Improving the spatial resolution of NICA ECAL through new reconstruction method

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Abstract

Shashlyk-type electromagnetic calorimeter (ECal) will be used in the Multi-purpose Detector at Nuclotron-based Ion Collider facility to study the properties of nuclear matter. In this experiment, ECal is responsible for measuring the energy and position of incident particles and identifying them together with the measurement of the time-of-flight system. This paper analyzes the position resolution of the Tsinghua ECal modules with the data from a beam test in DESY. Several reconstruction methods including the charge center of gravity and neural network are carefully studied to improve the resolution. The test results show that these ECal modules can achieve a position resolution of less than 3.8 mm for 1.6 GeV electron beam, and its relationship with the energy is also presented.

1 Introduction

Electromagnetic calorimeter (ECal) is an important component of the Multi-purpose Detector (MPD) at Nuclotron-based Ion Collider facility (NICA) at JINR, Dubna. The NICA collider is designed to provide collisions of heavy-ions over a wide range of atomic masses (from proton to Au) and operates at a luminosity of up to $L = 10^{27} \text{cm}^{-2} \text{s}^{-1}$ for $Au + Au$ collisions. The center-of-mass energy will be $\sqrt{s_{NN}} = 4 \sim 11 \text{GeV}$ [1]. The MPD is located at one of the two interaction points on NICA and is a $4\pi$ spectrometer capable of detecting charged hadrons, electrons and photons. This experiment is dedicated to study hot and dense strongly interacting QCD matter and search for a possible manifestation of the mixed phase formation and critical endpoint in heavy ion collisions [2].

The main goals of the electromagnetic calorimeter in MPD detectors are to participate in particle identification, measure photons flux, and reconstruct decays with photons involved [1]. These put forward certain requirements for the detector’s resolution on energy, time and position, as well as the granularity, occupancy and so on. Good positioning ability of ECal would allow an effective separation of overlapping showers and a precise reconstruction of the position, which is very important for both charged and neutral particles. Because for
charged ones, their signals in ECal have to be matched with the trajectories reconstructed from the tracking detector in order to make accurate particle identification. As for the neutral particles, especially photons that are important for the reconstruction of $\pi^0$, the only available measurement of the position comes from the calorimeter. So the study of nuclear physics will be benefited from a better positioning ability of ECal.

The positioning of showers is usually based on the method of Charge Center of Gravity (CCOG) and some accompanying corrections. This method takes the charge weighted average of the position of towers fired by this shower and is widely used in many position sensitive detectors. However, detailed studies on this method and the possible corrections for the ECal are rare, let alone new reconstruction methods. This paper carefully studies the position resolution of the ECal detectors designed by Tsinghua University, analyzes this CCOG method and presents several new corrections to improve the resolution. We also propose a new position reconstruction method based on a set of neural networks, and the results are proved to be even better.

The paper is organized as follows: Sec.2 describes the structure of Ecal towers and the experiment setup in DESY. Sec.3 describes the methods used to reconstruct the position. The charge center of gravity with multiple accompanying corrections are studied in detail in Sec.3.1, while the new algorithm based on neural network is proposed in Sec.3.2. Sec.4 shows and compares the results given by all the methods mentioned in this paper. Finally, Sec.5 concludes the paper.

## 2 Experiment setup

The electromagnetic calorimeter built in Tsinghua University is a Pb-scintillator sampling calorimeter of the shashlyk-type. It consists of many towers as the basic building elements, each of which contains 220 alternating tiles of Pb (0.3 mm) and plastic scintillators (1.5 mm). All the layers in each tower are optically combined by 16 longitudinally penetrating wavelength shifting fibers (WLS). These fibers are meant to collect the scintillation light, and the light is read out by the silicon photomultiplier (SiPM). Every tower is cut from two sides with an angle of 0.5 degree with respect to the axial direction. After such a cut towers will have a trapezoid shape in the $r\phi$ plain and this will significantly reduce dead zones effect compared to the rectangular towers. The comparison of the two geometries are shown in Fig.1. The pitch size of the rectangular tower is $4 \times 4$ cm, while for the trapezoid one, 4 cm is the size for the larger base. The red dashed lines in the figure represents the electron beams of the experiment.

