FAST CASCADE GENERATOR GAN IN THE P-ONE EXPERIMENT*

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The simulation of electromagnetic cascades and Cherenkov photon emission is a key element of event reconstruction in neutrino experiments such as P-ONE. Traditional Monte Carlo tools, including Geant4, provide high accuracy, but generating large data samples requires substantial computational resources and time. In this work, we present a fast cascade generator based on a Generative Adversarial Network (GAN), designed to reproduce the spatial and spectral structure of photon emission in water. The use of GPU acceleration enables the generation of cascades hundreds of times faster than in classical Monte Carlo simulations. This approach allows for the production of large datasets in significantly shorter time while maintaining high consistency with reference data.

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1. Introduction

The Pacific Ocean Neutrino Experiment (P-ONE) [1] is an experiment dedicated to the study of high-energy astrophysical neutrinos. The experiment is currently under construction in the Pacific Ocean, off the western coast of Canada. It consists of modular detectors designed to register Cherenkov radiation. The detection elements will be deployed at large depths of approximately 2.6 km below the sea surface. The location of the experiment in the Northern Hemisphere enables the observation of neutrinos arriving from the sky in the Southern Hemisphere. Cherenkov radiation detectors do not detect neutrinos directly; instead, they measure the secondary particles produced in neutrino interactions with atomic nuclei in the

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surrounding medium. The analysis of the temporal and spatial distribution of this radiation is a key element in reconstructing the parameters of the primary neutrino [2]. For this reason, realistic simulations of electromagnetic cascades in water constitute an important component of the research. Monte Carlo methods provide high physical accuracy; however, they require substantial computational resources and long data-generation times. Consequently, there is a need to develop alternative approaches that accelerate the simulation process while preserving adequate physical fidelity. In this work, we present a fast cascade generator based on a Generative Adversarial Network (GAN), designed to reproduce the spatial and spectral structure of photon emission in water. By utilizing computational acceleration on Graphics Processing Units (GPUs), cascades can be generated up to several hundred times faster than with conventional Monte Carlo simulations, while maintaining a high level of agreement with reference data [3–6].

2. Physical principles of neutrino detection

The observation of neutrinos is a challenging task because neutrinos do not participate in electromagnetic interactions. As a result, they can travel vast distances without interacting with matter. Therefore, their detection relies on indirect methods. One such method, employed in the P-ONE experiment, is the observation of Cherenkov radiation [2].

This radiation is emitted when a charged particle travels through a dielectric medium at a speed v greater than the phase velocity of light in that medium. The condition for the emission of Cherenkov radiation is given by

$$\beta > \frac{1}{n}\,, \tag{1}$$

where β is the velocity of the particle in units of the speed of light

$$\beta = \frac{v}{c}\,, \tag{2}$$

and n is the refractive index of the medium [2].

2.1. Neutrino interactions and secondary particles

Neutrinos interact with nucleons (N) in matter by both the charged-current (CC) and neutral-current (NC) interactions. The CC interactions can be expressed as

$$\nu_l + N \to l + X\,, \tag{3}$$

where l denotes a charged lepton corresponding to the neutrino flavor and X represents the hadronic final state produced in the interaction. Neutrinos

also interact via neutral-current (NC) interactions

$$\nu_l + N \to \nu_l + X\,. \tag{4}$$

The experimental signature in the detector depends on the interaction type and neutrino flavor. In CC interactions of muon neutrinos (ν_μ), a muon track and a hadronic shower are produced. For electron neutrinos (ν_e), the CC interaction results in both an electromagnetic and a hadronic cascade. In contrast, NC interactions produce only a hadronic cascade, regardless of the neutrino flavor.

CC interactions of τ neutrinos (ν_τ) lead to the production of a τ lepton. Its subsequent decay can result in either a muon track or a particle cascade, depending on the specific decay channel. For instance, the decay of a τ lepton may produce either a muon or an electron together with neutrinos [2, 7].

Particle cascades play a crucial role in the detection of cosmic neutrinos, as the Cherenkov radiation they emit enables the observation of interactions in water and ice detectors. Assuming the standard neutrino flavor ratio of 1:1:1 on Earth (resulting from neutrino oscillations), approximately two-thirds of CC interactions manifest as cascade events [2, 7].

3. Fast cascade generator GAN

GANs have been widely applied in the simulation of physical processes, including calorimetry and particle cascade modeling. This serves as an inspiration for further application of generative models in projects requiring the production of high-fidelity data while maintaining optimal computational efficiency [3–5].

3.1. Fundamentals of GANs

The concept of GANs relies on the use of two competing neural networks: a generator (G) and a discriminator (D). The G's task is to reproduce the distribution of the training data, while the D evaluates the probability that a given sample originates from the real dataset rather than from the G. During the training process, the two networks compete in a zero-sum game. The creators of GANs compare the generator to a team of counterfeiters attempting to produce fake but convincing banknotes, while the D represents the actions of the police, aiming to detect the forgery. This competition drives both models to improve their performance, with the ultimate goal of generating samples that are indistinguishable from real data [6].

