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A novel algorithm to reconstruct events in a water Cherenkov detector

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We have developed a novel approach to reconstruct events detected by a water-based Cherenkov detector such as Super- and Hyper-Kamiokande using an innovative deep learning algorithm. The algorithm is based on a generative neural network whose parameters are obtained by minimizing a loss function. In the training process with simulated single-particle events, the generative neural network is given the particle identification (ID) or type, 3d-momentum (p), and 3d-vertex position (V) as the inputs for each training event. Then the network generates a Cherenkov event that is compared with the corresponding true simulated event. Once the training is done, for the given Cherenkov event the algorithm will provide the best estimate on ID, p, and V by minimizing the loss function between the given event and the generated event over ranges of input values of ID, p and V. The algorithm serves as a type of fast simulation for a water Cherenkov detector with a fewer number of assumptions than traditional reconstruction methods. We will show some of the algorithm's excellent performance in addition of the architecture and principle of the network.

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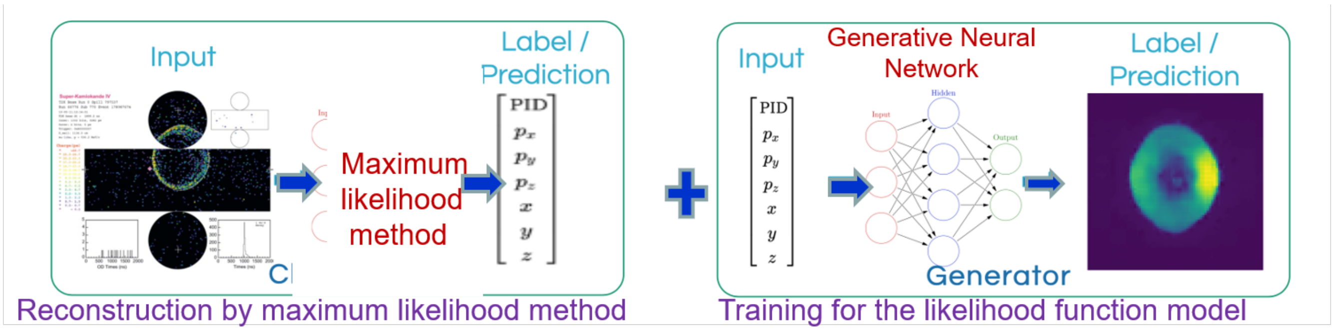

Figure 1: The traditional reconstruction method (left) + an addition to the new method

1. Introduction

Traditionally in high energy physics, we try to reconstruct the event for a giaven event image recorded by a detector and obtain the properties of the event such as the particle ID/type, 3D momentum, and event vertex (See Figure 1). Note that in this article we only describe single-particle events detected by a Super-Kamiokande (SK)-like water Cherenkov detector. To reconstruct the properties of the particle detected, the current state-of-the-art non-neural-network based algorithm for the SK event reconstruction is called FiTQun [1]. It uses the maximum likelihood estimation algorithm. While both FiTQun and the new method use a likelihood function, the likelihood functions are different from each other. The likelihood function for the new method is created by training the generative neural network dipicted in Figure 2, while that for FiTQun is modeled by consideration of physivs (refelection and scattering of Cherenkov photons etc.) based on full-simulation. See more details of the generative network in [2].

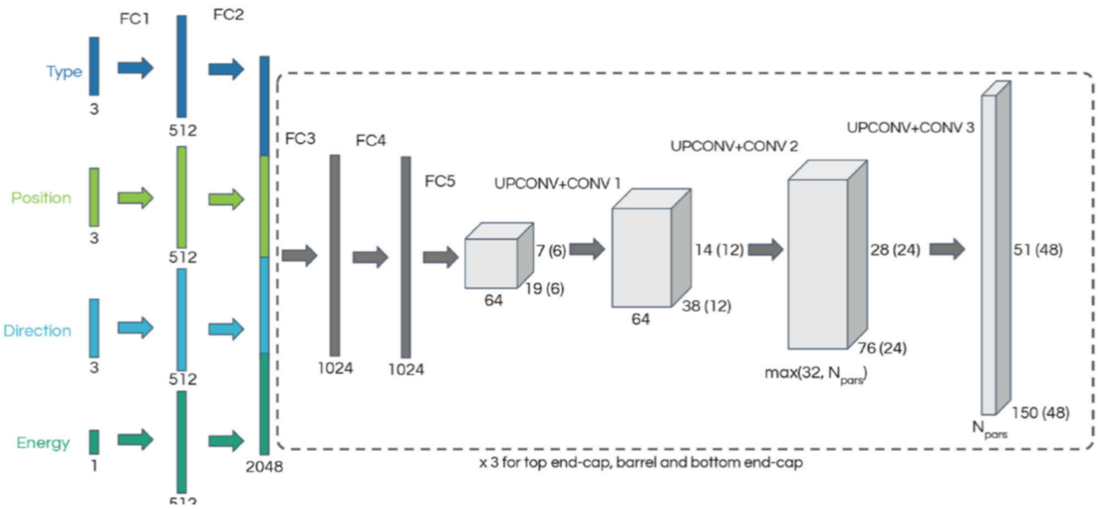

Figure 2: The architecture of generative neural network

2. Likelihood function for the new method and trainning of the nextwork

In the new method, we use -log likelihood function as the loss function to train the generative neurel network by minimizing it. The loss function is defined as

