A track reconstruction algorithm for the EicC central detector

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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 optimize 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 a combined track-finding and track-fitting algorithm designed for the Electron-ion Collider in China (EicC). The algorithm aims to

achieve high track reconstruction efficiency and is constructed modularly, leveraging an advanced cellular automaton model and the Kalman filter method for its core functionality. We optimize the algorithm using fully simulated Monte Carlo events within the EicCRoot software framework and validate its performance, 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 [**?**]. As a future high-energy nuclear physics project, the Electron-ion Collider in China (EicC) has been proposed [**?**]. The primary objectives of the EicC include conducting precision measurements of nucleon structure in the sea quark region, performing 3D tomography of nucleons \cite{3–5}, exploring the partonic structure of nuclei [**?**, **?**], and investigating how partons interact with the nuclear environment \cite{8–10}. Additionally, the EicC will focus on studying exotic states \cite{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 $2.0 \times 10^{33}\,\mathrm{cm}^{-2} \cdot \mathrm{s}^{-1}$ while maintaining polarization levels of approximately 80% for electrons and 70% for protons under collider conditions [**?**, **?**]. Driven by the physics program of the EicC, a conceptual design for a general-purpose spectrometer has been proposed [**?**, **?**], featuring 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 particle 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 by a superconducting solenoid positioned outside the central detector. This solenoid has a diameter of 3.36 meters and extends to a length of 4.0 meters, ensuring an optimal balance between field strength and coverage to provide 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 along the negative Z axis. The tracking detector in each region is described below.

The barrel region tracking detector consists of an inner silicon layer \cite{18–20} and an outer micropattern gaseous detector (MPGD) layer [**?**, **?**]. The inner silicon cylinder comprises three vertex layers and two tracking layers, occupying a region 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, while 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 chosen to cover the outermost barrel region, with mean radii of approximately 48 cm and 77 cm and a 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. An MPGD at Z = 165 cm provides forward coverage with a radial range of 8 cm to 150 cm. The geometry parameters, positions, and material budgets for the two endcap regions are listed in and .

The study of transverse-momentum-dependent (TMD) parton distribution functions (PDFs) at the EicC calls for detector and algorithmic capabilities beyond conventional designs. The central physics goal—probing the non-perturbative structure of nucleons by measuring hadrons at low transverse momentum ($P_{hT} < 1\,\mathrm{GeV}$)—imposes stringent requirements on track reconstruction performance. This involves efficiently reconstructing challenging final states, such as low-momentum leptons from sea quark processes, decay products of heavy-flavor hadrons, and particles at extreme pseudorapidities in exclusive reactions. These demands give rise to two intertwined algorithmic challenges. First, for low transverse momentum tracks ($p_T < 0.5\,\mathrm{GeV}$), pattern recognition robustness is significantly compromised by multiple Coulomb scattering in the detector material and high curvature in the solenoidal magnetic field. This motivates the development of adaptive track-fitting algorithms incorporating impact parameter weighting, along with rigorous optimization of the detector material budget to reduce scattering-induced resolution degradation. Second, particles at very forward angles ($\theta \to 0^\circ$), essential for reconstructing exclusive events, must be distinguished from a high background of beam-gas interactions and diffractive secondaries. To address this, Kalman filter (KF) [**?**]-based methods can be employed, leveraging outer tracking information to suppress background noise in the inner detector regions without degrading reconstruction efficiency for true physical signals. 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. The inherent parallelism of cellular automaton (CA) [**?**]-based algorithms makes them well-suited to meet these stringent real-time processing demands, ensuring efficient and fast pattern recognition under high event rates.

The CA 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 KF-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 [**?**]. 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 [**?**].

