Technical Report

Use of Generative Adversarial Neural Networks in Scattering Muography

Ruben Lopez Ruiz,[1] Celia Fernandez Madrazo,[2] and Pablo Martinez Ruiz del Arbol[1]

[1]*Instituto de Física de Cantabria, Avda. Los Castros s/n, 39005 Santander, Spain*

[2]*University of Boston, Boston, MA 02215, USA*

Corresponding author: Pablo Martinez Ruiz del Arbol
Email address: parbol@ifca.unican.es

Abstract

Many muography applications make extensive use of simulations to determine detector design or to train imaging or regression algorithms. The computing cost of producing these simulations is usually quite high, especially concerning the interaction of cosmic muons with matter. This work explores the possibility of using Generative Adversarial Neural (GAN) networks to produce a fast and realistic simulation of the multiple scattering process. The results of the network are confronted with GEANT4 simulations using a benchmark problem related to the measurement of the inner wear of industrial pipes. The GAN is able to reproduce the angular distributions and correlations with a speed-up factor of roughly 50 with respect to GEANT4.

Keywords: muography, muon tomography, machine learning
DOI: 10.31526/JAIS.2024.487

1. INTRODUCTION

Muography is an emerging technology in fields such as vulcanology [1], civil engineering [2], archeology [3], and others. This technique can be applied in two different flavors: transmission muography and scattering muography. The former uses a single muon detector to measure the muon flux attenuation, while the latter uses two muon detectors and measures muon angular deviations. Transmission muography is typically used for problems involving very large volumes (up to hundreds of meters) while scattering muography is typically applied for smaller volumes (a few meters and below).

In the context of the industry, scattering muography is used as a Nondestructive Testing (NDT) technique to perform preventive maintenance of the equipment, process quality control, or risk assessment. Among many examples of these applications, the assessment of the thickness of insulated pipes [4], the measurement of the metal-slag interface in furnace ladles [5], or the density assessment of scrap containers [5] is found.

Problems in the industry differ from other fields in which muography is applied because the nominal geometries under inspection are usually very well known. Indeed, factories usually have detailed designs of the facilities and the equipment. Muography algorithms do not need to reconstruct the full geometry but only to determine variations with respect to these nominal geometries. In many cases, the problem can be restricted to a small number of parameters of interest. This opens the possibility of using machine learning methods to perform a regression on those parameters, at the cost of requiring a large amount of simulated samples to train the algorithms.

Simulation in muography can be divided into three different components: simulation of the original muon flux or muon generation; simulation of the detector response or muon digitization; and simulation of the passage of muons through matter or muon propagation. There are several packages in the market providing muon generation, such as CRY [6]. Most of them use parameterized versions of the measured cosmic muon flux and produce energy and angular distributions accordingly. This process is relatively fast and does not require a large amount of computing resources. The digitization process depends strongly on the detectors and therefore is usually specific to each experimental setup. The most CPU-consuming task is the muon propagation. It implies the simulation of, at least, the multiple muon scattering and energy loss processes. This task is usually done by the GEANT4 [7] software using a multistepping technique.

This work studies the feasibility of replacing the muon propagation simulation with a Generative Adversarial Neural (GAN) network [8]. These architectures are becoming more and more popular in High Energy Physics in the last years [9]. A benchmark case in the context of muography applied to the industry has been used to quantify the goodness of the simulation. The GAN has been trained using GEANT4 simulations of a setup with one parameter of interest as described below. Finally, a comparison between GEANT4 simulations and the output of the GAN has been performed.

