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Abstract

This paper presents an algorithm that combines track finding and track fitting, designed for track reconstruction in the Electron-ion Collider in China (EicC). The algorithm's goal is to fulfill the criterion of high track reconstruction efficiency. The algorithm is modularly constructed, leveraging an advanced cellular automaton model and the Kalman filter method to implement its core functionality. We optimized the algorithm using fully simulated Monte Carlo events in the EicCRoot software framework. The performance of the method is validated, demonstrating excellent track reconstruction efficiency that fully meets the physical requirements of the EicC experiment.

Full Text

Preamble

A Track Reconstruction Algorithm for the EicC Central Detector∗

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This paper presents an algorithm that combines track finding and track fitting, designed for track reconstruction in the Electron-Ion Collider in China (EicC).

The algorithm's goal is to fulfill the criterion of high track reconstruction efficiency. The algorithm is modularly constructed, leveraging an advanced cellular automaton model and the Kalman filter method to implement its core functionality. We optimized the algorithm using fully simulated Monte Carlo events in the EicCRoot software framework. The performance of the method is validated, demonstrating excellent track reconstruction efficiency that fully meets the physical requirements of the EicC experiment.

Keywords: Track finding, Electron-ion collider in China, Cellular automaton, Kalman filter

Introduction

Lepton scattering is an established ideal tool for studying the inner structure of nucleons [1]. As a future high-energy nuclear physics project, EicC has been proposed [2]. The primary objectives of the EicC will include conducting precision measurements of the nucleon's structure in the sea quark region, performing 3D tomography of nucleons [3–5], exploring the partonic structure of nuclei [6, 7], and investigating how partons interact with the nuclear environment [8–10]. Additionally, the EicC will also focus on studying exotic states [11–13], particularly those containing heavy flavor quarks.

The EicC will operate at a center-of-mass energy range of 15–20 GeV, achieving a peak luminosity exceeding 2.0×10^{33} cm$^{-2} \cdot$ s^{-1} while maintaining polarization levels of approximately 80% for electrons and 70% for protons under collider conditions [14, 15]. Driven by the physics program of EicC, a conceptual design for a general-purpose spectrometer is proposed [16, 17], which has a cylindrical structure, built with different layers around the beam pipe.

Charged particles initially enter the tracking detector, where they interact with sensitive electronics to produce detectable signals (or "hits"). These hits are then analyzed to reconstruct both the particles' trajectories and their spatial origin. The layout of the vertex and tracking system is depicted in [Figure 1: see original paper]. The magnetic field within the tracking detector region is maintained at a strength of 1.5 Tesla, achieved by a superconducting solenoid positioned outside the central detector. This solenoid features a radius of approximately 3 meters and extends to a length of about 4 meters. Its design ensures an optimal balance between field strength and coverage, providing the necessary magnetic environment for accurate particle trajectory measurements. The central tracking system is segmented into three distinct regions: the barrel region, the ion-going region (aligned with the positive Z direction), and the electron-going region (aligned with the negative Z direction). This division reflects the directional motion of the beams: the ion beam progresses along the positive Z axis, while the electron beam travels oppositely along the negative Z axis. The tracking detector in each region is described as follows.

The tracking detector in the barrel region consists of an inner silicon layer [18–20] and an outer micropattern gaseous detectors (MPGD) layer [21, 22]. The inner silicon cylinder has three vertex layers and two tracking layers, occupying an area with a maximum radius of 15 cm and a total length of 28 cm. The vertex layer utilizes wafer-scale suture sensors that bend around a beam pipe made of a beryllium cylinder with a radius of 3.17 cm, and the tracking layers also use the same stitched sensors but with different support structures. The outer MPGD has two closely-spaced 2-D layers of Micro-Mesh Gaseous Detector (MMGD) which are chosen to cover the outermost barrel region. Their mean radii are approximately 48 cm and 77 cm, and their maximum total length of approximately 200 cm. The radii of each layer and their corresponding lengths along z are summarized in .