Our tracking work for the EicC is contextualized by parallel developments for the Electron-Ion Collider (EIC) at Brookhaven National Laboratory (BNL). The EicC's physics program—prioritizing low-P_T hadron reconstruction and forward coverage for TMD studies and exclusive reactions—imposes requirements distinct from those of the BNL EIC, which focuses more on high-momentum and high-multiplicity tracking. Our CA+KF algorithm is explicitly optimized for these EicC-specific challenges, including robustness at low curvature and high background in forward regions. The EIC has established a similar technical foundation, employing the Acts toolkit with a Combinatorial Kalman Filter for reconstruction and DD4hep for simulation. Their design also prioritizes a high-granularity, low-mass silicon tracker for large acceptance, achieving benchmark performance that meets the physics requirements outlined in the EIC Yellow Report [**?**]. The ongoing EIC effort to develop realistic pattern recognition and seeding for high-multiplicity events underscores a common challenge for next-generation colliders.

Moving charged particles, such as electrons, interact with material in a detector and leave behind signals (e.g., ionization or light). These signals are recorded at specific positions in the detector, typically using layers of sensors arranged in a geometric pattern as shown in [Figure 3: see original paper]. 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 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, $\mathbf{F} = q(\mathbf{v} \times \mathbf{B})$, 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:

$$
\begin{aligned}
x(s) &= x_0 + \frac{R}{h}\left(\cos\phi_0 - \cos\left(\phi_0 + \frac{hs\cos\lambda}{R}\right)\right) \\
y(s) &= y_0 + \frac{R}{h}\left(\sin\left(\phi_0 + \frac{hs\cos\lambda}{R}\right) - \sin\phi_0\right) \\
z(s) &= z_0 + s\sin\lambda
\end{aligned}
$$

Among these parameters, λ is the dip angle and $h = \pm 1$ indicates 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 ϕ_0 is related to the slope of the tangent to the circle at $s = 0$. The quantity R represents the radius of the circle.

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.

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 KF for track fitting. Cellular automata 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 [**?**, **?**, **?**, **?**]. 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 such as the Hough transform [**?**], one of the most significant advantages of CA is their inherent parallelism [**?**]. 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 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 [?]. 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 [?, ?]. Utilizing the EicCRoot software framework, which is an object-oriented framework built upon FairRoot [?], the algorithm reconstructs tracks based on the hits left by simulated tracks on the detector layers. The implementation process is as follows: (1) read all hit information from the simulation; (2) perform track finding using the CA method; (3) fit the found track candidates using the KF method to obtain track information.

The Application of CA to EicC Track Finding

As previously mentioned, the EicC tracking system 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 processing of hit information across these layers, we assign unique identifiers to each detector layer: 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 track-finding procedure is described below.

Definition of Graph. A graph is a data structure that encodes information about all detector layers, pairs of adjacent layers, and the root layer through which a particle travels. The root layer refers to the first detector layer a particle traverses after the collision. Graph construction is a crucial step in the algorithm's initialization process, with all subsequent operations building the necessary data structures based on the specific layer list of each graph. Using the EicC software framework, we generated 10,000 MC single-muon events with track momentum ranging from 0 to 5 GeV and angular distribution covering the full 0° to 360° range. 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 connect hit points from 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 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. We analyzed 10,000 events generated by MC simulation and examined 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 processed sequentially, and the algorithm evaluates all hit pairs according to the geometrical requirements obtained from simulation data. Hit pairs satisfying these requirements are saved to a specific data structure for further processing.

Cell Connection. The connection of cells is the key procedure for track finding with CA. The first step converts 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 and initialized to zero. The second step finds neighbors for each cell. Two cells are considered neighboring if they satisfy all of the following conditions: (1) they belong to different layer pairs; (2) they share a common hit, where the inner hit of one cell is the outer hit of the other; and (3) the corresponding constraints are satisfied in both the x-y and r-z planes. The angle between two neighboring cells in the x-y plane is illustrated in [Figure 6: see original paper].

To establish criteria for selecting neighboring cells, 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 simulation. The IDs of matched cells are stored to ensure that matched adjacent cells can be accurately identified in subsequent stages.

Evolution and Track Candidate Creation. After establishing the graph with 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 evolution, 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 layer pairs within it, with the total number of cycles 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 traversed, and sequential cells with descending state values are selected as track candidates. These candidates are subsequently stored for further analysis, completing the track-finding procedure.

