Supervised learning of photoelectron counting in scintillator-based dark matter experiments

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Abstract: Many scintillator based detectors employ a set of photomultiplier tubes (PMT) to observe the scintillation light from potential signal and background events. It is important to be able to count the number of photoelectrons (PE) in the pulses observed in the PMTs, because the position and energy reconstruction of the events is directly related to how well the spatial distribution of the PEs in the PMTs as well as their total number might be measured. This task is challenging for fast scintillators, since the PEs often overlap each other in time. Standard Bayesian statistics methods are often used and this has been the method employed in analyzing the data from liquid argon experiments such as MiniCLEAN and DEAP. In this work, we show that for the MiniCLEAN detector it is possible to use a multi-layer perceptron to learn the number of PEs using only raw pulse features with better accuracy and precision than existing methods. This can even help to perform position reconstruction with better accuracy and precision, at least in some generic cases.

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1 Introduction

Direct dark matter search experiments that are based on noble liquid targets read out by photomultiplier tubes (PMTs) often employ scintillation pulse shape discrimination methods to identify the particle causing the interaction. In this technique, the amount of light observed within the prompt time scale of scintillation (typically within $\sim 100$ ns of the event trigger for argon) relative to the total amount of light observed in the event, is used to distinguish between nuclear and electronic recoil events. This quantity is termed as the prompt fraction, $f_p$, and is expressed as:

$$f_p = \frac{\int_{t_0}^{t_{100}} V(t)dt}{\int_{t_0}^{tf} V(t)dt},$$

where $V(t)$ denotes the voltage waveform and the integral measures the light observed by the PMTs within the integral limits. The limits $t_0$, $t_{100}$ and $t_f$ denote the trigger time, first 100 ns and total time window in the event for light collection. Figure 1 shows that this integral is equivalent to counting the number of photoelectrons within the observed pulse. Clearly, the accuracy of $f_p$, which dictates the degree to which the nuclear recoil events and the electronic recoil events can be identified and separated, depends on how well the counting of photoelectrons can be performed.

From Figure 1 it is clear that this is a difficult task at shorter time scales of scintillation where the photoelectrons tend to overlap and cannot be resolved with clarity. In the context of the MiniCLEAN experiment [2], a Bayesian statistics based counting method was developed [3]. This technique demonstrated better performance compared to an averaging technique that attempts to count the desired number by dividing the total charge deposited in a pulse by the mean charge per
photoelectron. In this work, we intend to explore if we can further improve this limit to perform more accurate and precise counting of photoelectrons. This will benefit MiniCLEAN as well as other experiments in the global argon dark matter collaboration (e.g. DEAP-3600, DarkSide-20k etc.) which will employ pulse shape discrimination. It could potentially also improve the performance of any PMT-based single photon counting experiment. To this end, we carry out an exercise of supervised learning of the number of photoelectrons from the features of simulated PMT pulses.

2 Description of supervised learning technique

The data sample for this task has been generated using the RAT framework. The Monte Carlo program simulates the pulses generated by the PMTs and produces a realistic data sample in which all 92 PMTs of the MiniCLEAN detector, arranged centrally facing inside the spherical inner vessel, observe different number of pulses in an event. The waveforms are sampled into 4 nanosecond bins. We design a network that will learn the approximate number of photoelectrons observed by an individual PMT from the raw pulse features (mean time and width of the pulse waveform, the bin numbers containing the left and right edges of the pulse, the bin number where the peak of the pulse waveform is located, the charge contained within that bin and the total charge deposited in the pulse). Different events observe varying number of pulses, as seen in Figure 2.

It is assumed that a PMT can observe at most 100 pulses in an event. The floating point numbers for all the pulses representing their features are written to a vector. We employ zero-padding when the true number of pulses is less than 100 in an event. Hence, a multi-layer perceptron with dense connections is trained on the number of Monte Carlo photoelectrons for all the PMTs in MiniCLEAN with about 3 million events (training data) using the feature vector on an event by event basis. The detailed parameters of the network architecture are given in Table 1 in the appendix.

From the study of the PMTs in MiniCLEAN, it is observed that individual PMTs have different calibration coefficients and dark noise rates. Therefore, individual PMTs are trained in parallel in our work in the following manner. The feature vector prepared with the Monte Carlo sample for a given PMT is trained against the number of photoelectrons observed in that PMT itself, for all of the training data. The test data is a different Monte Carlo data sample with the same PMT calibration parameters. When the network prediction is seen to converge to the extent that the mean squared error between the network prediction and the true number of photoelectrons is very small (< 0.5) and stable for an arbitrary unseen validation data set, the training is stopped.
and the predicted number from all the 92 PMTs are added up to give the predicted number of photoelectrons in an event.

3 Training characteristics

For a training session with Argon-39 $\beta$ decay Monte Carlo events, distributed uniformly throughout the detector, it is seen that the loss function becomes progressively smaller during training, as seen in Figure 3a. Also, there is no evidence of overtraining. It is observed that different PMTs exhibit different degrees of accuracy in estimating the correct number of photoelectrons (see Figure 3b), which is expected because each PMT has unique single photoelectron calibration parameters and dark hit rate.

Figure 3: (a) The evolution of loss function observed during training the network; (b) different degrees of accuracy in estimation achieved by PMT#0 and PMT#11. Similar characteristics are observed in training other PMTs as well.
4 Outcome of network prediction

To evaluate if this approach of estimating the number of photoelectrons in an event is more accurate and precise compared to the Bayesian photoelectron counting [3], we investigated the network prediction for the Monte Carlo data samples from Argon-39 $\beta$ and Uranium/Thorium chain $\gamma$ backgrounds (the latter mostly originate from the edges of the inner and outer vessels and the PMTs) and compared the pull distributions, defined as:

$$ \text{pull} = \frac{\text{estimated} \# \text{ of photoelectrons} - \text{true} \# \text{ of photoelectrons}}{\sqrt{\text{true} \# \text{ of photoelectrons}}} $$

between the network prediction and Bayesian counting for identical sets of events. Figure 4 shows the performance of the network, where the relative improvement in the precision of estimation (standard deviation of the pull distribution) with respect to the Bayesian counting method has been highlighted in percentage (e.g. $\sim 30\%$ for Argon-39 $\beta$ events).

From Figure 4, it is clear that this method leads to a significant improvement in counting the number of photoelectrons in scintillator-PMT based experiments.

5 Application to vertex position reconstruction

Since the network provides a means to measure the amount of light observed by different PMTs arranged at different angular positions around the inner vessel, it is possible to perform a position reconstruction of the event vertex by invoking a likelihood-based technique, using the distribution of observed photoelectrons across the detector. Substitution of this improved photoelectron counting algorithm led to 3.6%, 12% and 14% improvement in the precision of position estimation in $z$, $x$ and $y$ coordinates, respectively.
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A Network architecture

| architecture     | weight initialization | learning rate                                      | optimizer |
|------------------|-----------------------|----------------------------------------------------|-----------|
| 2 layers, 1024 neurons | Xavier initialization | $\text{lr}=0.5, \beta_1 = 0.99, \beta_2 = 0.999, \epsilon = 1 \cdot e^{-8}$ | Adam      |
| regularization   | loss function         | batch size                                         | activation function |
| batch normalization | mean squared error    | 65,000                                             | ReLU       |

Table 1: Parameters used for training a multi-layer perceptron to learn the number of photoelectrons observed by individual PMTs in MiniCLEAN

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