Electron reconstruction and identification capabilities of the CBM Experiment at FAIR

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Abstract. The Compressed Baryonic Matter (CBM) experiment at the future FAIR facility at Darmstadt will measure dileptons emitted from the hot and dense phase in heavy-ion collisions. In case of an electron measurement, a high purity of identified electrons is required in order to suppress the background. Electron identification in CBM will be performed by a Ring Imaging Cherenkov (RICH) detector and Transition Radiation Detectors (TRD). In this contribution, algorithms which were developed for the electron reconstruction and identification in RICH and TRD detectors are presented. A fast RICH ring recognition algorithm based on the Hough Transform method was implemented. An ellipse fitting algorithm was implemented since most of the RICH rings have elliptic shapes. An efficient algorithm based on the Artificial Neural Network is implemented for electron identification in RICH. In TRD track reconstruction algorithm which is based on track following and Kalman Filter methods was implemented. Several algorithms for electron identification in TRD were developed and investigated. The best-performed algorithm is based on the special transformation of energy losses measured in TRD and usage of the Boosted Decision Tree (BDT) method as classifier. Results and comparison of different methods of electron identification and pion suppression are presented.

1. Introduction

The Compressed Baryonic Matter (CBM) [1] experiment will be a dedicated setup for the measurement of fixed target heavy ion collisions at the future FAIR accelerator at Darmstadt. It is being designed for the investigation of the properties of highly compressed baryonic matter [2]. A key item of the CBM physics program is the precise measurement of low-mass vector mesons and $J/\psi$ in their leptonic decay channel. For these studies a very good electron identification is required. In the CBM experiment electrons will be identified by the Ring Imaging Cherenkov (RICH) detector combined with several Transition Radiation Detectors (TRD) positioned behind a Silicon Tracking System (STS). Layout of the CBM experiment is shown in Figure 1.

The RICH detector in CBM will serve for electron identification from lowest momenta up to 10 GeV/c [3, 4]. CO$_2$ is foreseen to be used as radiator gas. Radiator length is 1.5 m. As photodetector MAPMTs from Hamamatsu (H8500-03) are foreseen. Total number of channels is around 55000. The dimensions of the sensitive pads of H8500-03 are 0.58x0.58 cm$^2$. This design provides about 21 hits per electron ring and ring radius for electrons about 5 cm. As the photodetector can only approximately be placed into the focal plane, rings are typically
Figure 1. Layout of the CBM experiment and typical event of Au-Au collision at 25 AGeV beam energy simulated with CBMROOT framework (only primary tracks are shown). STS — Silicon Tracking System, RICH — Ring Imaging Cherenkov detector, TRD — Transition Radiation Detector, ToF — Time of Flight detector.

distorted to ellipses with about 10% difference in the length of major and minor half axis. The ring and hit density on the photodetector plane is non-uniform. The inner part which is closer to the beam pipe has the highest ring densities.

The TRD detector is intended for tracking and improved electron identification for particles with momentum above 1.5 GeV/c. TRD consists of 3 stations, each station consists of 4 identical layers. Each layer consists of a multilayer dielectric radiator, where transition radiation (TR) is emitted by electrons, and of a gaseous detector (85% Xe + 15% CO₂) which measures deposited energy and TR.

The main challenges of the event reconstruction in the CBM experiment result from the large particle multiplicity in heavy-ion collisions. About 800 particles are registered in central Au + Au collisions at CBM energies in a detector acceptance (±25°). This high particles multiplicity leads to a high track and ring density in the detectors. CBM will run for a few months per year at an interaction rate up to 10 MHz and collect an enormous amount of data. This leads to special requirements for the event reconstruction software, which has to perform fast and stable in such environment.

2. Electron Reconstruction in the RICH detector

2.1. Ring reconstruction in the RICH detector

The developed ring reconstruction algorithm [5, 6] is standalone. It consists of three steps.