Kalman Filter in EicC Track Reconstruction

With track candidates representing stored hit information detected by the tracking detector, track information can be extracted by fitting the candidates using the KF method. The KF represents an iterative process designed to estimate the states of dynamic systems and can be employed in track reconstruction under the assumption that the track can be regarded as a discrete dynamic system. In the fitting process, 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 five coordinates in a local plane coordinate system, as 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:

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

where $\mu' = \frac{\vec{\alpha}\cdot\vec{\mu}}{\vec{\alpha}\cdot\vec{n}}$ and $\nu' = \frac{\vec{\alpha}\cdot\vec{\nu}}{\vec{\alpha}\cdot\vec{n}}$ are the directions of the state, and $\mu = (\vec{x} - \vec{o}) \cdot \vec{\mu}$ and $\nu = (\vec{x} - \vec{o}) \cdot \vec{\nu}$ represent the coordinates of the state in the local frame. Given the state vector $\vec{p}_{h-1}$, which delineates the state of the track at surface $k-1$, the system equation defines the propagated state vector $\vec{p}_h$ 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.

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

Track fitting involves iterating in two opposite directions, a process known as smoothing, to obtain the best estimate of track parameters. This bidirectional fitting helps refine the track estimate by incorporating information from both forward and backward passes, thereby improving accuracy. In the EicC track fitting approach, it is 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.

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 optimization criteria include: θ_{x-y} and θ_{r-z}, which are the angles between two vectors formed by the hit and the collision point in different planes when constructing a doublet; and α_{x-y} and α_{r-z}, which are the angles between two cells in different planes when connecting 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 presented below.

[Figure 11: see original paper] shows the FOMs as functions 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}.

Algorithm Performance

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

The main criteria for assessing track reconstruction quality include:

- **Hit efficiency:** Calculated as $\epsilon_{\text{hit}} = N_{\text{hit}}^{\text{rec}}/N_{\text{hit}}^{\text{gen}}$, where $N_{\text{hit}}^{\text{rec}}$ denotes the number of hits successfully reconstructed and $N_{\text{hit}}^{\text{gen}}$ represents the number of hits originally generated in a given track. This metric indicates how well the reconstruction algorithm identifies individual hits along particle trajectories.
- **Tracking efficiency:** Defined as $\epsilon_{\text{track}} = N_{\text{track}}^{\text{rec}}/N_{\text{track}}^{\text{gen}}$, representing the ratio of reconstructed tracks ($N_{\text{track}}^{\text{rec}}$) to generated tracks ($N_{\text{track}}^{\text{gen}}$). A track is considered successfully reconstructed if over 89% of the hits in its reconstructed trajectory originate from the same particle track.
- **Fake efficiency:** Defined as $\epsilon_{\text{fake}} = N_{\text{fake}}^{\text{rec}}/N_{\text{all}}^{\text{rec}}$, representing the ratio of reconstructed fake tracks ($N_{\text{fake}}^{\text{rec}}$) to all reconstructed tracks ($N_{\text{all}}^{\text{rec}}$). A track is defined as fake if its hit efficiency is less than 70%. This metric assesses the contamination from incorrectly reconstructed tracks in the tracking output.
- **Execution time:** Defined as the central processing unit (CPU) time consumed during the track reconstruction process.

The hit, tracking, and fake efficiencies were evaluated across different momentum ranges, track multiplicities, and pseudorapidity values using simulated events. The results are presented in [Figure 12: see original paper]. The hit efficiency demonstrates excellent performance, consistently approaching 100% over a wide momentum range. Furthermore, the trajectory reconstruction efficiency increases significantly with momentum, rising sharply between 0.4 GeV and 1.4 GeV. This characteristic is primarily dictated by the detector's acceptance and magnetic field configuration. Consequently, this low-momentum threshold must be considered in physics analyses sensitive to this region, such as measurements of TMD PDFs. When momentum surpasses 1.5 GeV, the efficiency nears perfection, approaching 100%. In the lower momentum range, the fake efficiency does not exceed 5%, increases slightly with track multiplicity, and essentially tends to zero at medium and high momentum. The hit efficiency remains relatively high in both central and forward regions, with a slight drop in the transition region. The fake rate is lowest in the forward region and increases gradually toward lower pseudorapidity. Overall, the tracking efficiency shows a strong dependence on pseudorapidity. For tracks with very low transverse momentum ($P_T < 300\,\text{MeV}$), the tracking efficiency remains high ($> 72\%$) across much of the pseudorapidity range. The efficiency decreases for tracks at small pseudorapidity (central region), primarily due to shorter track lengths. These soft, spiraling tracks traverse fewer detector layers, limiting the number of available hits for pattern recognition.