In the forward (ion-going) direction, five silicon tracker disks span z from 25 cm to 134 cm from the interaction point. Their radial coverage (minimum defined by beam/tube divergence, maximum 77 cm) ensures particle tracking. A MMGD at $z = 165$ cm provides forward coverage with 8 cm to 150 cm radial range.

In the backward (electron-going) direction has five silicon disks. These disks start at 25 cm along the z-axis from the point of interaction and extend back to 145 cm. The minimum radius of the disc is determined by the divergence of the beam tubes, which ensures that they do not interfere with the beam path. The maximum outer radius of the disc is about 77 cm, providing ample coverage to track particles in the receding area. All the geometry parameters and position, as well as the material budget in the two endcap regions, are listed in and .

The transverse momentum dependent (TMD) parton distribution functions (PDFs) studies at the EicC demand detector and algorithmic capabilities beyond conventional designs. Due to the physical necessity of probing small hadron transverse momentum ($PhT < 1$ GeV) to constrain the intrinsic parton kT distribution and test TMD factorization, the detector must maintain efficient tracking performance even in extreme kinematic limits. These conditions create two intertwined algorithmic challenges. For tracks with low transverse momentum ($p < 0.5$ GeV), multiple Coulomb scattering in detector material and extreme curvature in solenoidal magnetic fields significantly degrade pattern recognition robustness. This not only demands adaptive track fitting algorithms incorporating impact parameter weighting but also necessitates stringent optimization of detector material budgets to minimize multiple scattering-induced resolution loss. Meanwhile, particles traversing near-zero polar angles ($\rightarrow 0°$) must be disentangled from beam-gas backgrounds and diffractive secondaries, adding computational overhead for real-time background rejection without sacrificing efficiency. To achieve physics objectives under the EicC's high-luminosity regime, the tracking software stack must simultaneously maximize reconstruction efficiency ($> 95\%$) across a wide momentum range, maintain wide polar angle coverage, and operate with sub-microsecond latency per event to process 10^5–10^6 interactions per second.

The cellular automaton (CA) [23] algorithm is adopted for track reconstruction at the EicC due to its capability in resolving low-momentum and large-angle particles under high occupancy. By modeling detector hits as spatially correlated cells, the CA naturally avoids combinatorial explosion inherent to Kalman filter-based methods while allowing curvature-aware hit merging in solenoid magnetic fields. This hybrid strategy combining physics-informed cellular evolution enables robust pattern recognition in the EicC's beam-gas-background-dominated regimes.

The CA method is widely adopted as a track-finding algorithm in particle physics experiments. For instance, in the Belle II experiment, signals measured by the Central Drift Chamber are filtered, reconstructed using a CA algorithm, and subsequently fitted to tracks via a deterministic annealing filter [24]. Similarly, the CMS experiment employs a parallelized CA-based track-seeding method in its Phase-1 upgraded pixel detector to efficiently resolve combinatorial complexity under extreme pile-up conditions [25].

II. Track Reconstruction for EicC

Track reconstruction involves determining the paths of charged particles as they propagate through a particle detector. When particle beams collide, the resulting charged particles move through a gaseous or solid-state medium under the influence of a uniform magnetic field. The Lorentz force, F = q(v × B), acts perpendicularly to both the particle velocity and the magnetic field, causing the particles to follow curved trajectories. In the central detector region, where the magnetic field is typically uniform and perpendicular to the transverse plane, these particles trace out helical paths, as illustrated in [Figure 2: see original paper]. The trajectory of the particle's motion is described by the following equation:

$$x(s) = x_0 + R\left[\cos(\phi_0 + hs/R) - \cos\phi_0\right] \tag{1}$$

$$y(s) = y_0 + R\left[\sin(\phi_0 + hs/R) - \sin\phi_0\right] \tag{2}$$

$$z(s) = z_0 + s\sin\lambda \tag{3}$$

Among them, the parameter λ is the dip-angle and h is $±$1 which is the sense of rotation of the helix. The projection of this trajectory on the x-y plane is a circle, as shown in the right panel of [Figure 2: see original paper]. The parametric equation of this circle is:

$$(x - x_0 + R\cos\phi_0)^2 + (y - y_0 + R\sin\phi_0)^2 = R^2$$

Here, the parameters x_0 and y_0 are the coordinates at s=0, and $_0$ is also related to the slope of the tangent to the circle at s=0. The quantity R represents the radius of the circle.