First, a local search of ring-candidates is performed which is based on the Hough Transform (HT) method [7]. In its straight-forward implementation for a circle curve recognition it requires very large combinatorics which makes it too slow. Therefore instead of combining all possible hit triplets in the photodetector plane, the fact that the RICH rings have a maximum radius $R_{\text{max}}$ is used. Hit triplets are only combined in a local area of the ring-candidate (see Fig. 2, left). The center and radius are calculated using HT equations for every triplet of selected hits and Hough histograms are filled. When the histograms are built, strong peaks
in each histogram should correspond to the expected position of ring center (2D histogram, see Fig. 2, right) and radius (1D histogram). If the peak is higher than a prescribed cut this ring-candidate is accepted and shifted to the ring-candidate array, otherwise rejected.

**Figure 2.** Left: Preliminary local hit selection in a region defined by the maximum ring diameter plus a safety margin. Right: Schematic view of the 2D histogram of ring centers.

The second step is a **ring selection**, in which ghost and clone rings are rejected based on their quality calculated by an artificial neural network.

The third step is an **ellipse fitting** of found rings. An ellipse fitting algorithm based on the Taubin method [8] was implemented.

### 2.2. Electron Identification in the RICH detector

After rings are found, they are matched with STS tracks to get momentum information. In the Figure 3 one can see the ring radius in dependence on momentum for pions and electrons. For electron ring radius is always the same which makes possible to distinguish between electrons and pions using cuts on a ring radius value.

**Figure 3.** Left: RICH ring radius in dependence on momentum for electrons and pions. Right: Output value of the artificial neural network for electrons (red) and pions (blue) identification in the RICH detector.

In order to improve electron identification efficiency an advanced algorithm was implemented. It is based on artificial neural network. The input parameters for an ANN are: major and minor
half axis, rotation angle of ellipse, radial angle and radial position of the ring, \( \chi^2 \) of ellipse fit, number of hits, distance to the closest track, momentum of the track. The ANN derives one output value from nine parameters. Figure 3 illustrates the distributions of the ANN output values for electrons and pions. The cut on output value depends on the required electron identification efficiency (90% by default).

3. Electron Reconstruction in the TRD detector

3.1. Track reconstruction in the TRD detector

The track reconstruction in TRD is based on a track following method using reconstructed tracks from the STS detector as seeds. The track reconstruction method in STS is based on the cellular automaton method [9]. STS track parameters are used as starting point for the following track prolongation. This track following is based on the standard Kalman filter technique [10] and is used for the estimation of track parameters [11] and trajectory recognition.

The track propagation algorithm estimates the trajectory and its errors in a covariance matrix while taking into account three physics effects which influence the trajectory, i.e., energy loss due to ionization (Bethe-Bloch formula) and bremsstrahlung (Bethe-Heitler formula) [12], multiple scattering and the influence of a inhomogeneous magnetic field applying the 4\textsuperscript{th} order Runge-Kutta method [14]. A detailed description of the developed track propagation can be found in [15, 16, 17].

In the track finding algorithm tracks are prolonged subsequently from one detector station to the next adding additional hits in each detector (see Figure 4). For the attachment of hits a validation gate is calculated, according to the chosen probability for rejecting the correct hit. A nearest neighbor and branching methods are implemented to choose the hit to be assigned to a track. In the first approach algorithm attaches the nearest hit if lying in the validation region at all. In the second approach a separate branch is created for each hit in the validation region. After the hit is attached, track parameters are updated with the Kalman Filter. The algorithm allows for missing hits.

