Neural Networks for Peak Amplitude Estimation at Particle Detectors in High-Rate Environments

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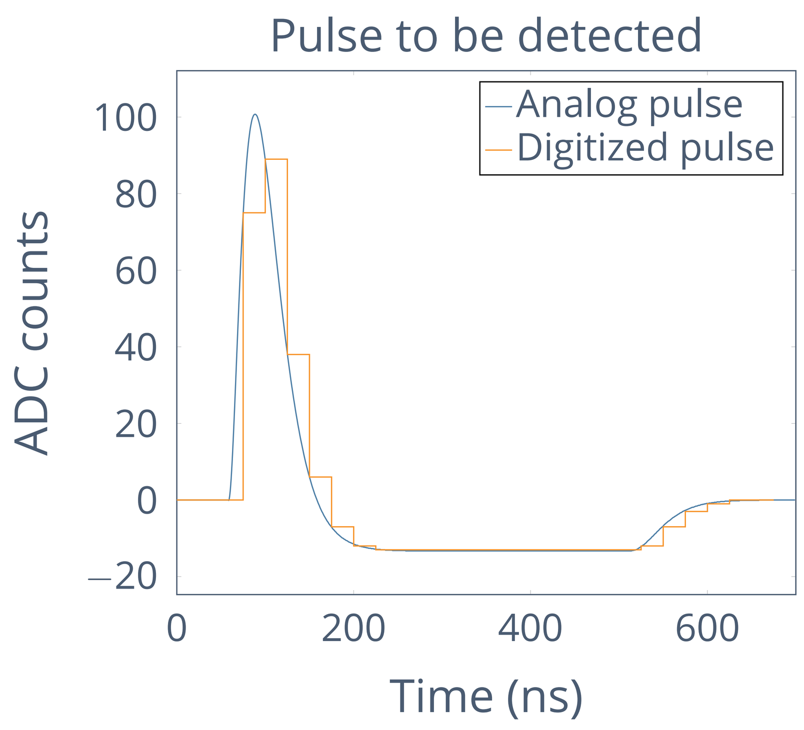
Abstract

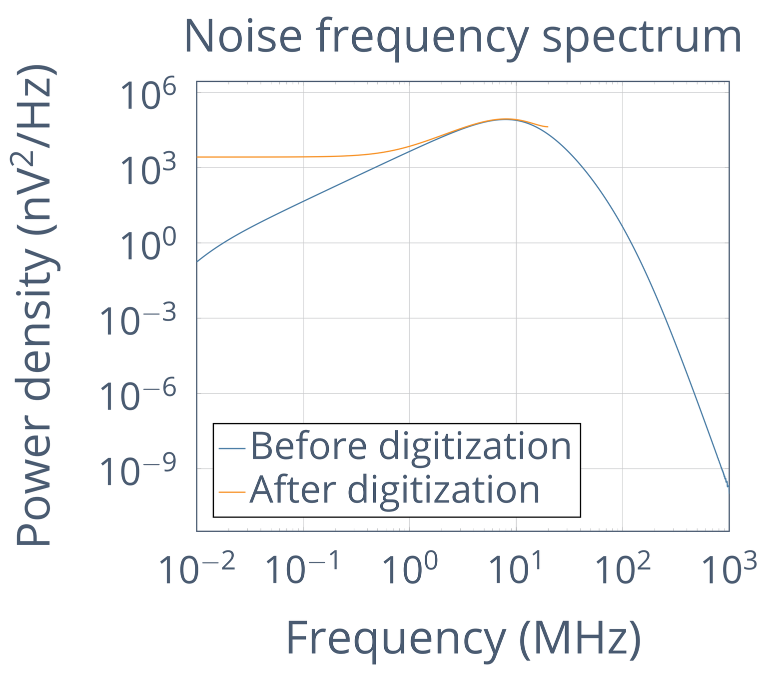
One of the challenges in energy reconstruction at particle detectors such as ATLAS is estimating the amplitude of the pulses induced into the detector electronics by particle hits. Thermal noise, quantization errors, and overlapping pulses are the main sources of uncertainty. The algorithms usually must run on FPGA firmware and with sub-μs latency. This poster presents an approach to this problem using neural-networks-based techniques.