Moving charged particles, e.g. electrons, interact with the material in a detector and leave behind signals (e.g. ionization or light). These signals are recorded at specific hits in the detector, typically using layers of sensors arranged in a geometric pattern as shown in [Figure 3: see original paper]. The trajectory reconstruction consists of two parts: track finding and track fitting. Track finding refers to analyzing the spatial distribution of these signals (hits) and determining candidate particle trajectories. Track fitting involves applying a track model to fit the points associated with a single candidate trajectory in order to determine key particle properties such as momentum, charge, and vertex position.

A. The Process of Track Reconstruction

By leveraging the geometric structure of the EicC detector, we have implemented a tracking algorithm that integrates a CA-based track finding approach with the Kalman Filter (KF) [26] for track fitting. CA are computational models comprising discrete grid cells, each adhering to finite states and evolving through localized rules based on their current state and neighborhood interactions. Their parallelism, ability to model spatial correlations via proximity-driven rules, and adaptability to hierarchical patterns make them suitable for high-energy physics track reconstruction [24, 25, 27, 28]. They efficiently resolve particle trajectories from detector hits by iteratively connecting adjacent signals while suppressing noise through localized decision-making. Compared to traditional track finding methods, e.g. Hough transform [29], one of the most significant advantages of CA is their inherent parallelism [25]. In track finding, where large amounts of data from detectors need to be processed simultaneously, the ability to process many elements in parallel significantly reduces the overall computation time, and CA algorithms can be efficiently implemented on parallel hardware, such as Graphics Processing Units or dedicated parallel computing clusters.

The KF is an optimal estimation algorithm used to predict and correct the state of a dynamic system over time, based on noisy or incomplete measurements. It operates recursively by combining prior knowledge (predictions) with new data (observations) to improve accuracy in estimating unknown variables [30]. In tracking particles in detectors, its ability to handle noisy measurements, estimate the state of a system over time, and optimize trajectory reconstruction makes it highly effective in various experimental scenarios.

This algorithm processes tracks generated by Monte Carlo (MC) simulations [31, 32]. Utilizing the EicCRoot software framework, which is an object-oriented framework built upon FairRoot [33], the algorithm reconstructs tracks based on the hits left by simulated tracks on the detector layers. The implementation process of the algorithm is shown as follows: (1) Read all the hits information from the simulation. (2) Perform the track-finding algorithm by the CA method. (3) Fit the found track candidates by the KF method to obtain the track information.

B. The Application of CA to EicC Track Finding

As previously mentioned, the tracking system of the EicC is divided into three regions: the barrel, the ion-going endcap, and the electron-going endcap. As shown in [Figure 4: see original paper], the barrel consists of nine layers, the ion-going region has six layers, and the electron-going region contains five layers. To facilitate the processing of hit information across these many layers, we assign unique identifiers to each detector layer. Specifically, layer IDs in the barrel are numbered from 0 to 8, in the ion-going region from 9 to 14, and in the electron-going region from 15 to 19. The detailed description of the full track finding procedure is presented below.

Graph Creation: Using the EicC software framework, we generated 10,000 MC single-muon events, where the track momentum ranges from 0 to 5 GeV and the angular distribution covers the full 0 to 360 degrees. We analyzed all track trajectories and recorded every possible combination of detector layers that a track can pass through as shown in . The table's left column lists the layer combinations, while the right column displays the frequency of each specific combination's occurrence. These combinations, referred to as graphs, form the basis for the subsequent track-finding algorithm.