![Figure 4. Visual representation of the track reconstruction algorithm based on the track following and Kalman filter methods.](image)

3.2. Electron Identification in the TRD detector

The goal of the electron identification algorithm is to distinguish electrons and pions using set of energy loss measurements. Distribution of energy losses in one TRD layer for electrons and pions are shown in Figure 5. The energy loss measurements are equal for all TRD layers. Usage of standard cuts on a sum of energy losses for all layers does not provide sufficiently high pion suppression level, which can be explained by a long tail of energy loss distribution for pions.
Advanced algorithms were developed which allow to reach required pion suppression of 200 – 500 at 90% electron efficiency. The following methods were implemented:

- Likelihood function ratio (LFR) [19].
- Ordered statistics (median).
- Algorithm based on energy loss transformation and Artificial Neural Network (ANN) classifier [18].
- Algorithm based on energy loss transformation using LFR and Boosted Decision Tree (BDT) classifier.

In this report only two algorithm are described: median and BDT. Description of other methods can be found in the references.

3.2.1. Ordered statistics (median) For each reconstructed TRD track the median value of an array of energy loss measurements is calculated by arranging all the measurements from the lowest value to the highest value and picking the middle one. If there is an even number of measurements, then the median is defined to be the mean of the two middle values. Using the cut on the median value one can distinguish between electrons and pions.

The main advantage of this algorithm is simplicity and extremely fast calculation speed and at the same time it gives reasonable results. The median method is more robust in comparison to the cut on sum of energy loss measurements as it helps to overcome difficulties with long tails of energy loss distributions.

3.2.2. Boosted Decision Tree First a preparation step is performed in order to obtain probability density functions (PDF) which are needed for energy loss transformation. PDFs are obtained separately for pions and electrons. For each TRD track a set of energy loss measurements are taken and sorted from the lowest value to the highest one. Then a set of histograms are filled such that the lowest energy loss value goes to the first histogram, the next one to the second histogram and so on. Finally these histograms are normalized to the integral one, and stored in file.

During the reconstruction step the array of energy losses corresponding to one track is sorted. And for each energy loss $E_i$ new ”normalized” values $L_i$ are calculated according to the equation: $L_i = PDF^p_i(E_i)/PDF^e_i(E_i) + PDF^e_i(E_i)$, where $PDF^p_i(E_i) —$ value of the PDF for pions for
the \( i \)th energy loss, \( PDF_i(E_i) \) — value of the PDF for electrons for the \( i \)th energy loss. An array of ”normalized” energy losses is an input for Boosted Decision Tree (BDT) classifier [21]. The cut on evaluated BDT output value is set assuming 90% electron identification efficiency.

4. Results
In order to test the developed algorithms, central \( Au + Au \) collisions at 25 AGeV beam energy were simulated using UrQMD [20] and propagated through the CBM setup using CBMROOT framework. These events were used to estimate the background in which the interesting signal (\( \omega \) meson decaying into \( e^+e^- \) pair) was embedded.

Figure 6 shows the RICH ring reconstruction efficiency and the TRD track reconstruction efficiency in dependence on momentum. The integrated RICH ring reconstruction efficiency for signal electrons is 89%, the integrated TRD track reconstruction efficiency for signal electrons is 88.5%.

Table 1 represents results of pion suppression level in the TRD detector corresponding to 90% efficiency of electron identification applying different methods. One can see that ANN and BDT methods show the best performance.

| Method       | \( \pi \) suppression |
|--------------|-----------------------|
| BDT          | 660                   |
| ANN          | 530                   |
| Likelihood   | 170                   |
| Mediana      | 140                   |
| Cut on \( \Sigma E_i \) | 5                      |

The RICH detector alone yields a pion suppression factor of 260 at an electron identification efficiency of 72% for momentum range from 0 to 6 GeV/c. In combination with TRD a factor \( 2 \times 10^4 \) is reached at 53% efficiency (see Figure 7). Thus RICH and TRD detectors provide good electron identification in terms of electron identification efficiency and pion suppression to allow feasibility of low-mass vector meson and \( J/\psi \) measurements.
Figure 7. Left: Electron identification efficiency in dependence on momentum. Right: Pion suppression level in dependence on momentum.

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