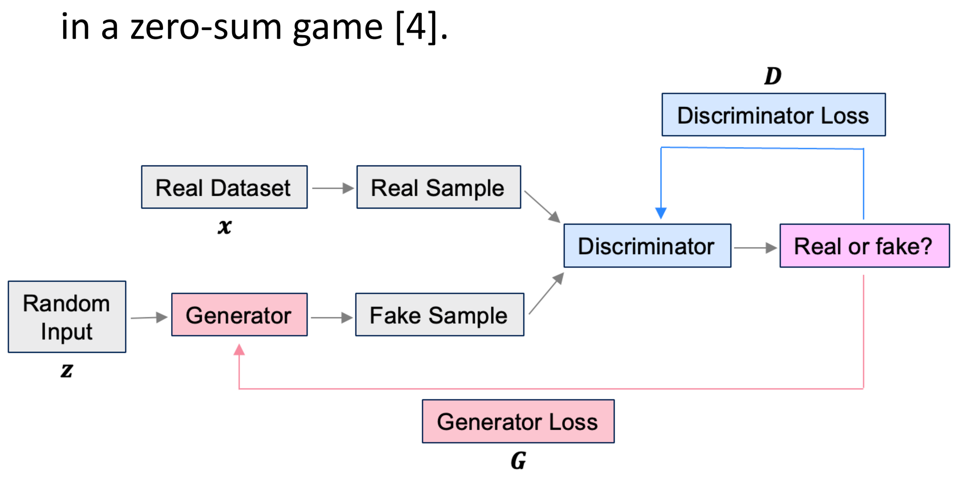



Fig. 5: A basic architecture of GAN.

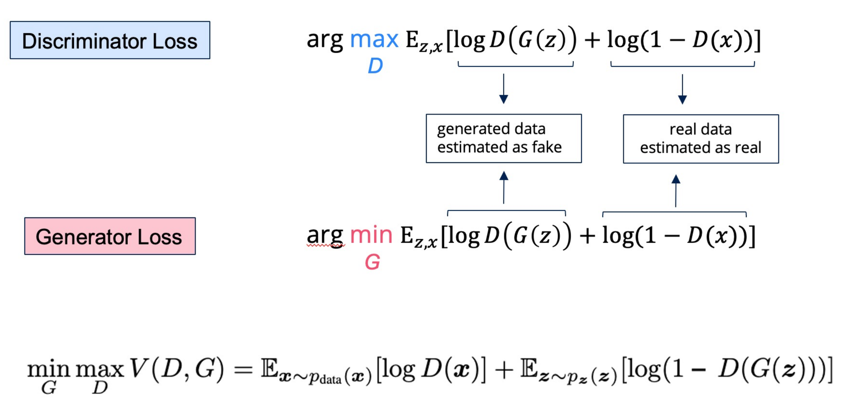



Fig. 6: Shows each model's loss function based on [4].

## CycleGAN

- A CycleGAN consists of two pairs of generators and discriminators → can be used to both remove electronic noise from detector signals and generate artificial noisy signals for detector simulation
- Maps a sample from X domain to Y domain and vice versa
- A cycle consistency is enforced between the two mappings using an additional loss to minimize the difference between the reconstructed output and the original input
- Learns transformations across domains using **unpaired data**, i.e. does not require corresponding sample and target pairs
- Can be trained **without simulated data (ground truth)**

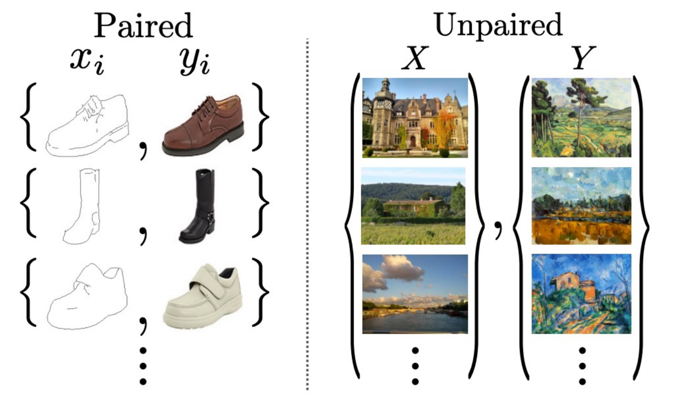



Fig. 7: Example of paired versus unpaired data [5].