Creation of Cells: After graph creation, we need to connect the hit points of adjacent layers to form a doublet, which serves as a cell in the graph. The core component of the algorithm involves determining whether two hits from adjacent layers can be linked to form a doublet. Given that a particle's trajectory in the tracking system is helical, we decompose the trajectory into two planes: the x-y plane and the r-z plane. On these two planes, we evaluate whether the angle formed by connecting the two hit points to the coordinate origin meets a predefined critical value, thereby determining if hits between adjacent layers can be linked to form a doublet. We analyze 10,000 events generated by MC simulation and examine the angles formed by adjacent hit points on each real track. According to this study, as the cutting becomes more relaxed, the efficiency increases accordingly. As illustrated in [Figure 5: see original paper], the coverage efficiency of true hit pairs exhibits a strong dependence on the angular selection thresholds in both the transverse (x-y) and longitudinal (r-z) planes. On the x-y plane, relaxing the threshold beyond 2.5 mrad ensures that over 99% of true hit pairs are retained, with full efficiency (100%) achieved near 4 mrad. Similarly, on the r-z plane, a threshold exceeding 0.009 mrad recovers 98% of true hits, while full coverage is attained around 0.03 mrad. These thresholds define critical boundaries for selection optimization, maximizing efficiency while minimizing contamination from false hit pairs in mixed samples. All adjacent layers in a graph are given to a function in turn, and the algorithm judges all hit pairs according to the geometrical requirement obtained from the simulation data shown above. Then all the hit pairs that satisfy the requirement are saved to a specific data structure for further processing.

Definition of Graph: A graph is a data structure that encodes information about all detector layers, the pairs of adjacent layers, and the root layer through which the particle travels. The root layer refers to the first detector layer a particle traverses after the collision. The construction of the graph is a crucial step in the algorithm's initialization process, with all subsequent algorithmic operations building the necessary data structures based on the specific layer list of each graph.

Cells Connection: The connection of cells is the key procedure for track finding with CA. The first step is to convert all doublet data structures into cell data structures. Starting from the root layer of each graph, a state variable, CAState, is assigned to each cell, initialized to zero. The second step consists of finding neighbors for each cell. Two cells are considered neighboring cells if all of the following conditions are satisfied: Firstly, they belong to different layer pairs. Secondly, they share a common hit, where the inner hit of one cell is the outer hit of the other. Finally, the corresponding constraints are satisfied in both the x-y and r-z planes. The angle between two neighboring cells in x-y plane is illustrated in [Figure 6: see original paper].

To establish the criteria for selecting neighboring cells in the x-y and r-z planes, we simulated 10,000 events. As shown in [Figure 7: see original paper], the coverage efficiency of actual cell connections depends significantly on the angular selection thresholds in both the transverse (x-y) and longitudinal (r-z) planes. On the x-y plane, a threshold exceeding approximately 0.6 mrad retains over 99% of true connections—nearly reaching full efficiency. Meanwhile, on the r-z plane, a more lenient threshold beyond 0.0009 mrad ensures complete (100%) coverage. These thresholds serve as approximate boundaries for cut optimization when distinguishing true connections from background mixtures in later analyses. For each graph, the algorithm evaluates adjacent cells based on these criteria derived from the simulation. The IDs of matched cells are stored to ensure that matched adjacent cells can be accurately identified in subsequent stages of the algorithm.

Evolution and Track Candidate Creation: After establishing the graph, including all cells and their relationships, the final step in track finding is to select the longest path from a root cell within the graph. A root cell is characterized as a node with no incoming connections, meaning it has no neighboring cells preceding it in the graph structure. This is accomplished by evolving the graph over several generations according to a specific rule, allowing the longest path to be identified based on the state values of the cells. Initially, the state of each cell in the graph is set to zero. During the evolution process, the state values of all cells are updated based on the state value of the cell under investigation and its neighbors. A cell's state value is incremented by one if it matches the state value of any of its neighbors. The algorithm begins at the root layer of each graph and iterates over all the layer pairs within it. The total number of cycles is determined by the number of layers minus two in the graph. [Figure 8: see original paper] illustrates the state values of all cells for a four-layer graph after two cycles of evolution.

After the evolution process, the algorithm conducts a depth-first search starting from a root cell to generate track candidates. The entire graph is then traversed, and sequential cells with descending state values are selected as track candidates. These candidates are subsequently stored for further analysis and the track finding procedure is completed.