The beam test is conducted at Deutsches Elektronen-Synchrotron (DESY) in August, 2018. The energy of electron beam at DESY ranges from 1 to 6 GeV. The ECal prototype tested in the experiment consists of 32 towers arranged in 4 rows and 8 columns. Towers are stuck together in the way shown in Fig.1. In order to study the position resolution, beam is moved along the X and Y directions respectively, each time a small step (on the order of millimeters), for example, from beam 1 to beam 4 in Fig.1. When the beam moves in the X(Y) direction, its position in Y(X) is fixed in the center of the tower. The scanning of the position is performed at different energies range from 1.0 to 2.2 GeV, in order to study the the relationship between position resolution and beam energy. From all the 32 towers, only
those in the middle 2 rows and several middle columns are analyzed in this paper, since the information available of the edge clusters is limited by the geometry.

3 Method of position reconstruction

3.1 Charge center of gravity with corrections

Charge center of gravity (CCOG) is a simple but effective method to estimate the position of the incident particles and is therefore extremely widespread in scientific position sensitive detectors [3–5], including the electromagnetic calorimeters [6]. Photons or electrons coming from the interaction point would produce showers in the medium of ECal modules, leading to signal responses in a bunch of towers, which are regarded as clusters. The center of gravity method estimates the position of the particle by calculating the charge weighted average of the position of all the fired towers:

\[ X' = \frac{\sum_i E_i X_i}{\sum_i E_i} \]  

Since this method is essentially a linear operation, its estimation is unbiased only when the energy deposited in each tower has a linear correlation with the real position. However, for the calorimeters, the incident particles would deposit a large amount of energy in their vicinity, while little far away. The amount of energy drops rapidly with the distance, which is apparently non-linear. Then the use of CCOG will introduce a systematic error in measurement, which is shown in Fig.2 by the black squares. Since the position scanning in this experiment is actually one dimensional at a time, so only the results in X direction is shown in this part. Every square in the plot represents the average value of the error in this scanning point. The error in Fig.2 has a "sin" shape or "S" shape if part of squares are considered. This periodic trend can be described by the sum of a trigonometric and a linear function:

\[ f(x) = a_0 x + a_1 \sin(a_2 x + a_3) + a_4 \]  

In Fig.2, the black squares are fitted with the function of Eq.2. The undetermined coefficients are shown on top right of the plot and the fitting curve is drawn in red. The
blue straight line shows the linear part of the function. This shape is highly related to the detector geometry, and the reasons for the trigonometric and linear part of the function is different. For the trigonometric part, the peak and valley correspond to the beam shot at 1/4 and 3/4 of the tower respectively, while the center points correspond to the center or edges of a tower. From the plot, it is clear that errors are larger than the linear function at all the 1/4 region, smaller at 3/4, while relatively accurate at center and edges. This illustrates that the estimated value of CCOG is biased toward the center of the towers. The linear part of the fitting function is increasing with the measured position. This is caused by the geometry of the trapezoid tower shown in Fig.1. Taking beam No.3 as an example, it is right in the middle of the 3rd rectangular tower, but in between the 3rd and the 4th for the trapezoid geometry. The pitch of the tower used to calculate the estimation with Eq.1 is the same as the pitch of the rectangular geometry, resulting in an upward trend of the overall systematic error when beam goes from the 1st to the 4th tower.

Therefore some position corrections should be applied to remove this bias and achieve good precision. Fig.3 shows the error with respect to the measured position after two 1 dimensional corrections. Correction method 1 corrects the bias by fitting it with Eq.2 and subtracts the corresponding function value for every data point. The corrected bias is shown with the red squares in Fig.3a. Method 2 uses the same fitting function but with a larger \( a_1 \) to better eliminate the bias, which is shown in Fig.3b. Fig.3 proves that method 2 works better from the perspective of the average of the errors, but this does not mean it will definitely deliver a better precision than method 1.

In this paper, an iterative "bin correction" is also proposed. The estimated position of CCOG is filled into a histogram with a very small bin width. The "sin" shape also
exists between the error and the estimated position, but the relation is characterized more accurately since the bin width is very small. This method corrects the error for every single bin of the estimated position, and the two dimensional histogram before and after the correction is shown in Fig.4. The bin correction is supposed to be better than the above two, because the bin width is defined by the users and is much smaller than the step size of the position scan in the experiment. In addition, this correction is iterated multiple times until the periodic trend is finally eliminated.