It is important to note that this study does not account for beam-related background, which would dramatically increase the number of hits in the detectors, many of which are uncorrelated with the primary vertex or tracks of interest, substantially increasing the fake track rate. To mitigate these anticipated challenges, we envision implementing advanced clustering and noise rejection techniques at the hit level to filter out isolated, low-energy, or geometrically inconsistent deposits before track pattern recognition begins. Furthermore, we will employ a suite of quality selection criteria based on the kinematic and topological properties of tracks.

We also assessed the quality of trajectory reconstruction by evaluating momentum and angular resolutions. [Figure 13: see original paper] (top left) shows that the momentum resolution dP_T/P_T increases approximately linearly with particle transverse momentum. This trend is well understood, as higher-momentum tracks produce smaller curvature, reducing the measured sagitta and consequently degrading momentum resolution. Particularly in the low-momentum regime, the resolution curve bends upward because momentum resolution is dominated by multiple scattering. The lower the momentum, the more significant the impact of multiple scattering, leading to poorer resolution. As momentum increases, the effect of multiple scattering gradually diminishes, and the spatial resolution of the detector becomes the dominant factor. At higher momenta, the trajectory becomes increasingly straight and the sagitta decreases, resulting in progressively worse resolution. Superior momentum resolution is critical for TMD measurements, as shown in Ref.~[**?**], as it minimizes the smearing of low-transverse-momentum hadrons to ensure clean extraction of spin asymmetries. Furthermore, high tracking efficiency and vertex resolution are essential for reducing combinatorial background in heavy-flavor tagging, which tightens constraints on gluon PDFs [**?**]. The angular resolution deteriorates as particle transverse momentum increases, as evidenced in the top right and bottom left panels. This trend is attributed to the reduction of multiple scattering effects at higher momenta.

Computational performance was measured on an Intel Xeon Gold 6248R processor (24 cores, 3.0 GHz base frequency). The CPU execution time increases with the number of tracks, as shown in the bottom right panel of [Figure 13: see original paper]. The increase in track multiplicity can also lead to increased multi-threading overhead, resulting in a significant rise in execution time.

This study establishes the high tracking efficiency and precision momentum resolution that form the essential foundation for robust vertex reconstruction at the EicC. While a full characterization of the vertexing algorithm is beyond the scope of this paper, its performance is a direct consequence of the track quality demonstrated here. Excellent vertex resolution is paramount for the EicC's flagship physics programs, such as gluon PDF extraction via open charm measurements, where precise identification of displaced secondary vertices is required to suppress combinatorial background. A dedicated analysis of primary and secondary vertex finding efficiency and resolution, building upon this tracking foundation, is the immediate next step in our software development chain and will be presented in a forthcoming publication.

Summary

This paper proposes a trajectory reconstruction algorithm for the EicC central detector, 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.

While the presented CA+KF algorithm establishes a robust baseline with excellent reconstruction performance, its computational profile requires further optimization to meet the EicC's stringent sub-microsecond latency target. Our current profiling indicates the primary bottleneck is the precise helicoid propagator within the KF. To address this, we are actively pursuing a multi-faceted strategy that includes simplifying the propagator geometry to reduce per-step calculation time, fully exploiting massive parallelization across CPU cores to process thousands of track candidates simultaneously, and implementing a faster parameterized magnetic field model to minimize lookup overhead. These targeted optimizations, inspired by methods from high-luminosity experiments and benchmarks like Graph Neural Networks [?], are projected to synergistically reduce processing time by orders of magnitude, bridging the gap between our current baseline and the required real-time performance.

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Note: Figure translations are in progress. See original paper for figures.