2. SIMULATION SETUP

The simulation setup replicates the scattering muography setup implemented by Muon Systems and consists of two detectors located on the top and below the object under study. Figure 1 shows a picture of the detectors and a simple scheme of the setup. The upper detector is composed of two muon chambers while the lower detector is composed of three, although only two of them were used. The chambers are multiwire proportional chambers (MPCs), which are designed to provide good spatial and angular resolutions. The employed MPCs consist of an array of parallel anode wires located in between cathode planes with a high voltage difference. The full system is inserted in a hermetic box with electrically grounded walls. The wires have a separation of 4 mm and are embedded in a mixture of argon and CO_2. Within each detector, a minimum of two layers of wires are positioned perpendicular to one another to measure the X and Y coordinates within a plane that runs parallel to the Earth's surface. The configuration of these layers ensures coverage across an effective area of about 1 m^2. Each detector provides a measurement for the position $\vec{x}$ at which the cosmic muon crosses the layers and the direction $\vec{v}$ of the trajectory.

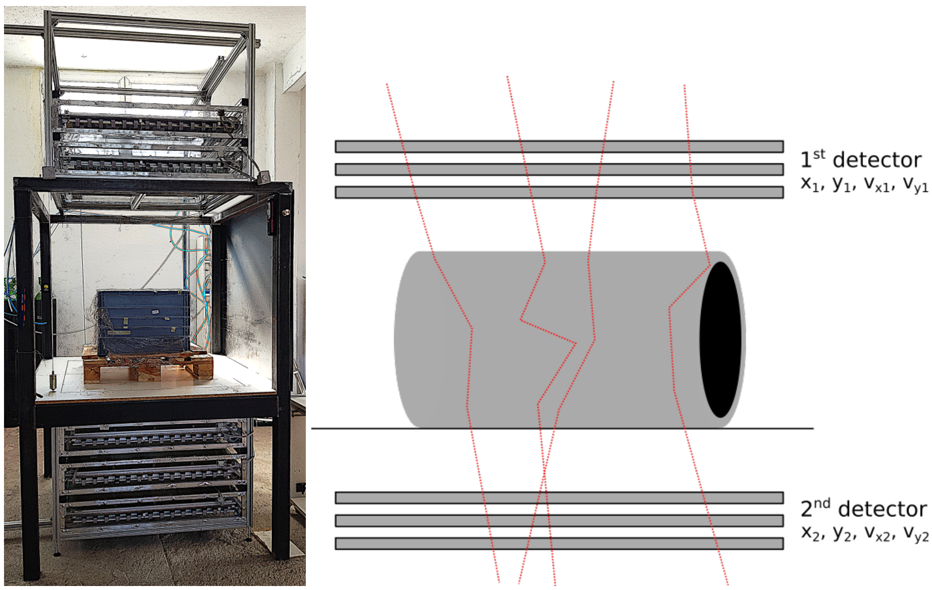

FIGURE 1: Real picture of the set up at Muon Systems (left). Scheme of the setup (right).

Cosmic muons are generated using the CRY generator. The propagation of muons through matter is performed using GEANT4 including typical physics processes used in muography applications. A realistic description of both the detectors and the pipes is provided to GEANT4. The detector response is simulated with customized software calibrated to match the response of the detectors of Muon Systems.

This work studies the problem of the estimation of the corrosion in the inner walls of insulated pipes. A set of simulations with pipes of different sizes have been performed. Pipes are made of steel and have a surrounding 2 mm-thick layer of aluminum. The outer radius of the pipe is 20 cm while the inner radius varies according to the simulation. The number of samples used for training and evaluation is summarized in Table 1.

Pipe thickness (mm)	Number of training samples	Number of evaluation samples
4	619605	300000
6	618798	300000
8	617951	300000
10	616700	300000
14	614944	300000
16	615216	300000
18	614109	300000
20	613692	300000
12*	—	300000

TABLE 1: Dataset composition. *Only used to evaluate interpolation capabilities.

The information provided to the GAN network as a single element of the data sample is the position (x, y) and the vector direction $(v_x, v_y, 1)$ of the muon in the first and the second detectors, and the value of the thickness of the pipe that the muon went through (r), constituting a total of 9 variables.

