Simultaneous track finding and track fitting by the Deep Neural Network at BESIII

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Abstract: In this work we introduce PointNet++ to the track reconstruction of the BESIII drift chamber. Preliminary results show our framework is able to group hits of different tracks and give the candidate parameters of tracks simultaneously.

Keywords: machine learning, drift chamber, tracking, track finding, track fitting

1 Introduction

Track reconstruction of the Multi-layer Drift Chamber (MDC) [1] of the BESIII detector [2] at the Beijing Electron Positron Collider II (BEPCII) [3] is one of the most important tasks of the offline data analysis. The structure of the BESIII is shown in Figure 1, and the MDC is illustrated in Figure 2. The MDC aims to provide spatial, momentum and dE/dx measurements for the charged particles. It is essential to reconstruct charged particle tracks accurately with high efficiency across a range of particle momenta and dip angles. Although traditional tracking algorithms have been successfully employed in the reconstruction of BESIII, optimization of track reconstruction can be done for the low momentum, large dip angle sample and the noisy events.

One of the most powerful advantages of deep learning techniques is the ability to find patterns from data. For particle track reconstruction, the process of partitioning space points into disjoint groups is a challenging pattern recognition task. A variety of deep learning approaches have shown promise in the problem of particle track reconstruction at high energy physics experiments. The method presented here explored new perspectives for track reconstruction on drift chamber detector data using deep learning techniques.

2 Methodology

The deep learning approaches to particle track reconstruction have mainly focused on silicon detectors. A point-based neural network was explored for hits clustering and track fitting in the context of 2-dimensional data from the drift chamber detector in the BESIII. Hit signals from the MDC can be thought of as point clouds, each point has unique 2-D position coordinates representing a sense wire and its inherent features as input for the point-based neural network. Track reconstruction typically proceeds in two tasks: track finding and track fitting.

Track fitting and track hit classification is highly relevant, hence these two approaches could benefit each other. For example, if we know the underlying

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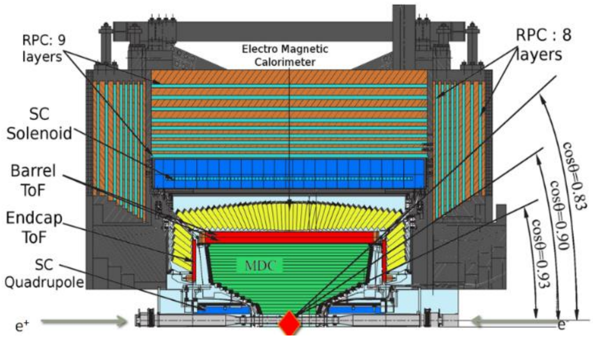

Figure 1. The structure of BESIII.

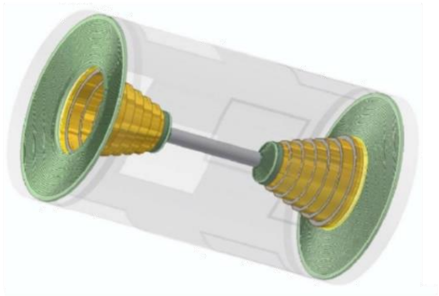

Figure 2. Main Drift Chmber.

parameters of a track, then track hits associated with the track can be easily identified. On the other hand, if we know the hits of a track, then we can get underlying parameters by fitting them. Most existing works take the second scheme by classifying track hits and then estimating track parameters. Inspired by the above observations and the success of multi-task training, we propose a unified framework to address track fitting and track hit classification simultaneously in an end-to-end fashion. The method takes hits from multiple tracks as inputs, where each hit holds 3-dimensional features, including position and drift time. We feed these inputs to a backbone network to extract hit level features. Then the network is divided into two branches. One branch is a reconstruction branch, which estimates the parameters of each track and its existence. The other branch is a track segmentation branch, which takes learned features of PointNet++[4, 5] and track features to determine a hit-wise track assignment. In essence, we can assign each track hit to its potential track to classify track hits.

Our full network architecture is visualized in Figure 3. The network has three key modules: the PointNet++ as trunk network to extraction features from all the points, following by two branch networks for hits clustering and track fitting, and an attention implementation from track features to hits clustering. Training has been done with Monte-Carlo simulation data of multi-track sample.