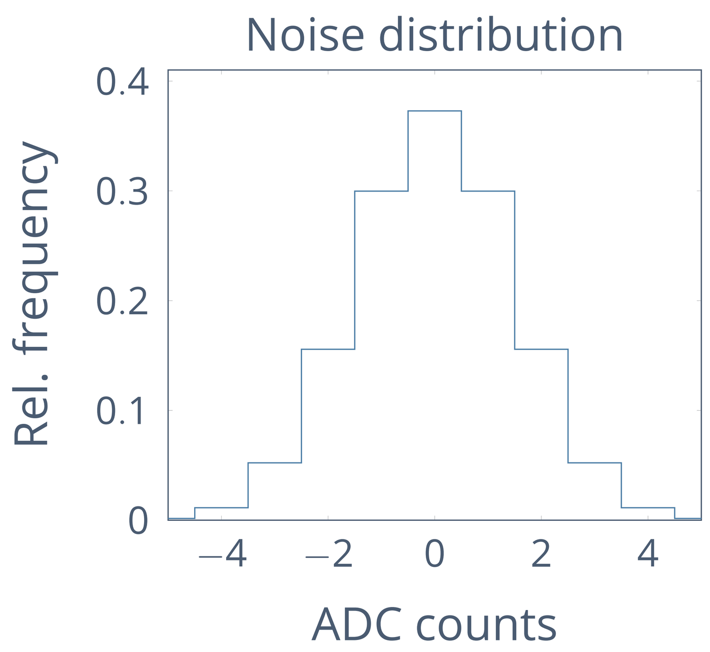
Pulse Shape



- bipolar pulse
- 600 ns long
- sampled every 25 ns
- peak amplitude uncertainty even without noise
- if hits arrive at sampling rate, there is a lot of overlap