C. Kalman Filter in EicC Track Reconstruction

With the track candidates, which represent subsequently stored hits information detected by the tracking detector, the track information can be extracted by fitting the track candidates with KF method. The KF represents an iterative process designed to estimate the states of dynamic systems. It can be employed in track reconstruction on the assumption that the track can be regarded as a discrete dynamic system. In the fitting, the state of the track at each detector surface i is characterized by the state vector $\vec{p}_i$. The state p is parametrized with 5 coordinates in a local plane coordinate system, as already shown in [Figure 9: see original paper]. The cartesian position $\vec{x}$ and direction $\vec{a}$ translate into plane coordinates according to the following equations:

$$\vec{P} = (\vec{\alpha} \cdot \vec{\mu}, \vec{\alpha} \cdot \vec{n}, \mu', \nu', \mu, \nu)^T$$

where

$$\mu = (\vec{x} - \vec{o}) \cdot \vec{\mu}, \quad \nu = (\vec{x} - \vec{o}) \cdot \vec{\nu}$$

Given the state vector $\vec{p}_{k-1}$, which delineates the state of the track at surface k-1, the system equation defines the propagated state vector $\vec{p}_k$ at the subsequent surface k. As shown in [Figure 10: see original paper], the KF utilizes both previous and current measurements to estimate the current state.

The track fitting involves iterating in two opposite directions, a process known as the smoothing procedure, to obtain the best estimation of track parameters. This bidirectional fitting helps refine the track estimate by incorporating information from both forward and backward passes, thus improving accuracy.

When implementing KF for the trajectory fitting algorithm of EicC, a measurement plane is first constructed for each hit in the candidate trajectory. For the initial evolution, we need to estimate the initial state parameters, including the momentum direction and magnitude. We use the direction of the hit point closest to the origin as the initial direction of the trajectory. The first three measurements are fitted by a helical track model using the least-squares method to obtain the initial momentum.

In the track fitting approach for EicC, it's common for the same root cell to have multiple candidate tracks, particularly when hit points from different tracks are in close proximity. To address this, the algorithm selects the best track candidate based on the smallest chi-square value obtained during the KF fitting procedure. The chi-square value serves as a measure of fit quality, allowing the algorithm to identify the track candidate that best represents the observed hits with the least statistical deviation, ensuring the most accurate track reconstruction.

D. Algorithm Optimization for Track Finding

The geometric criteria for hit-pair formation and CA cell connections were optimized using simulated events. To evaluate performance, we generated 10,000 simulated events with tracks spanning a momentum range of [0-1] GeV and polar angles between [20-160] degrees. Each event contained five tracks to benchmark the algorithm's efficiency under moderate track multiplicity conditions.

The criteria in the optimization include: θ_{x-y} and θ_{r-z} are the angles between two vectors formed by the hit and the collision point in different planes in constructing a doublet; α_{x-y} and α_{r-z} are the angles between two cells in different planes when connecting two cells as illustrated in [Figure 6: see original paper]. The Figure-of-Merit (FOM) quantifies the purity of reconstructed doublets and connections: for the transverse and longitudinal angles (θ_{x-y} and θ_{r-z}), it is defined as the ratio of correctly identified doublets to all reconstructed doublets, while for the orientation angles (α_{x-y} and α_{r-z}), it measures the fraction of topologically valid connections relative to all found connections. The optimized results are shown below:

[Figure 11: see original paper] presents the FOMs as a function of the angular requirements for doublet and connection reconstruction. Panel (a) shows the FOM dependence on θ_{x-y}, with an optimal value of 0.8727 mrad. Similarly, panel (b) evaluates θ_{r-z}, yielding an optimal threshold of 0.0122 mrad. For connection angles, panel (c) reveals that $\alpha_{x-y} = 0.4537$ mrad maximizes the FOM, while panel (d) identifies 0.00014 mrad as the ideal value for α_{r-z}.

