Discrimination of Simulated Neutron-Gamma Pulses using Artificial Neural Network

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Introduction

Artificial Neural Network (ANN) have been widely used in classification tasks for various data types viz. images, audio etc. This paper brings out the efficacy of ANNs in discriminating between simulated Neutron-Gamma pulses, a binary classification problem, under differing Gaussian noise conditions.

Data Generation & Feature extraction

The simulated Neutron and Gamma pulses are generated using the Marrone's Model [1]. These simulated pulses are distorted through superimposition of Gaussian noise to make them resemble the experimental Neutron-Gamma pulses and are used as testing data set.

Neutron-Gamma pulse profiles are almost similar during their rise time but differ in shape during their fall time. This distinguishing feature is utilized to train the ANN. Pulse profile from near its peak to 40ns towards their tail region, sufficient to discriminate between pulses [2], is extracted from full pulse profile and used as input feature to train the ANN.

Pulse shape discrimination through ANN

A dense ANN is trained on the simulated Neutron-Gamma data set with no additional Gaussian noise. Training data set is concatenated with appropriate labels (1 for Neutron pulses and 0 for Gamma pulses) and randomized before serving examples for training the ANN model.

ANN consists of a single input, hidden and output layer containing 40, 20 and 1 units respectively. Sigmoid function was used as an activation function to introduce non-linearity in the ANN model. The input layer size was matched to feature length. Fig. 1 shows the processing workflow for the classification task.

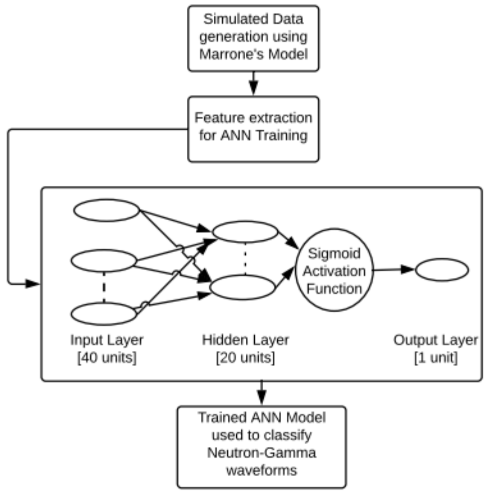

FIG. 1: Workflow used for Discrimination of Neutron-Gamma waveforms using ANN.

The ANN is trained through mini-batch stochastic gradient descent (SGD) optimizer over 100 epochs to progressively reduce training loss. Learning rate and Batch size for SGD are kept at 0.1 and 50 respectively. The learned weights and biases, after the ANN model converges, is used to make predictions on the testing data set.

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Predictions by trained ANN model

The trained ANN model outputs probability of being Neutron/Gamma pulse when presented with an input feature. A representative result for an equally partitioned Neutron-Gamma waveform data set is shown in Fig. 2. Predicted probability closer to 1 and 0 are indicative of Neutron and Gammas respectively. Points labeled in blue and red denote original Neutron and Gamma pulses respectively.

Neutron labeled pulses whose computed probability is < 0.50 and Gamma labeled pulses whose computed probability is ≥ 0.50 are examples which are incorrectly predicted by trained ANN.

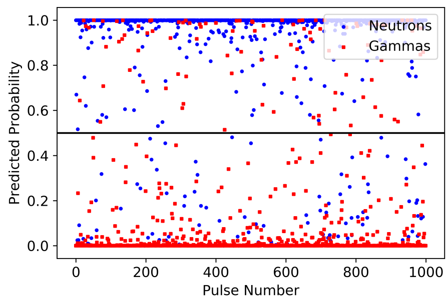

FIG. 2: Prediction of trained ANN model on data with Gaussian noise of 0 μ and 0.15 σ. Classification threshold (black horizontal line) kept at 50%.

Evaluation Metric

Testing data set comprises of pulse profiles whose nature is known a priori. The results are evaluated for its correctness through recorded instances of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) predictions. Here, Neutron pulses have been considered as positive class and Gamma pulses as negative class. Building on these, we have taken Accuracy as our evaluation metric. Accuracy is the fraction of prediction the trained ANN model got right. Put differently,

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$$

Results

Prediction accuracy of trained ANN as a function of varying Gaussian noise levels is shown in Table I.

TABLE I: Prediction accuracy(in %) of trained ANN as a function of varying Gaussian noise levels. Classification threshold kept at 0.5. Gaussian noise in all data set has 0 μ value.

σ	0	0.05	0.1	0.15	0.2
Accuracy(Neutron)	100	99.9	96.9	89.7	80.6
Accuracy(Gamma)	100	100	97.3	90.2	82.4
Accuracy(Total)	100	99.95	97.1	89.95	81.5

The prediction accuracy of the trained ANN model comes down with increasing noise level as Neutron-Gamma input pulse features become intertwined at elevated noise levels as shown in Fig. 3.

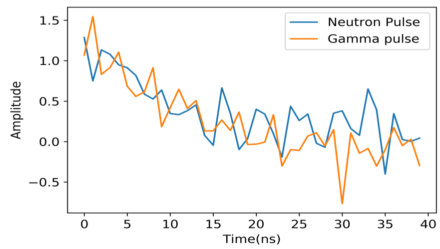

FIG. 3: Intertwining of Neutron-Gamma Pulse input features at elevated noise levels.[μ-0, σ-0.2]

Conclusion

The ability of ANN to carry out Neutron-Gamma discrimination on truncated pulses under varied noise condition has been validated. Reduced input feature size has resulted in fast model training and convergence, crucial for real time deployment of ANNs.

References

[1] S. Marrone et al., Nucl. Instr. and Meth. A **490**, 299 (2002).
[2] G. Liu et al., Nucl. Instr. and Meth. A **607**, 620 (2009).