3. GAN ARCHITECTURE

The objective of this work is to train a conditional GAN model to generate the position and direction of the outgoing muon, using as input the coordinates of the incoming muon and the thickness of the pipe, which is defined as the parameter of interest. Therefore, the input of the desired model will be conformed by three parts: the position and direction (x and y coordinates) of the incoming muon, the thickness r of the pipe, and 16 latent variables that seed the generation. The output of the model will be determined by 4 variables that represent the shift in position and trajectory of the muon with respect to the straight line. These are defined as follows:

$$\Delta x^* = x_2 - x_1 + Lv_{x1}, \quad \Delta y^* = y_2 - y_1 + Lv_{y1}, \quad \Delta v_x = v_{x2} - v_{x2}, \quad \Delta v_y = v_{y2} - v_{y2}, \tag{1}$$

where L is the vertical distance between the two detectors. These 4 variables contain all the relevant information about the muon propagation process.

The architecture considered for the training of the model has been the Wasserstein GAN with Gradient Penalty (WGAN-GP) [10]. The generator network (G) has 3 hidden layers with 32, 64, and 128 nodes, activated with Leaky ReLU functions, and outputs 4 values. The critic (C) inputs the 8 variables plus the thickness label and has the same hidden layers as G but in reverse order. This configuration was obtained after a process of hyperparameter optimization based on trial and error in which the network architecture was varied, as well as the dropout intensity (finally discarded), and the activation functions.

The model has been trained for 1000 epochs using the Adam optimizer with a learning rate of 0.0001. Batches of 5000 samples have been used, and the C weights have been updated 5 times for each G update. Nearly 620000 samples for each pipe thickness were used for the training, keeping the class population balanced. Samples corresponding to pipes with thickness $r = 12$ mm are not used in the training but are kept for testing purposes exclusively.

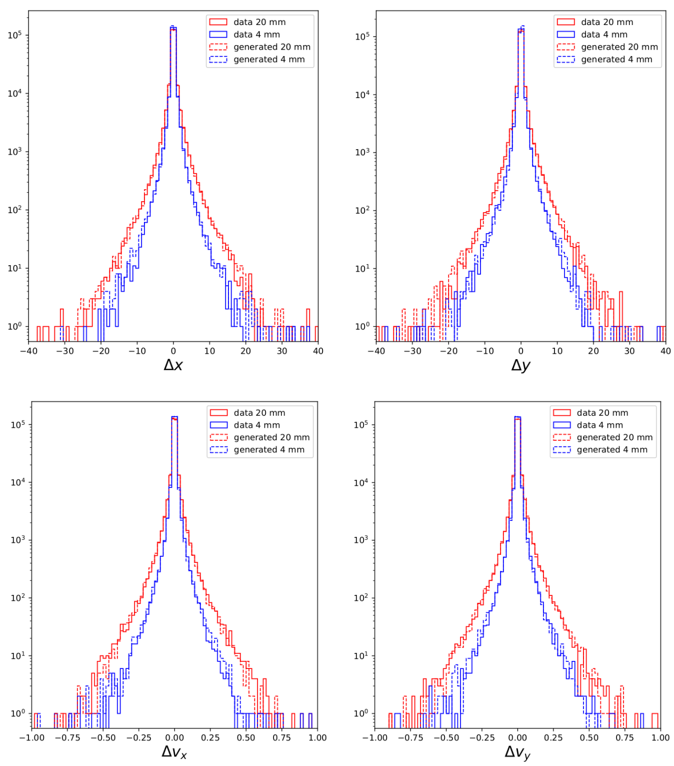

FIGURE 2: Distributions of real (solid) and generated (dashed) samples corresponding to two different values of thickness.