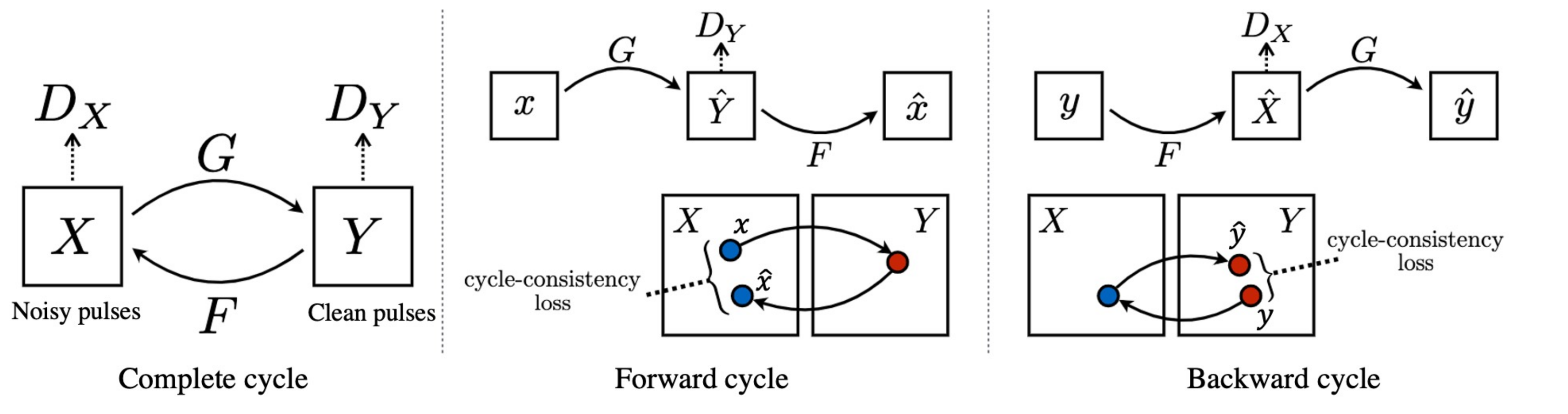
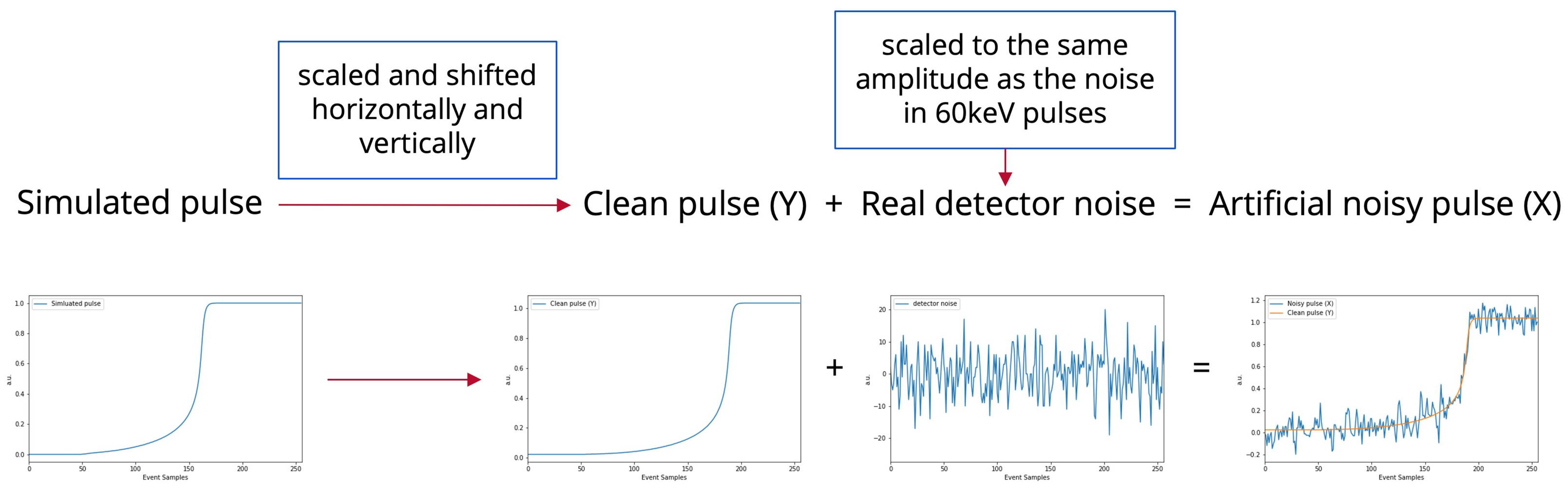



Fig. 8: CycleGAN architecture from [5], edited based on our purposes.

## Training Data




In training data:

- Approximately 1.2 million of single-site events, 100k of multi-site events
- Samples in both X and Y are randomly shuffled to create unpaired datasets.