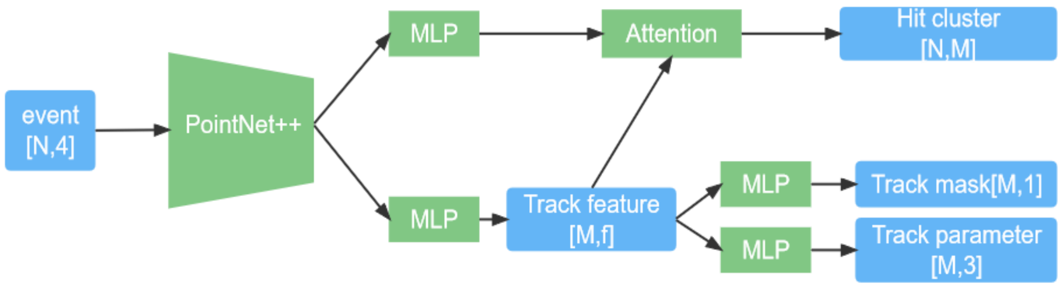

Figure 3. Model architecture.

3 Results

Tracking performance has been assessed across hit efficiency, hit purity, track efficiency, momentum resolution and spatial resolution. Comparison between current tracking algorithm performance and other on-going tracking studies has been done.

3.1 Hits clustering

Performance of hits clustering is shown as hit efficiency for track, hit purity for track and track efficiency versus transverse momentum with respect to all truth hits. For each track, the ratio of correctly identified signal hits to the total number of truth signal hits is defined as the hit efficiency. And for each track, the ratio of correctly identified signal hits to the total number of hits identified as signal is defined as the hit purity.

$$\varepsilon_{clustering\ hit\ efficiency} = \frac{N_{correctly\ identified\ signal\ hits}}{N_{truth\ signal\ hits\ on\ one\ track}} \quad (1)$$

$$\varepsilon_{clustering\ hit\ purity} = \frac{N_{correctly\ identified\ signal\ hits}}{N_{hits\ identified\ as\ signal\ on\ one\ track}} \quad (2)$$

The Figure 4 displays the number of clustering hit efficiency of tracks as a function of transverse momentum, representing the number of tracks with respect to each hit efficiency and transverse momentum bin. The majority of events in Figure 4 exhibit a total clustering hit efficiency as approximately 100% across all transverse momentum regions. The average total hit efficiency is calculated to be 96.4%. The clustering hit purity as a function of transverse momentum is illustrated in Figure 5. The total average clustering hit purity is 94.7%. Figure 6 shows the track efficiency as a function of transverse momentum, showing consistently high efficiency within a relatively low transverse momentum range.

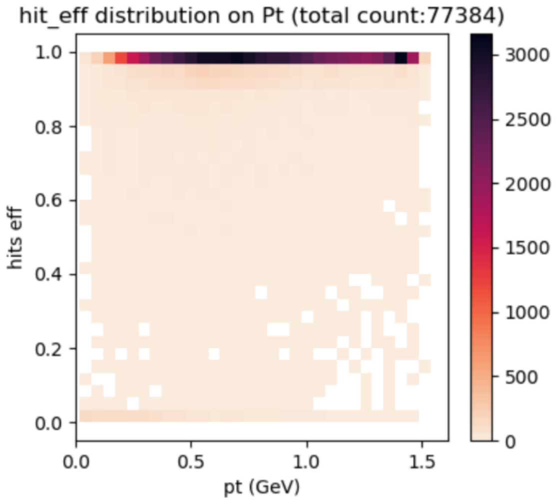

Figure 4 Clustering hit efficiency as a function of transverse momentum.