III. Algorithm Performance

A large number of collision scenarios are generated using MC simulation to validate the performance of the track reconstruction algorithm within the EicC simulation framework. The angular range in the simulation is uniformly set from 0° to 360°, with muons selected as the reference particle type. A total of 100,000 events are produced, covering track multiplicities of 2, 4, and 6. Momentum values are sampled within the range [0–3] GeV. These simulated datasets are then processed by the algorithm, and the results are used to evaluate its performance.

The main criteria for assessing track reconstruction quality include:

- **Hit efficiency**: Hit efficiency is calculated as $\epsilon_{\mathrm{hit}} = N_{\mathrm{hit}}^{\mathrm{rec}}/N_{\mathrm{hit}}^{\mathrm{gen}}$, where $N_{\mathrm{hit}}^{\mathrm{rec}}$ denotes the number of hits successfully reconstructed, and $N_{\mathrm{hit}}^{\mathrm{gen}}$ represents the number of hits originally generated in a given track. This metric provides an indication of how well the reconstruction algorithm identifies individual hits along particle trajectories.

- **Tracking efficiency**: The tracking efficiency, defined as $\epsilon_{\text{track}} = N^{\text{rec}}_{\text{track}}/N^{\text{gen}}_{\text{track}}$, represents the ratio of reconstructed tracks ($N^{\text{rec}}_{\text{track}}$) to generated tracks ($N^{\text{gen}}_{\text{track}}$). A track is considered successfully reconstructed if over 89% of the hits in its reconstructed trajectory originate from the same particle track.
- **Fake efficiency**: The fake efficiency, defined as $\epsilon_{\text{fake}} = N^{\text{rec}}_{\text{fake}}/N^{\text{rec}}_{\text{all}}$, represents the ratio of reconstructed fake tracks ($N^{\text{rec}}_{\text{fake}}$) to all reconstructed tracks ($N^{\text{rec}}_{\text{all}}$). A track is defined as a fake track if the hit efficiency is less than 70%. This metric is used to assess the contamination of incorrectly reconstructed tracks in the tracking output.
- **Execution time**: The execution time is defined as the central processing unit (CPU) time consumed during the track reconstruction process.

The hit, tracking and fake efficiencies are evaluated across different momentum ranges and track multiplicities using simulated events. The results of these studies are presented in [Figure 12: see original paper]. The hit efficiency demonstrates excellent performance, consistently approaching 100% over a wide range of momenta. Furthermore, the trajectory reconstruction efficiency demonstrates a gradual ascent in tandem with an increase in momentum. Notably, there is a substantial surge in momentum from 0.4 GeV to 1.4 GeV, and when momentum surpasses 1.5 GeV, the efficiency nears perfection, approaching 100%. In the lower momentum range, the fake efficiency does not exceed 5%, slightly increases with the increase of the multiple number of the trajectory, and the fake efficiency basically tends to zero at medium and high momentum.

We also verified the resolution of momentum to measure the quality of trajectory reconstruction. [Figure 13: see original paper] left shows that the momentum resolution dp/p increases approximately linearly with particle momentum. This trend is well understood, as higher-momentum tracks produce a smaller curvature, reducing the measured sagitta and consequently degrading the momentum resolution. The computational performance is measured on an Intel Xeon Gold 6248R processor (24 cores, 3.0 GHz base frequency). The execution time of the CPU will increase with the increase of the number of tracks as shown in the right panel of [Figure 13: see original paper]. The increase in track multiplicity can also lead to an increase in multi-threading overhead, thereby resulting in a significant increase in execution time.

IV. Summary

This paper proposes a trajectory reconstruction algorithm for the EicC central detectors, combining CA graph-based pattern recognition with KF refinement. The CA method first identifies candidate tracks by analyzing hit connections across detector layers and selecting the longest path, while the KF method then optimizes these tracks to precisely determine momentum, charge, and vertex position. Simulation results confirm high single-track hit efficiency, excellent reconstruction accuracy within the ideal momentum range, and a low fake-track rate—all meeting EicC's physics requirements. The algorithm's robust performance and computational efficiency make it a viable solution for the EicC detector system, demonstrating both effectiveness and precision in real-world applications.

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