MACHINE-LEARNING-BASED TRACKING FOR MUonE EXPERIMENT*

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The anomalous magnetic moment of the muon is one of the promising sectors for probing New Physics. Recent results from $g-2$ experiments indicate a possible deviation of about 5σ from the Standard Model prediction. The MUonE experiment was designed to precisely measure the hadronic contribution to the muon anomalous magnetic moment, which could increase the significance to at least 7σ and thereby confirm potential discovery. Several crucial milestones have already been achieved by the MUonE project, and the results of the ongoing 2025 test run analysis will serve as the foundation for the full-scale 40 station proposal to be implemented after the LHC Long Shutdown 3. However, classical event reconstruction will face a significant challenge due to combinatorial scaling in this final configuration. To address these challenges, the use of Graph Neural Networks (GNNs) is proposed for the pattern recognition stage, as they offer the flexibility to process irregular geometries while maintaining the low latency required for a trigger. This allows for robust track reconstruction even in scenarios where detector hits may be missing, ensuring accurate performance under imperfect or incomplete data conditions.

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1. Introduction

When a particle interacts with a static magnetic field, its magnetic moment $\vec{\mu}$ is proportional to its spin $\vec{S}$ via the gyromagnetic constant (g-factor)

$$\vec{\mu} = g\left(\frac{e}{2m}\right)\vec{S}\,.$$

While the Dirac equation predicts a g-factor of exactly 2 for point-like fermions, quantum corrections from electromagnetic, weak, and strong interactions cause it to be slightly higher. This deviation is defined as a_μ,

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the anomalous magnetic moment

$$a_\mu = \frac{g-2}{2}\,.$$

For electrons, the anomaly has been measured with extreme accuracy and has become a crucial stress test for the Standard Model. Due to the much higher mass ($m_\mu \approx 207 m_e$), the muon's anomalous magnetic moment is significantly more sensitive to corrections arising from potential heavy-loop contributions associated with New Physics phenomena. Hence, efforts to improve the precision of measurement has lasted for decades. Currently, a significant tension exists between the experimental average (shown in Fig. 1) and the Standard Model prediction, corresponding to a discrepancy of about 5σ [1, 2].

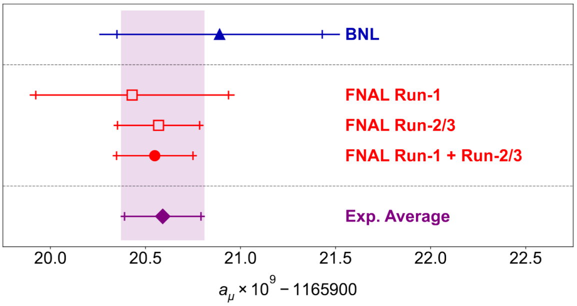

Fig. 1. Values of a_μ measured experimentally. Vertical marks indicate statistical part of the total uncertainty. Figure taken from [1].

The Standard Model prediction carries an uncertainty that is, at best, on the same level as that of the measurement. Meanwhile, the hadronic contributions — the Hadronic Vacuum Polarization (HVP) term and the Hadronic Light-by-Light (HLbL) term — account for about 99.8% of this uncertainty and cannot be calculated using perturbative methods. At present, the leading-order contribution from hadronic vacuum polarization ($a_\mu^{\text{HVP, LO}}$) is estimated either with data-driven methods or through lattice-based calculations. Although lattice approaches appear to better agree with the experimental measurements, the underlying tension remains unresolved.

2. MUonE experiment

The limited precision of integrating hadronic cross sections constitutes the primary constraint of data-driven approaches of calculating the hadronic contribution to a_μ. This limitation is further enhanced by the presence of numerous resonances and threshold effects. The MUonE project provides an alternative procedure that can measure the hadronic contribution to a_μ. In this approach, the integral involves a smooth function of the hadronic component [3]. From the experimental point of view, this reduces the problem to measuring the differential cross section of a single $\mu + e \to \mu + e$ scattering. This creates an opportunity to extract the hadronic contribution with extreme accuracy, as all other contributions can be calculated perturbatively. Moreover, systematic uncertainties can be significantly suppressed by taking the ratio of the cross section in the elastic signal region to that in a reference region where the angular correlation is negligible.