$$Loss = \sum_{i} - \ln P_{unhit}(y_i) + \sum_{i_{hit}} - \ln P_{qt}(q_{i_{hit}}, t_{i_{hit}}),$$

where $P_{unhit}(y_i)$ is the unhit probability where i runs over all photomultiplier tubes (PMTs) and y_i is 0(1) for (un)hit PMT. $P_{qt}(q_{i_{hit}}, t_{i_{hit}})$ is the probability density function of charge q and time t registering charge $q_{i_{hit}}$ at time $t_{i_{hit}}$. This function is modeled by multiple-Gaissian functions with or without correlation between charge q and time t. During the training of the generative neural network, the parameters for the Gaussian functions are optimized. In Figure 3(a), the hit probability $P_{hit} = 1 - P_{unhit}$ is plotted for electrons (left) and muons (right) where the top figure is simulated distribution and the bottom figure is predicted by the generative network. In Figure 3(b), the charge probability density function for a PMT at the center of the Cherenkov ring is plotted for electrons (left) and muons (right) where the results with 1-, 3-, 5- and 10-Gaussian approximation are shown.

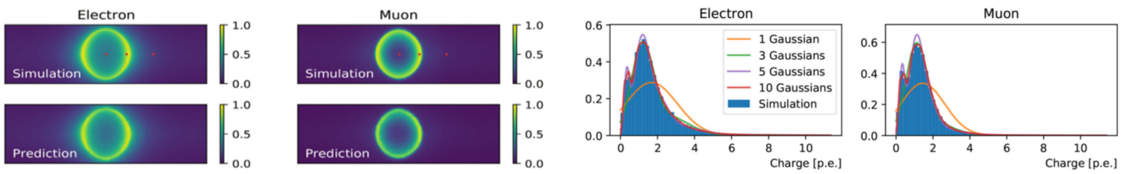

Figure 3: (a) Four left figures: Hit probability simulated (top) and predicted (bottom) for electrons (left) and muons (right); (b) Two right figures: Charge probability density for electrons (left) and muons (right)

We train the network using 75% of simulated events with the remaining 25% used for validation. During the training, the loss function show steady decrease and become more stable with increase in the number of training epochs.

3. Performance of the New Method

For reconstruction of events, all the inputs are fixed at the true values but the one we are interested in. Among some distributions to assess how the new method performs, we show two distributions: the energy residual defined as $\Delta E = (E_{rec} - E_{true})/E_{true}$, and the particle ID capability to distingush between electrons and muons. E_{rec} is the reconstrcuted energy and E_{true} is the true energy. The particle ID capability is assessed by the difference in the loss function between electron and muon hypothesis definded as $\Delta Loss = \ln L_\mu - \ln L_e$ where L_μ and L_e are the likelihood functions for muon and electron hypothesis, respectively. $\Delta Loss$ is basically the log liklihood- ratio between the two hypotheses. If $\Delta Loss > 0$, the event is muon-like. Otherwise the event is electron-like. Figure 4(a) shows the distributions of energy residuals for muons (left) and for electrons (right) with 1-,3-,5- and 10-Gaussian fit to the charge distribution of each PMT where only charge is used without timing information. Figure 4(b) shows the $\Delta Loss$ distributions with 1-Gaussian (left) and 10-Gaussian (right) fit to the charge distributions. The histograms in orange are from muon events, while those in blue are from electron events. The spikes at zero are

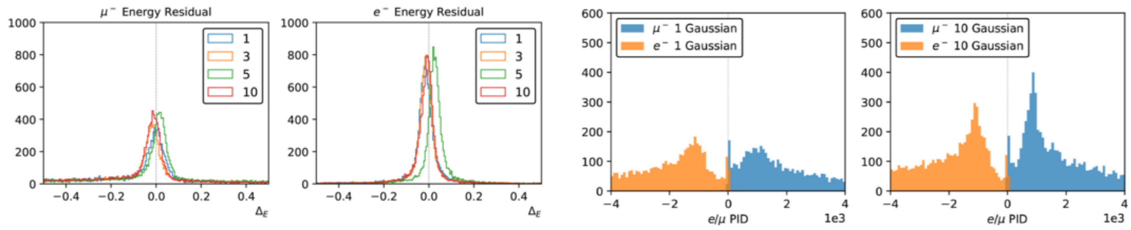

Figure 4: (a) Two left figures: Energy residual distribution for muons (left) and for electrons (right); (b) Two right figures: $\Delta Loss$ with 1-Gaussian fit (left) and with 10-Gaussian fit (right)

due to escaping events from the detector in which there is not enough information to distinguish electrons from muons. In fact if we apply a cut on the distance to the detector wall, the spikes are significantlly reduced.

4. Conclusions and Future Prospect

We have shown the promising first results from a new way of reconstructing events detected by a Super-Kamiokande type water Cherenkov detector based on a generative neural network. See our published article [2] for further details. The next step is to try full reconstruction without fixing values for some inputs to the network. This is in progress. We are also looking into a possibility of distinguishing gammas from electrons. It is obviously important to try to reconstruct multi-particle events. There are other neural network algorithms such as a variety of Generative Adversarial Networks (GANs) that may improve the performance in reconstruction.

5. Acknowledgements

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