3.2. Training data

The training data used for model learning were obtained from simulations performed with Geant4 [8]. They were organized in a table format containing six columns, each corresponding to a feature describing a single Cherenkov photon. Each row of the table represents a set of six parameters characterizing an individual photon. The first three features correspond to the spatial coordinates of the photon emission point (x, y, z). The next two describe the emission angle relative to the z-axis and the Cherenkov photon wavelength. The final feature is the kinetic energy of the primary particle that initiated the cascade, which is identical for all photons within that cascade.

3.3. Cascade generator model architecture

The cascade generator architecture described in this work consists of two neural networks: a G and a D. The G network is composed of four linear layers [9]. Its task is to transform a vector of random noise into data that replicate the physical parameters of Cherenkov photon emission. The D network also consists of four linear layers. Its role is to classify input data as either "real" (originating from the training dataset) or "fake" (generated by the G model).

4. Preliminary results

Preliminary results are presented for a model based on a Generative Adversarial Network, which was developed to simulate Cherenkov photon cascades induced by an electron with a kinetic energy of 1 GeV propagating in water. The distributions shown in Figs. 1–3 are normalized to unity, and the vertical axes are displayed on a logarithmic scale to highlight the level

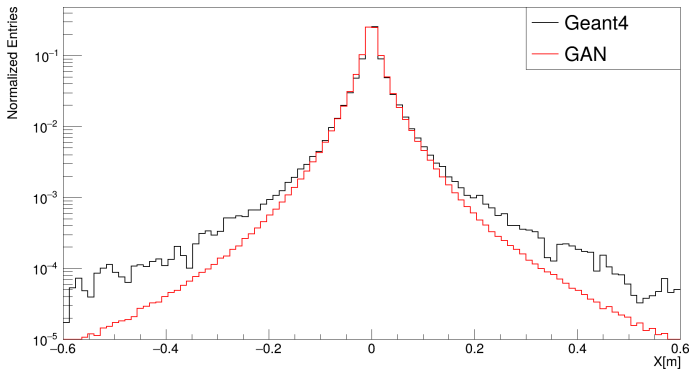


Fig. 1. Comparison of the distributions of the x-coordinate of Cherenkov photon emission.

of agreement. The distributions correspond to the spatial coordinates of the photon emission points (x, y, z) in water. The z-axis is aligned with the cascade propagation direction, and the z coordinate takes only positive values, whereas the x and y coordinates can take both positive and negative values. The GAN-generated distribution is indicated by a red line, while the Geant4 simulation is represented by a black line.

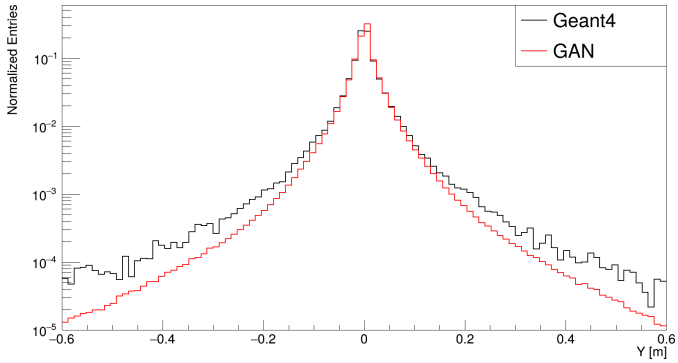


Fig. 2. Comparison of the distributions of the y-coordinate of Cherenkov photon emission.

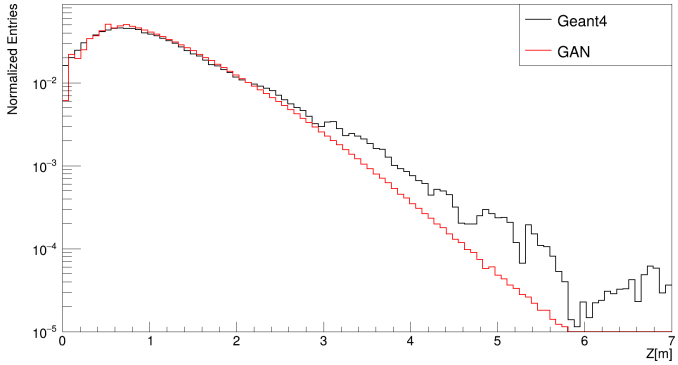


Fig. 3. Comparison of the distributions of the z-coordinate of Cherenkov photon emission.

In the analyzed cases (Figs. 1–3), the best agreement between the compared samples (GAN *versus* Geant4) was observed in the region of the distribution maximum, whereas more significant discrepancies appear in the tail regions. User-time measurements for data generation using the GAN model were performed. To evaluate computational performance, the calculations were carried out on both an NVIDIA Tesla V100 GPU and an Intel Xeon E5-2683 v4 CPU [10, 11]. A substantial performance advantage of the GPU

over the CPU was demonstrated, depending on the number of generated Cherenkov photons. For a sample containing 10^7 photons, the CPU/GPU execution time ratio was approximately 60; for 10^8 photons, about 270; and for 10^9 photons, around 380.

5. Conclusions

The preliminary results presented in this work indicate the feasibility of developing a GAN model for generating Cherenkov photon cascades in water. The model shows high agreement with reference data in the region of the distribution maximum, while significant discrepancies are observed in the tail regions. Performance measurements revealed a substantial advantage of GPUs over CPUs for sample generation, with the speedup depending on the number of generated photons. Ongoing work focuses on developing an alternative GAN model incorporating different types of neural network layers to further improve the quality of the generated data.

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