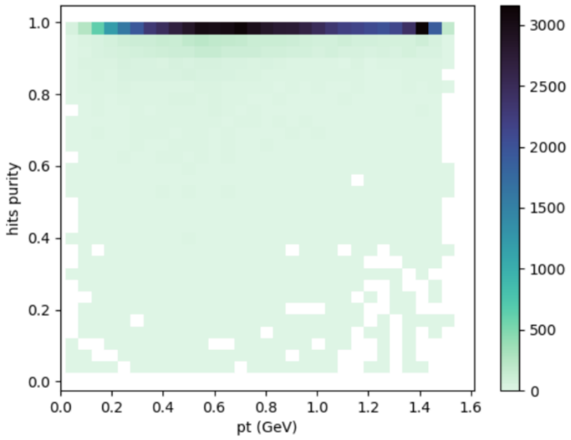

Figure 5. Clustering hit purity of tracks as a function of transverse momentum

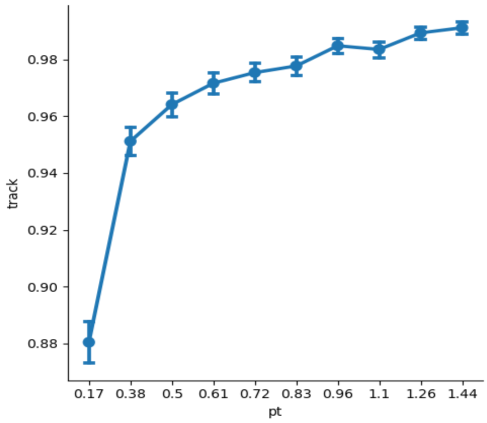

Figure 6. Track efficiency as a function of transverse momentum

3.2 Track parameter estimation

The evaluation of tracking performance involves the consideration of both momentum resolution and spatial resolution as key metrics. Figure 7 presents a comparison between predicted and true transverse momentum, revealing a transverse momentum resolution of approximately 147 MeV/c. The prediction of impact parameter is depicted in Figure 8. In this study, the 2-D circle track model is employed to describe the tracks. While the center and radius of the circle of the first hit on the track are utilized as references during training, the distance between the predicted track and the wire is not enforced as a constraint. Consequently, the spatial resolution is approximately 14.5 cm, which is inferior to that achieved by traditional methods. The impact parameter resolution of the traditional method is less than 1mm for transverse momenta exceeding 100 MeV/c. This indicates that the drift time measurements are crucial for the estimation of the hit position and track and should be considered in the future training.

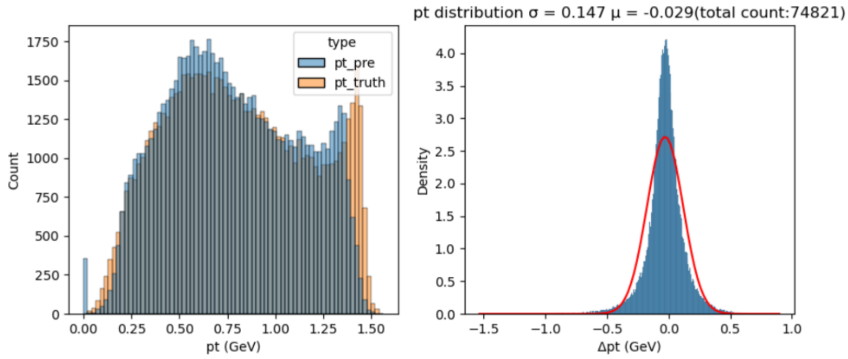

Figure 7. Distribution of p_T prediction and p_T truth(left) and Δp_T distribution(right).

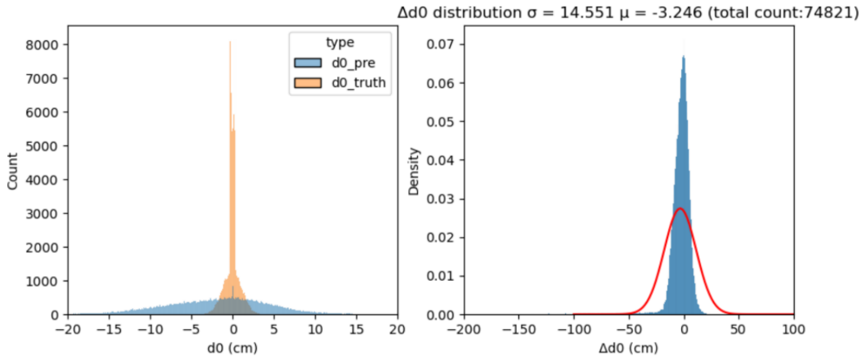

Figure 8. Distribution of d_0 prediction and d_0 truth(left) and Δd_0 distribution(right).

4 Conclusion

A point-based machine learning method designed for track reconstruction of drift chamber detector was studied. This method allows us to predict the track parameters of a track candidate while conducting hit classification. Preliminary results indicate our framework is able to group hits from different tracks and give the candidate track parameters simultaneously. The estimation of the track parameter should be optimized by introducing the distance between track and hits in training

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