Track reconstruction in high density environment

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Abstract

The reconstruction algorithm in the ALICE barrel detectors [1] based on Kalman-filtering and Maximum Information Approach (MIA) is presented. The reconstruction algorithm is able to cope with non-Gaussian noise and ambiguous measurements in high-density environments. The algorithm consists of the following parts: space point localization, track finding and fitting (done in parallel with V0 and kink topology finding).

The occupancy in the main tracking device - the Time Projection Chamber (TPC) can reach up to 40 %. Usually, due to overlaps, a number of points along the track are merged or significantly displaced. First, the clusters are found and the space points are reconstructed. The shape of a cluster provides information about the overlap. An unfolding algorithm is applied to clusters with distorted shapes. Then, the expected space point error is estimated using information about the cluster shape and track parameters. Further, the available information about local track overlap is used.

The distance between the TPC and the Inner Tracker System (ITS) is rather large and the track density inside the ITS is so high that the straightforward continuation of the tracking procedure is ineffective. Using only χ^2 minimisation leads to a high probability of assigning a wrong space point to the track. Therefore for each TPC track a candidate tree of the possible track prolongations in the ITS is build. Finally the most probable track candidates are chosen.

The approach has been implemented within the ALICE simulation/reconstruction framework (ALIROOT) [2], and efficiency has been estimated using the ALIROOT Monte Carlo data.

Introduction

Track finding and fitting algorithms in ALICE barrel detectors, Time Projection Camber (TPC) [3], Inner Tracking System (ITS) [4], Transition Radiation Detector (TRD) [5] and Time of Flight Detector (TOF) [6] based on the Kalman-filtering are presented.

The Time Projection Chamber (TPC) is the main tracking device of the ALICE experiment. It is used for track finding, momentum measurements and particle identification (PID) by dE/dx measurement.

The Inner Tracking System (ITS) of ALICE is one of the central detectors used for track recognition, particle identification, and secondary vertex finding. In the environment of predicted multiplicity densities up to $\mathrm{d}N_{\mathrm{ch}}/\mathrm{d}y = 8000$ (charged primary particles per unit rapidity), track finding is one of the most challenging tasks in the ALICE experiment. The ITS ionization measurement will contribute to PID in the lower momentum range (i.e. up to 500 MeV/c) with a similar significance as the TPC dE/dx measurement. The ITS detector was optimized to provide the measurement of the Distance of the Closest Approach (DCA) between the track extrapolation and the primary vertex (track impact parameter) with an excellent resolution, especially in the transverse projection. The secondary vertex finding thus is done by the ITS.

The main purpose of the TRD is to provide electron identification and tracking in the momentum range above 1 GeV. Therefore it has to be assured that a sufficient pion suppression can be achieved, even in the high multiplicity environment. Additionally, a high tracking efficiency and good momentum resolution for high momenta particles (above 0.5 GeV) is required.

Combined Tracking Strategy

Track finding for the predicted particle densities is one of the most challenging tasks in the ALICE experiment. It is still under development and here the current status is reported. Track finding is based on the Kalman-filtering approach. Kalman-like algorithms are widely used in high-energy physics experiments and their advantages and shortcomings are well known.

Because of high occupancy the standard Kalman filter approach was modified. To gain almost optimal results, so called Maximum Information Approach (MIA) was applied. During the reconstruction process new information is extracted and remembered for later use. We can make better use of the original information, when this new information is available.

We tried to use the maximum available information during the cluster finding, tracking and particle identification. Because of too many degrees of freedom (up to 220 million 10-bit samples) we had to find smaller number of independent parameters.

An incremental approach to combined reconstruction was chosen. Algorithms and data structures were optimized for fast access and usage of all relevant information.

To allow the use of the optimal combination of local and global information about the tracks and clusters, a parallel hypotheses Kalman filter tracking method was proposed. Several hypotheses are kept and investigated in parallel. In the following the additional information which was used will be underlined.

The main attractive properties of the parallel Kalman-filter approach are following:

- It is a method for simultaneous track recognition and fitting.
- There is a possibility to reject incorrect space points (outliers) ‘on the fly’, during only one tracking pass. Such incorrect points can appear as a consequence of the imperfection of the cluster finder. They can belong to noise or they can be points from other tracks accidentally captured in the list of points to be associated with the track under consideration. In many other tracking methods one usually needs an additional fitting pass to get rid of incorrectly assigned points.
- In case of substantial multiple scattering, track measurements are correlated and therefore large matrices (of the size of the number of measured points) need to be inverted during a global fit. In the Kalman-filter procedure we have to manipulate small matrices (typically 5×5 matrices) at each measured point, which is much faster.
- Using this approach one can handle energy losses in a simpler way than in the case of global methods.
- Kalman filtering is a natural way to find the extrapolation of a track from one detector to another.

