Pulse Shape Simulation and Discrimination using Machine Learning Techniques

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Introduction

The backbone of any particle-detection experiment is an efficient signal-background discrimination. Pulse shape discrimination (PSD) is a basic method for this purpose in many nuclear, high-energy and rare-event search experiments where scintillator detectors are used. Conventional techniques exploit the difference between decay times of the pulse of signal and background events or pulse signals caused by different types of radiation quanta to achieve good discrimination. However, such techniques give good results only when the total light emission is sufficient to get a proper pulse profile. This is possible when there is significant energy deposition in the detector. Also, if the signal rate is comparable to the background rate, one can choose to have a tighter cut on the discriminating parameters so as to have a high signal purity. But, rare-event search experiments like neutrino or dark-matter direct search experiments cannot afford tighter cuts, since the signal rate and magnitude is low to begin with, compared to the background. Hence, it becomes imperative to have a method that can deliver a very efficient discrimination.

Network based machine learning algorithms have been used for classification problems in many areas of physics especially in high-energy experiments and have given better results compared to conventional techniques. Here, we present results of our preliminary investigations of a neural network based method for pulse shape discrimination.

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Pulse Shape Simulation

The simulation for the pulse is done for 662 keV γ-rays emitted from a ^{137}Cs γ-ray calibration source, incident on a BGO scintillator. GEANT4 simulation package [1] was used. This particular setup was taken since experimental data from [2] was used to validate the simulation result as shown in Fig. 1. The motivation behind the simulation is to have the capability to produce large no. of samples for training the network.

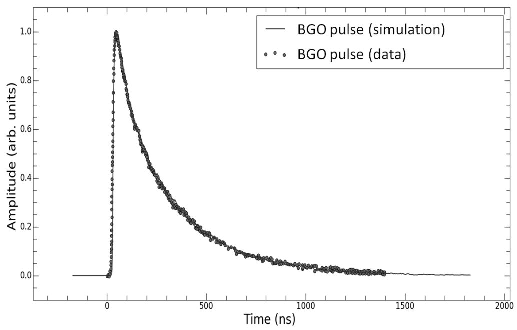

FIG. 1: BGO pulse comparison

Detector Geometry and Simulation

The baseline geometry for the simulation includes a point source of 662 keV γ rays placed in front of a BGO scintillator coupled to a photomultiplier (PMT). The BGO crystal is 13 mm in diameter and 2 mm thick, enclosed inside a copper shield of 10 mm thickness with glass window matching with the PMT readout. The emission spectrum and the decay times of the slow and fast components of BGO are given as input to GEANT4, based on which the scintillation photons are generated. The output taken from GEANT4 is wavelength of these photons and the time when they hit the PMT window. The PMT window is included in the simulation as a place-holder since it is diffcult to incorporate a PMT in GEANT4.

Photomultiplier Simulation

The overall pulse shape obtained from the anode of a PMT can be simulated once its effect on a sufficiently narrow pulse is reproduced.There are two main effects: an increase in the amplitude (depending on the gain of PMT) and a spread in time. A separate code was written to implement these two effects on the output of GEANT4.

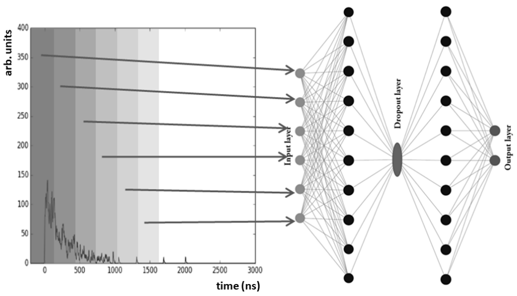

FIG. 2: Deep Neural Network for discrimination

Network-based Discrimination

In order to study the performance of the network for PSD, the second category of pulse is generated by simply increasing the decay times of scintillation in GEANT4. The slow decay time component was increased from 300 ns to 350 ns and the fast component from 60 ns to 80 ns. 40K samples were generated for each category for a total of 80K samples out of which 64K samples were used for training and 16K for testing.

The network used for PSD consists of an input layer of 6 nodes, 2 hidden layers having 10 nodes each and the output layer having 2 nodes. The area under pulse starting from t=0 to various cut points in time is used as the input to the network as shown in Fig. 2. The accuracy of the discrimination as a function of the training epoch [3] is shown in Fig. 3. As the network trains through the epochs and sees more events, albeit the same set, it's accuracy in classifying the events into the correct category increases.

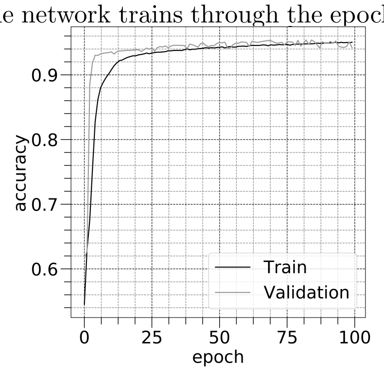

FIG. 3: Accuracy of the network in discrimination

Conclusion

The network architecture used here is a basic one and the results look promising with a discrimination accuracy of about 95%. There is a plan to test few other network architectures and an improved result is expected.

References

[1] Geant4-a simulation toolkit, S. Agostinelli et al., Nucl. Instrum. Meth. A 506, 250-303 (2003). doi:10.1016/S0168-9002(03)01368-8.

[2] Signal pulse emulation for scintillation detectors using Geant4 Monte Carlo with light tracking simulation, R. Ogawara and M. Ishikawa, Review of Scientific Instruments 87, 075114 (2016). doi:10.1063/1.4959186

[3] Deep Learning, I. Goodfellow, Y. Bengio and A. Courville, p. 243, MIT Press (2016)