4. RESULTS

The performance of the network has been evaluated in two ways: first, by producing samples conditioned to the same thickness classes used in training and by testing the similarities between the real and generated samples. The comparison between the distributions generated with GEANT4 and the GAN can be found in Figure 2. Then, the interpolation capabilities of the model have also been tested by producing samples conditioned to a thickness value in the middle of two values already seen by the model. In this way, the network's capability to generalize and interpolate results out of the points in which it was trained is tested. The results can be seen in Figure 3. From these figures, it can be seen, qualitatively, that the model is capable of replicating the distributions of the 4 kinematic variables, both in the bulk and in the tails. Also, it can be observed that it is possible to tune its generation using a parameter and that the model is able to interpolate and generate samples that correspond to thickness values to which it was not exposed in the training process. Indeed, the Wesserstein distance between the GEANT4 and the GAN distributions is 0.024 ± 0.007 cm and 0.00051 ± 0.00008 for the spatial and angular coordinates, respectively, where the average over all the pipe thickness cases has been used. The distance between the interpolated case of $r = 12$ mm and the corresponding GEANT4 simulation is 0.021 cm and 0.0004 indicating that the interpolation works as well as the other simulations.

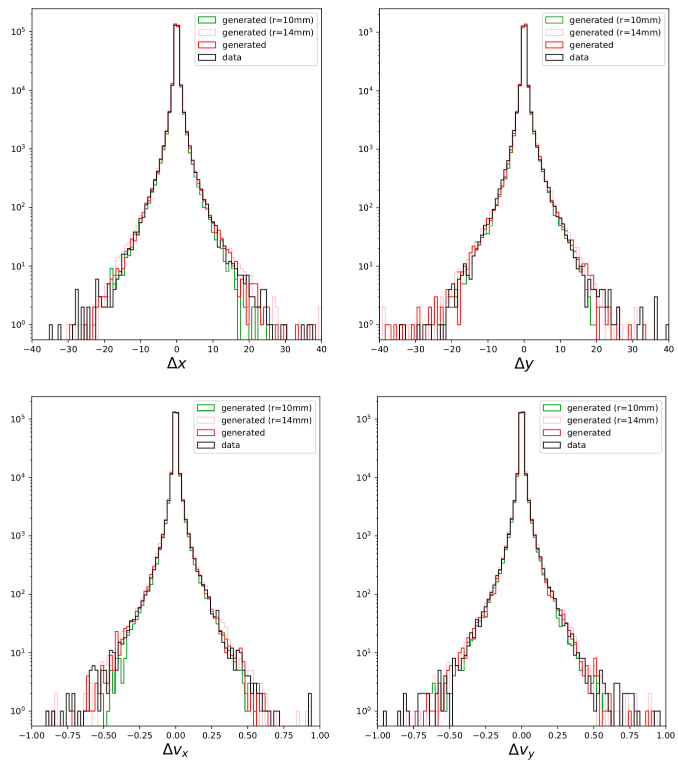

FIGURE 3: Distributions of real (black) and generated (red) samples corresponding to a value of $r = 12$ mm, which the model never learned.

It should be noted that in this work we are aiming for a model that generates a 4D distribution. Therefore, the model should reproduce not just the 4 kinematic variables but also the correlations among them. Figure 4 shows the correlations of the predicted variables. In this setup, the strongest correlations are found between the pairs of variables Δx^*-Δv_x and Δy^*-Δv_y. The figure shows, qualitatively, that the trained model is able to reproduce well these correlations, meaning that the sample-by-sample generation is good.

Finally, the gain in computation time with respect to GEANT4 has been evaluated. For this, 10000 muon events have been generated in a controlled environment. The muon propagation part took GEANT4 about 37 seconds, while for the GAN model this time is reduced to 0.7 seconds. This constitutes an improvement of roughly a factor of 50, which is very significant when producing large amounts of simulation data. It should be noted that the sampling of the GAN was not optimized and probably sampling more than one event, as it was done, at the same time could speed up this factor much more when using a GPU.