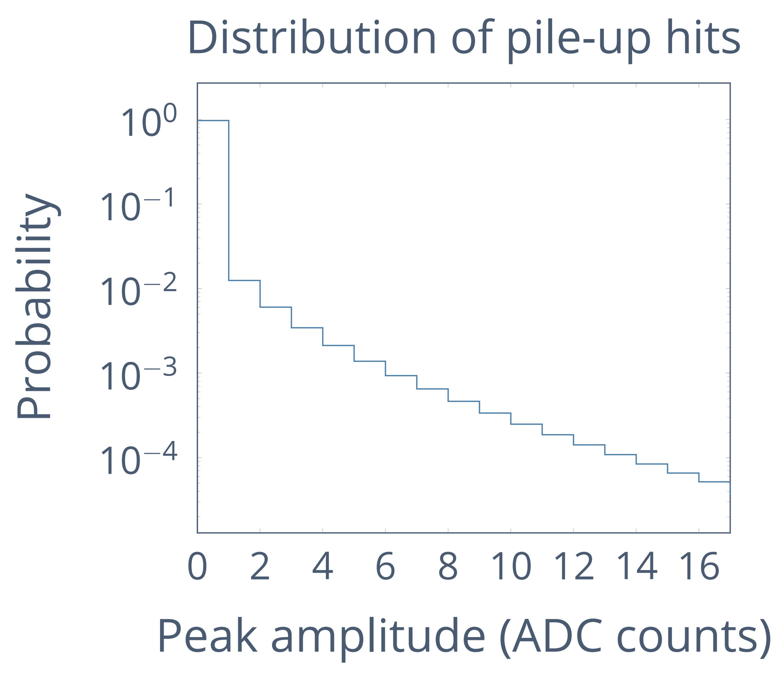
Electronics Noise

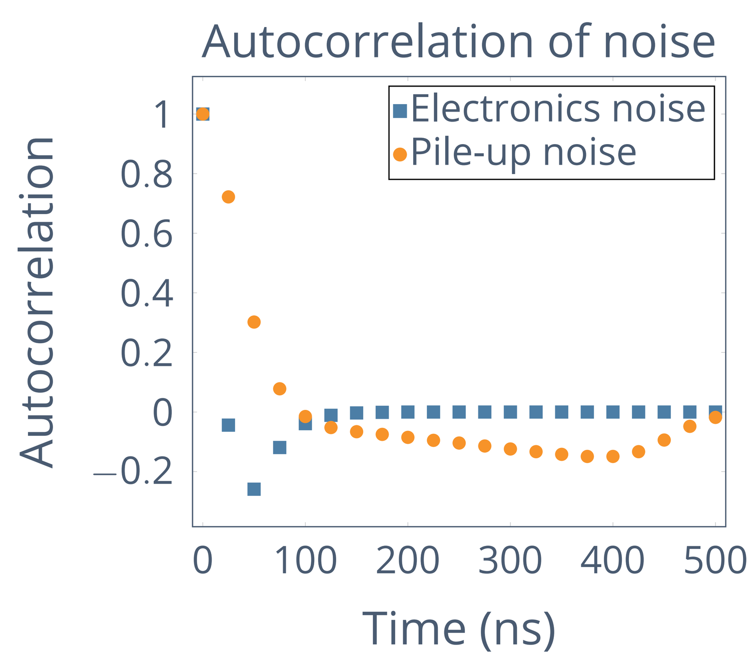




- thermal noise in the readout electronics
- almost perfectly Gaussian
- almost perfectly white (after sampling)
- difficult to predict and suppress

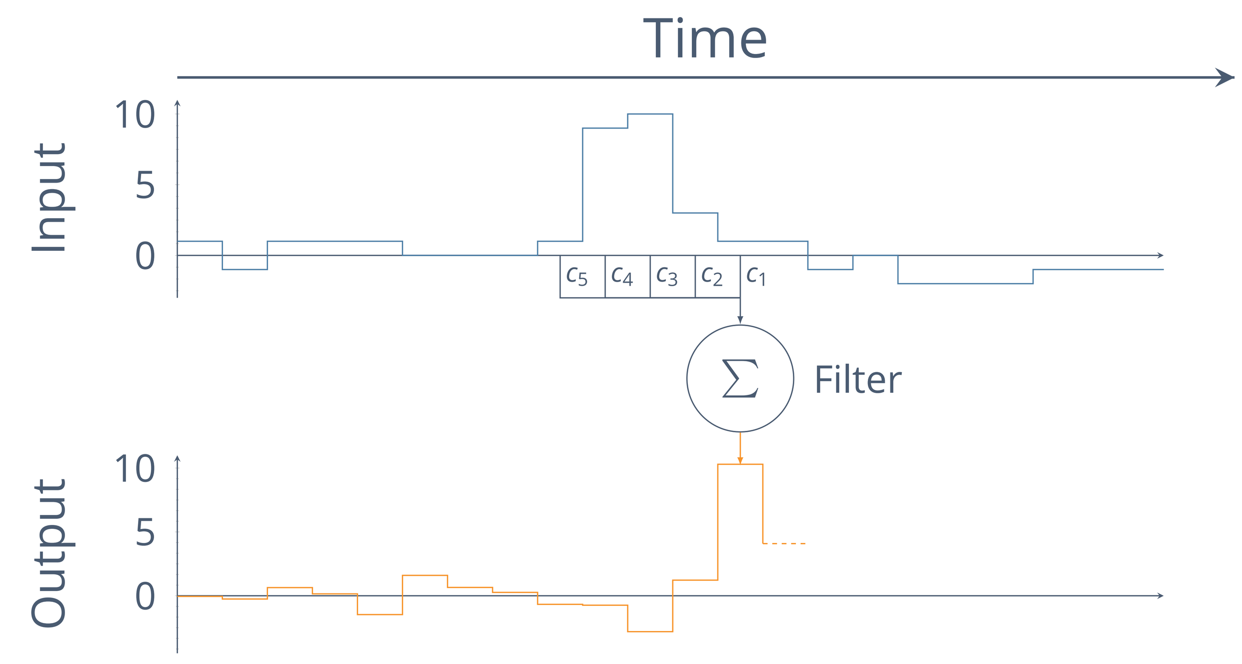
Pile-Up Noise





- low-energy events occur all times and overlay interesting signal
- often multiple pile-up hits at the same time
- strongly depend on the detector region
- appear as highly correlated noise due to the long pulses

Optimal Filter[1]