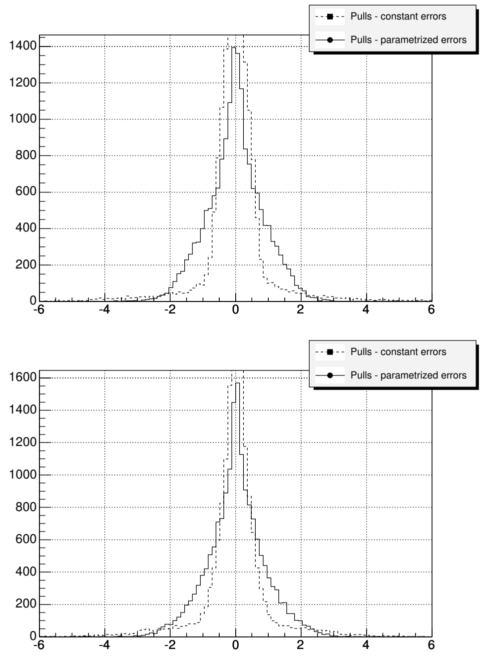

Figure 1: Pulls in the ITS detectors ($(x_{meas.} - x_{true})/\sigma_x$). Upper part, pulls in the transverse direction, lower in the longitudinal direction

In the present version of the Kalman filter, we used two assumptions: The errors of the space points used for Kalman filtering are described by a Gaussian distribution with known width. The space point errors between the layers are not correlated. Occupancies up to 40% in the inner sectors of the TPC and up to 20% in the outer sectors are expected; clusters from different tracks may overlap; therefore a certain number of clusters gets merged, and some others may be significantly displaced. These displacements are rather hard to take into account. Moreover, these displacements are strongly correlated depending on the distance between two tracks.

To fulfill the given assumption in the high flux environment following algorithms were developed:

- To resolve cluster overlaps, the single cluster shape was parameterized as a function of track parameters. An unfolding algorithm based on the cluster shape was used for clusters with extended shape.
- A multidimensional error parametrization in the space of observables was introduced. The space points found during the clusterization algorithm are characterized by the position, charge, shape parameters and charge ratio for unfolded clusters. The space point errors are assigned to the point only at the moment when the estimates of the tracks parameters are known and can be used. Given parameterizations were implemented for all tracking detectors, TPC, TRD and ITS (see example Fig. 1)).

To reduce the influence of wrongly associated clusters on the track parameters following strategies were used:

- If the error of the track prolongation is comparable with the mean distance between the clusters, the tree of the hypotheses is build (ITS).
- Fast, track segment finding algorithms (seeding algorithms) over the full detector system were implemented. For tracks with doubtful behavior (according to χ^2 criteria), multiple hypotheses are considered and tracked. Parallel tracking - best track candidates choosing algorithms are used during the full process of reconstruction.
- For kink and V0 topologies the tracks are refitted towards the found vertex.

The reconstruction algorithm is done in incremental way. To minimize CPU requirements only three iterations are performed (see Fig. 2):

- Forward tracking from the TPC to the ITS towards the vertex.
- Back propagation from the ITS through the TPC and TRD towards the TOF detector.
- Refit inwards the vertex.

Continuous seeding - track segment finding are performed in each tracking detector. In the TPC the seeding is done

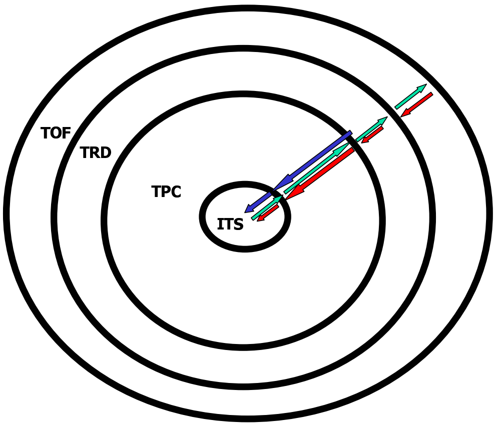

Figure 2: Schematic view of the combined tracking.

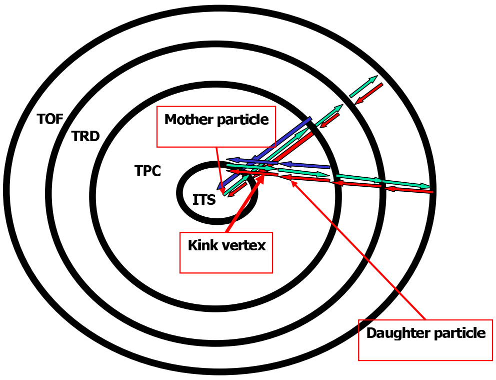

Figure 3: Schematic view of kink topology reconstruction.

in the first iteration, in the ITS and TRD during the second reconstruction iteration.

The reconstruction strategy for kink topologies is shown in picture 3). The number of iterations is also restricted to three. The algorithm for the kink topology finder is following. The DCA for pairs of short tracks are calculated. For pairs with DCA smaller then a critical value, the kink hypotheses are registered. During the second reconstruction pass the kink parameters for the mother particle are updated, using information from the ITS detector. In the third reconstruction pass the information about the daughter particle of the kink are updated. The main advantage of such approach is that the track parameters used for kink construction are optimal close to the kink position, and, moreover the track parameters are not spoiled by the presence of fake space points either from the daughter (mother) particles or from the space points created by background tracks.