2.1. MUonE experimental setup

The MUonE experiment apparatus is being operated at the upgraded M2 beam of the CERN SPS, which delivers high-intensity muons with an energy of 160 GeV, as well as low-intensity calibration beams [4]. It is required that systematic effects must be controlled at the same level as the statistical precision. To achieve this, the MUonE apparatus is designed as a modular system consisting of up to 40 identical tracking stations. Each station begins with a low-Z target, such as beryllium or carbon, followed by a high-precision tracking system. Within every station, six layers of silicon strip sensors are used. These are arranged in a specific configuration: an initial XY pair, followed by two stereo planes — U and V — tilted at 45 degrees, and a final XY pair (see Fig. 2). At the end of the detector, an electromagnetic calorimeter and a muon chamber are located. The sensors provide a hit resolution of approximately 10 microns.

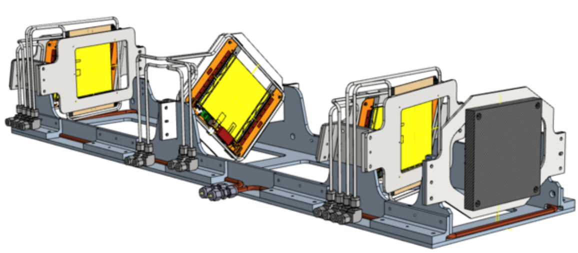

Fig. 2. A schematic view of a single MUonE tracking station. Figure taken from [5].

2.2. Status of the MUonE experiment

The MUonE project has progressed through several critical milestones. In 2018, a successful proof of concept was demonstrated downstream of the COMPASS experiment, where the ability to extract a clean sample of elastic events was achieved [6]. By 2022 and 2023, the project moved to a more realistic pilot-runs. Utilizing a beam at 40 MHz, approximately one hundred million events were collected. These runs served to validate the DAQ system, onboard electronics, and sensor alignment procedures [5]. The 2025 run is the most realistic configuration to date, featuring three fully instrumented tracking stations integrated with the calorimeter and muon identification system. With the analysis currently underway, these results will form the technical basis for the full-scale proposal of 40 stations following the LHC Long Shutdown 3.

3. Machine learning techniques for MUonE tracking

Classical event reconstruction will face a significant challenge due to combinatorial scaling in the final MUonE configuration. This creates a massive computational overhead, which is particularly problematic since the experiment demands real-time, trigger-level reconstruction. Pattern recognition has been identified as the primary bottleneck in the reconstruction chain. To address these conditions, the use of Graph Neural Networks (GNNs) [7] is proposed for the pattern recognition stage. Since detector hits are inherently distributed as points in space, a graph serves as the most natural representation of the data. Consequently, GNNs provide the flexibility to process irregular geometries with the low latency necessary for real-time triggers. Previous studies using Deep Neural Networks demonstrated that machine-learning-based approaches can achieve angular resolutions comparable to those obtained with conventional reconstruction algorithms [8]. In this proposal, the model acts as an edge classifier, assigning weights to potential connections between hits. A weight of one indicates a true track fragment, while zero indicates a false connection.

4. GNN-based pattern recognition

The data representation for this study utilizes a three-station setup, consistent with the 2025 test run geometry. A key feature of this approach is that only raw 2D strip information is used as input. Figure 3 illustrates a plot of a typical training event. Only hits from stations located after the target — specifically stations two and three are considered.

The proposed model demonstrates a high edge-classification accuracy of approximately 99.4% (see confusion matrix in Fig. 4). It should be noted that these statistics refer specifically to the edge-classification task rather than the final track reconstruction efficiency. An example of a fully successful classified graph is shown in Fig. 5.