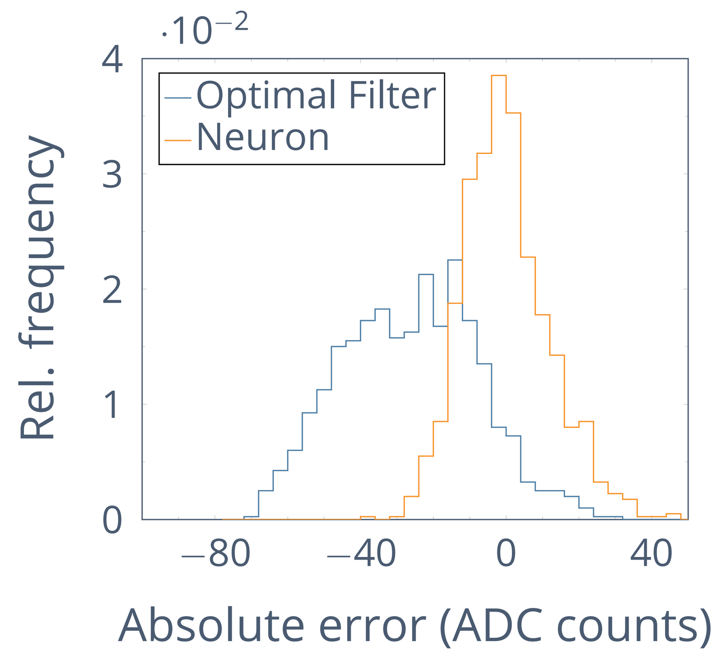


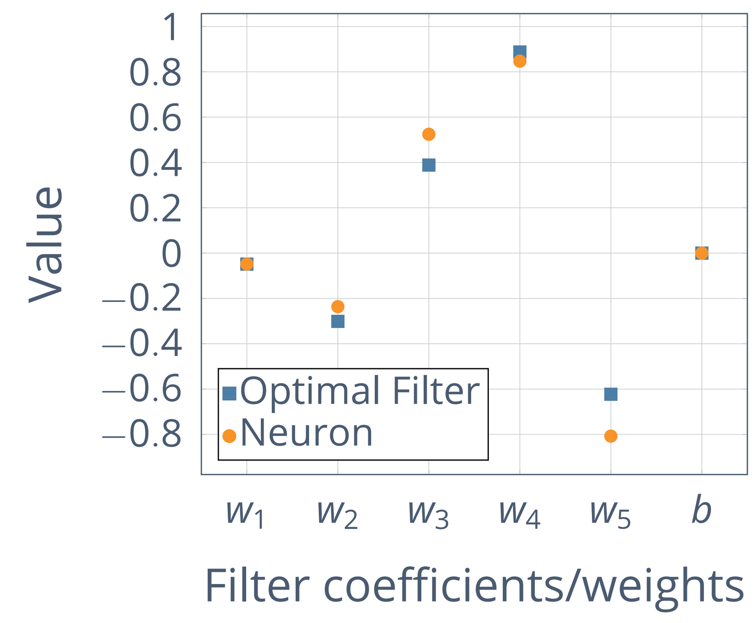
- widely used filter algorithm for energy reconstruction
- sliding-window filter that calculates a weighted sum
- coefficients based on analytic solution of least-squares fit
- equivalent to single-neuron convolutional layer without bias

Training via FANN[2]

- single neuron with 5-samples receptive field
- RProp[3] training for 10 000 epochs on 30 pulses
- trained only on known peaks, not on background

Results





- high pile-up: neuron outperforms OF
- low pile-up (not shown): same performance
- OF misses bias correction
- similar neuron/OF weights

Filter	Bias (ADC counts)	Noise (ADC counts)
OF	−26.2	18.6
Neuron	0.0	12.0

Current Challenges and Approaches

- Keras optimizers show bad convergence behavior
- adding more layers gives no clear improvement
- gated recurrent units might be more efficient

References

[1] W. Cleland and E. Stern, *Signal Processing Considerations for Liquid Ionization Calorimeters in a High Rate Environment*, Nucl. Inst. Meth. **A 338** (1994) no. 2, 467–497. `https://www.sciencedirect.com/science/article/pii/0168900294913323`.

[2] S. Nissen, *Implementation of a fast artificial neural network library (fann)*, tech. rep., Department of Computer Science University of Copenhagen (DIKU), 2003. `http://leenissen.dk/fann/wp/`.

[3] C. Igel and M. Hüsken, *Improving the Rprop Learning Algorithm*, in *Proceedings of the Second International ICSC Symposium on Neural Computation*, p. 115–121. 2000.

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