The TPC-ITS matching is difficult, because the distance between the TPC and the ITS sensitive elements is rather large and the track density inside the ITS is so high that the naive continuation of the tracking procedure used for the TPC will be ineffective. In this case there is a high probability of assigning a wrong hit to the track if we use just the criterion of minimal χ^2 in a given ITS layer. Therefore we have implemented several improvements of the Kalman filter procedure.

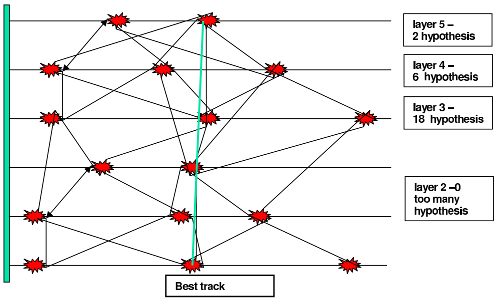

Figure 4: Building of the track tree hypothesys in the ITS detector

First, we try to assign to the track, one by one, all the hits within the predicted window having a χ^2 below a given limit, not only the one with minimal χ^2. This way we are building from each TPC track a candidate tree through all of the ITS layers. To speed-up the building of the track tree hypotheses, track hypotheses are sorted after each layer according to χ^2 criteria and only gold track branches and a restricted amount of non gold tracks are propagated further down (see Fig. 4). Finally we choose the most probable candidate (i.e. the path along the tree). The following information is taken into account:

- Sum of the space χ^2s.
- Probability that a track is in the dead zone.
- Missing clusters because the track crosses a dead ITS channel.
- Clusters below threshold.
- Probability that secondary tracks miss ITS layers as a function of impact parameter in z and r-ϕ
- For shared clusters, the probability of the cluster to be shared as a function of the cluster shape

The current best track hypothesis is registered to all the clusters which belong to that track. A restricted amount of track candidates is kept for further parallel tracking. In case of secondary track hypotheses also short best tracks are kept, for further V0 study.

After the ITS tracking procedure, the overlap factors between the best track and all other tracks are calculated. If the overlap factor is higher than a critical value, the parallel tracking algorithm is started (see Fig. 5).

For a given best track a non correlated track (from another TPC seed) with the biggest overlap is chosen. Afterwards, in the double loop over all possible pairs of branches, the weighted χ^2s of two tracks are calculated. The effective probability of cluster sharing and for secondary particles the probability not to cross a given layer are taken into account.

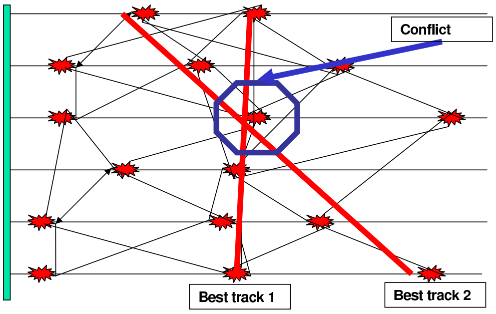

Figure 5: Parallel tracking in the ITS detector

The third improvement is that we use the primary vertex constraint explicitly. For tracks with χ^2 bigger than critical value, the tracking procedure is repeated without vertex constraint. Before deletion of the tree of hypotheses the V0 candidates are localized. The V0 finding algorithm is following:

- The DCA calculation for pair of best tracks defined in parallel tracking.
- Rough cuts for V0 candidates are applied. DCA, pointing angle and causality informations are used.
- For a given V0 the best pair of track hypotheses at the point after the V0 vertex is found.
- Stronger cuts are applied.
- An accepted V0 object is registered.

After this procedure the tree of the track hypotheses is deleted, only best tracks are kept. Vertex parameters are updated furthermore in the third tracking iteration, knowing the informations from all other detectors.

Conclusion

A reconstruction algorithm in ALICE barrel detectors based on Kalman-filtering and Maximum Information Approach (MIA) was developed. Applying the MIA strategy the performance of the reconstruction was improved. It works well even in the case of highest expected multiplicities ($\mathrm{d}N_{\mathrm{ch}}/\mathrm{d}y = 8000$, see fig. 6). Applying the described algorithms the kink finder efficiency was improved by factor 2.5. The TPC tracking efficiency reaches almost 100% even in the case of highest expected multiplicities. The TPC $\mathrm{d}E/\mathrm{d}x$ resolution was improved from 9.5% down to 6.9%. Alice experience from combined tracking in the high flux enviroment indicates that the used approach leads to considarable improvements compared with tracking based on the zero-level approximation.

REFERENCES

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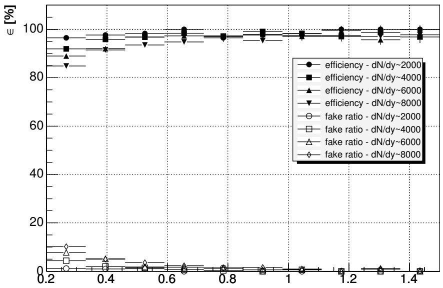

Figure 6: Combined tracking efficiency as the funtion of momenta for different track multiplicities.