5. CONCLUSIONS

This work studies the application of generative ML models and, more in particular, Generative Adversarial Networks, for simulation purposes in the context of muon tomography for industrial applications. This first approach on the subject shows that it is indeed possible to train a GAN model to simulate the propagation of muon events through different objects and also that the model has interesting capabilities, such as modulation of the output and interpolation between labels. Nevertheless, this work is intended as a starting point for the exploration of many other new generative ML models for the same purpose. More exhaustive tests will be done in the future in order to assess the suitability of generated samples to replace the GEANT4 simulation.

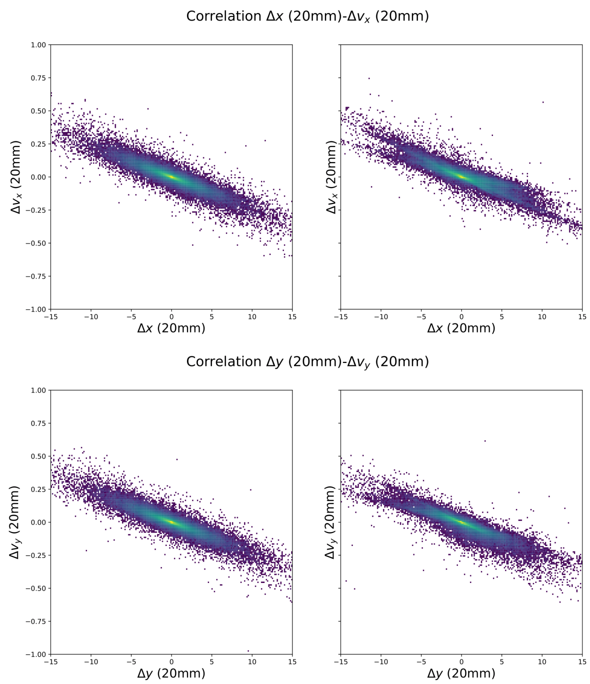

FIGURE 4: Correlations of real (left) and generated (right) samples corresponding to a thickness of $r = 20\,\text{mm}$.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] Raffaello D'Alessandro et al., Volcanoes in Italy and the role of muon radiography, Phil. Tran. A, 377 (2137 2019), doi:10.1098/rsta.2018.0050.
[2] László Oláh et al., Improvement of cosmic-ray muography for Earth sciences and civil engineering, vol. 358. Sissa Medialab Srl, July 2019, doi:10.22323/1.358.0377.
[3] Luis W. Alvarez et al., Search for hidden chambers in the pyramids, Science 167 (39191970), pp. 832–839, doi: 10.1126/science.167.3919.832.
[4] P. M. Ruiz-Del Arbol et al., Non-destructive testing of industrial equipment using muon radiography, Phil. Tran. A, 377 (2137 2019), doi:10.1098/rsta.2018.0054.
[5] P. Martinez Ruiz del Arbol et al., Applications of Muography to the Industrial Sector, Journal of Advanced Instrumentation in Science, vol. 2022, Apr. 2022.
[6] Chris Hagmann, David Lange, and Douglas Wright, Cosmic-ray shower generator (CRY) for Monte Carlo transport codes, vol. 2. 2007, pp. 1143–1146, doi:10.1109/NSSMIC.2007.4437209.
[7] S. Agostinelli et al., GEANT4—A simulation toolkit, Nuc. Ins. Meth. A, vol. 3, 250–303, doi:10.1016/S0168-9002(03)01368-8
[8] Goodfellow, Ian, et al., Generative Adversarial Nets, Proceedings of the International Conference on Neural Information Processing Systems (NIPS 2014). pp. 2672–2680.
[9] R. Kansal et al., Evaluating generative models in high energy physics, Phys. Rev. D, 107, 076017 (2023), doi:10.1103/PhysRevD.107.076017.
[10] Gulrajani et al., "Improved Training of Wasserstein GANs," 10.48550/ARXIV.1704.00028 (2017).