## CycleGAN Model: Noisy pulse ↔ Clean pulse

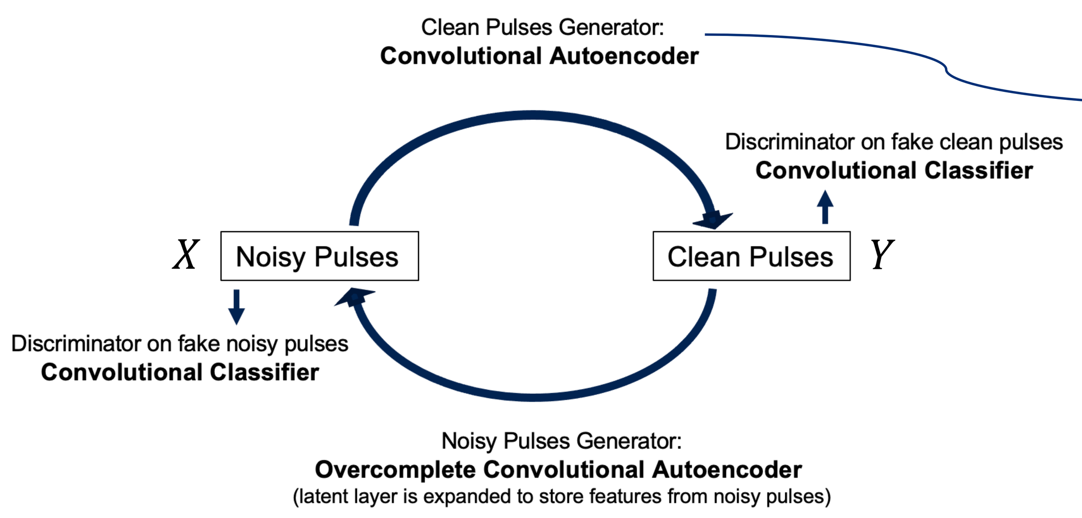



Fig. 9: Our CycleGAN diagram showing networks used in generative and discriminative models.

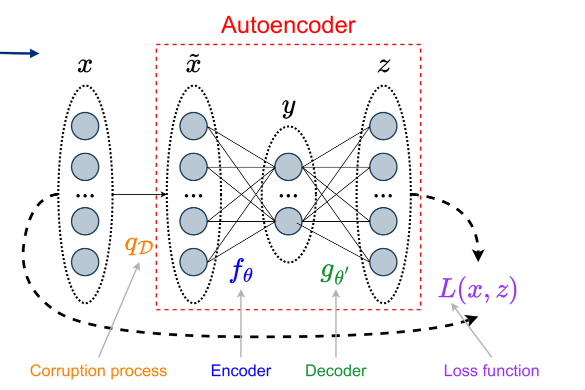



Fig. 10: Structure of autoencoder used in our work [3].

## Preliminary Results

The mean squared error of the clean pulse generator, evaluated by denoising the artificial noisy test dataset, is on the order of $10^{-4}$.

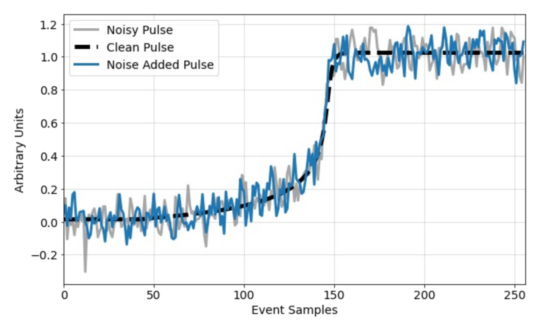



Fig. 11: noisy signal generated by the noisy pulse generator.

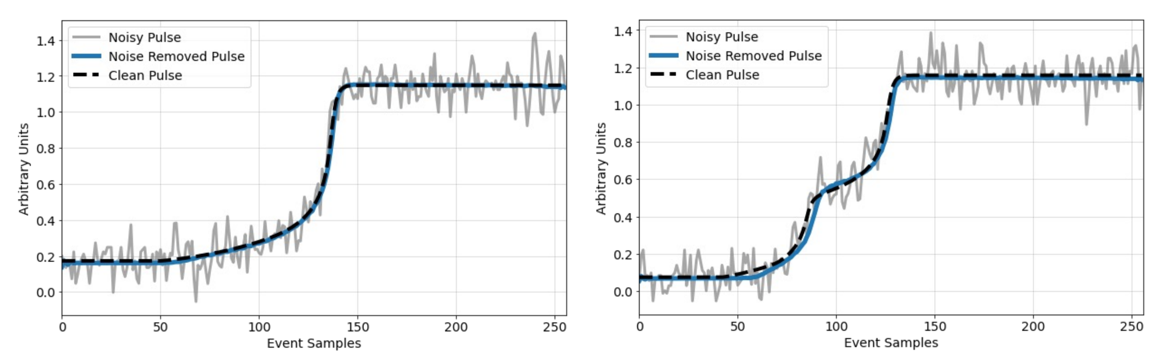



Fig. 12: denoised single-site event (left) and multi-site event (right).

## CycleGAN Model: Noisy pulse ↔ Noise traces

**In working progress**

- If CycleGAN learns transformations between X and Y domains well, then given noisy signals as one domain and detector noise traces as the other, the model should be able to learn to differentiate the noise from the underlying pulse shape in a noisy signal
- This would allow us to denoise signals and generate artificial noisy signals without the need for simulated data

## References

[1] Elliott, S. R. "Experiments for Neutrinoless Double-beta Decay," 2003
[2] Edzards et al. "Surface characterization of p-type point contact germanium detectors," 2021. arXiv:2105.14487v2
[3] Anderson et. al. "Performance of a convolutional autoencoder designed to remove electronic noise from p-type point contact germanium detector signals," Eur Phys J C Part Fields. 2022;82(12):1084. arXiv:2204.06655.
[4] Goodfellow et al. "Generative Adversarial Networks," arXiv.1406.2661
[5] Zhu et al. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks." arXiv.1703.10593

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