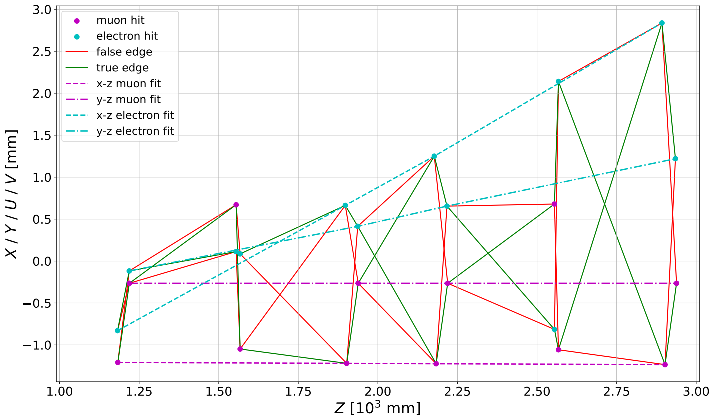

Fig. 3. A representative training event. The horizontal axis represents the beam direction (z), while the vertical axis shows the hit position. It should be noted that all hits are projected onto a single plane regardless of their original orientation. Consequently, while X and Y hits appear to form straight lines, the hits from rotated stereo modules U and V appear offset. In this graph representation, green lines represent edges to be classified as true track segments, while red lines denote false combinatorial connections.

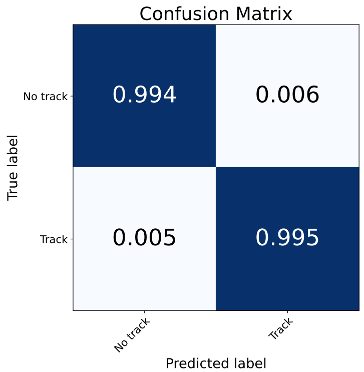

Fig. 4. Confusion matrix of the network recognizing edges building a track.

4.1. GNN for particle identification

The GNN model can also be easily extended to incorporate particle identification by modifying the output to a three-class probability vector. This allows the model to classify edges as false segments, muons, or electrons within a single step. The inclusion of this additional particle information did not decrease the efficiency of the primary track-*versus*-no-track clas-

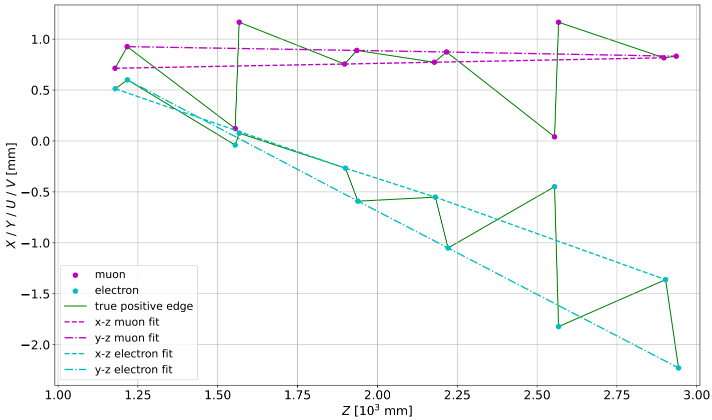

Fig. 5. The plot follows the same format as the previous one but shows the graph after classification. For clarity, edges classified as false are omitted, leaving only the predicted true track segments. Two track candidates identified by the model in this event can be observed.

sification. While a cross-classification rate of 12 to 14% is currently observed between muons and electrons, this approach demonstrates that track reconstruction and particle identification can be performed simultaneously without compromising overall performance.

5. Summary

The MUonE experiment represents a promising avenue for exploring New Physics through the precise measurement of the hadronic contribution to the muon anomalous magnetic moment. The project is well advanced, with full-scale data collection expected to start following the LHC Long Shutdown 3. Classical event reconstruction will become increasingly difficult at online stage due to combinatorial scaling in the final MUonE configuration. The use of Graph Neural Networks is proposed to mitigate this issue, as they can provide an effective solution for pattern recognition within the trigger system. Even without providing explicit detector orientation data to the model, it maintained high reconstruction accuracy. Moreover, the model can be easily extended for simultaneous particle identification. Future work will focus on further optimizing the architecture for high-performance, real-time applications.

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