ABSTRACT

This report details the application of neural networks to a data challenge in the classification of pulses generated by an ultra-low background proportional counter (ULBPC) developed at Pacific Northwest National Laboratory (PNNL). In addition to true radioactive decay events there can be spurious pulses detected due to baseline noise, microdischarge, and pileup events. In order to distinguish these events, we leveraged the ability of neural networks to make fine distinctions between inputs. We find that a fully-connected neural network is able to properly classify events in datasets with significant microdischarge and noise contributions.

1 INTRODUCTION

Ultra-low background measurements are subject to various sources of noise, including microdischarge events in the electronics, cables, and connectors, pulse pileup, digitizer saturation, power supply fluctuations, and abnormal triggers. To study these spurious detection events in more detail, PNNL developed a method which calculates the similarity of pulses to a template gas gain pulse shape (called an exemplar) using the sum of square errors (exemplar sum of square errors, or ESSE). When the pulse ESSE values are plotted versus their energy, the data form clusters by classification type (Figure 1).

Figure 1: ULBPC data mapped out in energy vs. ESSE space. The data form clusters based on similarity of each event to a defined “good” gas gain pulse shape. Depicted here are good pulses (1, near the x-axis), microdischarge pulses (2), and pileup pulses (3).

While the majority of microdischarge pulses can be eliminated by carefully cleaning various components (signal cables, preamps, etc.) [Aalseth et al. (2013)], the spurious pulses due to power supply
fluctuations and pileup events remain. In an ESSE space with clean separation between classification types, these pulses can be excluded in post-processing by defining an ESSE threshold cutoff value that distinguishes the good pulses from noise in the energy vs. ESSE space. However, the cluster of pileup pulses can dip below the ESSE cutoff value and overlap with the good event data. Furthermore, noisy low-energy pulses can exhibit good gas gain characteristics, but will still be excluded due to a relatively high calculated ESSE value. Thus, it can be difficult to define a single ESSE threshold value that prevents both false positives and false negatives. It would be desirable to develop a method that can properly classify these events, as well as exclude invalid pulses more generally. For this purpose, we developed a simple neural network that operates on the raw data and identifies good gas gain pulses.

2 MATERIALS AND METHODS

Several datasets generated by ULBPC detectors were obtained from PNNL’s Shallow Underground Laboratory [Aalseth et al. 2012]. A typical dataset contains 10,000-100,000 pulses, with a roughly 50-50 mix of good and spurious detection events. A dataset of 40,648 labeled pulses was selected and randomly divided into an 80-20 split of training pulses and test pulses.

A two-layer fully-connected neural network was constructed in Keras [Chollet et al. 2015] using the TensorFlow [Abadi et al. 2015] backend. In the first layer, 1,024 neurons were used, and 512 neurons were used in the second layer. A 50% dropout rate between the first and second layers was used for regularization. Several activation functions were tried, and we found that exponential linear units (ELUs) gave slightly better results on the test set, though this effect was not very large (<1% performance improvement). A softmax activation was used to classify pulses as acceptable or unacceptable. We did not attempt to sub-classify the various failure modes, in order to reduce the risk of class imbalance. The network was trained for 30 epochs using the Adam optimizer, with learning rate decay for stability.

After training, the performance was tested by running several challenge datasets (i.e. datasets that included noisy data or significant microdischarge contribution) through the network and then comparing the network label assignments to the label assignments that would have been made by an ESSE threshold cutoff. A Python script flags points of disagreement between the two methods. These points of disagreement are sent unlabeled to a physicist for manual assignment. The relative performance of the methods is judged by the percentage of cases that agree with the subject matter expert (SME) / physicist determination.

3 RESULTS AND DISCUSSION

The trained network achieved 99.89% classification accuracy on the test set. Looking at the test pulses where the network disagreed with the pulse labels in more detail, we find that most of these are due to improperly triggered (no leading baseline) pulses that were mislabeled in the original dataset as good pulses. Therefore, the network classification accuracy is potentially even higher than this.

The network was tested using challenge sets with significant noise and microdischarge contributions. One of these is shown in Figure 2. This dataset is relatively clean (i.e., few microdischarge pulses); however, the cluster of good gas gain events exhibits a curvature in the energy vs. ESSE space due to a non-linear energy correction that was applied to the raw data. As a result, it is impossible to define a single ESSE cutoff value that prevents both false positives and false negatives. A blind SME review of these pulses determined that the neural network correctly flagged these pulses 100% of the time.

A challenge set from a detector with a significant amount of microdischarge pulses was shown in Figure 1. The ESSE cutoff was intentionally set high in order to minimize the false negative rate. The neural network flagged 400 out of 10,000 pulses in this dataset as mislabeled by the ESSE cutoff. A blind review by a SME determined that the neural network correctly flagged these pulses 94.3% of the time.

A final challenge set was particularly interesting, since it included several preamp saturated pulses, which show up in the energy vs. ESSE plot as a cluster of points that intersect with the cluster
Figure 2: Left: Energy vs. ESSE plot of a challenge set with a non-linear energy correction applied to raw data. The dashed line shows the ESSE threshold cutoff. Blue data points were labeled as good by the network, while red are bad. Darker points show points of disagreement with the cutoff method. Right top: A low-energy but acceptable pulse labeled as bad by the cutoff method. Right bottom: A pulse with no leading baseline (early trigger) labeled as good by the cutoff method. The network correctly assigns both pulses.

of good gas gain pulses (Figure 3). An ESSE-based cutoff method would not be able to exclude these pulses, even if the cutoff value was made energy-dependent. The neural network was able to correctly flag these events as spurious pulses. Thus we can demonstrate a clear advantage to using neural networks for pulse discrimination.

Figure 3: Left: Energy vs. ESSE plot for all data points below the ESSE threshold cutoff of a challenge set. This dataset includes preamp saturated pulses (red) that form a cluster that intersects with the good gas gain pulses (blue) in this space. Right: Typical pulses from these clusters.

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REFERENCES


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