### 3.2 Pulse shape analysis with neural networks

Since only the total energy deposition in the related towers are used to reconstruct the position, it can be regarded as a simple solution. In order to further improve the position resolution, it is also necessary to explore some other reconstruction methods. In recent years, deep learning and neural networks have successfully solved a lot of nonlinear problems and have been widely used for particle reconstruction in various high energy physics detectors [7–9]. As early as 1998, CMS has tried to apply fully-connected neural networks to the reconstruction algorithm of its ECal detectors [10]. However, due to the simple structure of the network and the difficulty of the training, the performance of this new method is just as good as the traditional charge center of gravity. This paper designed a more general and powerful convolutional neural network (CNN), train and validate the network with recently developed hardware and technologies. The performance is indeed better than the center of gravity.

The original signals read out by the electronics of every event are waveforms from a collection of neighboring towers. For every event, the tower with the largest signal is considered to be the center tower. Waveforms from the center tower and its 8 nearest neighbors are
selected and fed into the neural network, because they contain the position distribution of the energy deposition, which is most relevant to where the particle is. The real position for every event is unified in the coordinate with respect to the center tower.

![Figure 4: 2D distribution of the error and the measured position. (a) is the distribution before the bin correction, while (b) after the correction](image)

Figure 4: 2D distribution of the error and the measured position. (a) is the distribution before the bin correction, while (b) after the correction

The structure of the network is shown in Fig.5. The first layer is the input which is the original waveforms of the related towers. The middle 3 layers denoted as ”Conv2D” are CNN layers with a same kernel size of 2. The last few layers are fully-connected layers.

![Figure 5: The structure of the convolutional neural network. The first layer is the input which is the original waveforms of the related towers. The middle 3 layers denoted as ”Conv2D” are CNN layers with a same kernel size of 2. The last few layers are fully-connected layers.](image)

Figure 5: The structure of the convolutional neural network. The first layer is the input which is the original waveforms of the related towers. The middle 3 layers denoted as ”Conv2D” are CNN layers with a same kernel size of 2. The last few layers are fully-connected layers.

The structure of the network is shown in Fig.5. The first 4 layers have 3 dimensions, which are represented by x, y and channel respectively. The dimension of the input layer is (9,9,3), and it is the original waveforms from the 3 \times 3 towers mentioned above. The middle 3 layers denoted as ”Conv2D” are CNN layers with a kernel size of 2. Their dimensions are (7,7,10), (5,5,24), (3,3,64), respectively. Fully-connected layers in the end flatten the data and the final output is transformed into a single value, namely the real position. Dropout is applied to all the middle layers to avoid overfitting. The size of the training and validating data is 300,000 and 100,000. The loss is the mean squared error between the estimation
and the truth, and it converges very quickly in the training. Fig.6 shows the distribution of the residual of position estimated by the CNN network. A gauss function is fit to the distribution within $3\sigma$ and drawn in red. The mean value of the bias is almost 0, which shows that CNN is an unbiased estimation of the position.

![ECal: position residual with CNN](image)

Figure 6: Distribution of the position residual. The mean value of the residual is almost 0.

### 4 Results

Fig.7 shows the position resolution in the Y direction of different towers in 2 different rows. Different markers in the plot are the results estimated by different reconstruction methods. The resolution is from 3.6 to 5 mm for all the towers scanned in the experiment, except the 5th tower in row 2. This is because the readout SiPM of this channel was not working properly in the experiment and this also slightly affects the nearby 2 towers. From these 2 plots, it is clear that the resolution of method 1 is smaller than 2, even if method 2 is a little bit better considering only the average bias of every scanning point, which is shown in Fig.3. This implies that the average error of 0 should not be the only focus. This is not only because outliers would affect the mean value, but also because the distribution of the error itself is an important feature for judging whether the correction is effective.

Compared to two 1D correction methods, bin correction improves the position resolution for all the towers shown in Fig.7. This demonstrates that the bin-wise correction makes the distribution of errors more reasonable. It is also worth noting that the resolution obtained with CNN is even better than the combination of CCOG with any corrections. From an algorithmic point of view, charge center of gravity plus correction is just one of many effective models for position estimation. However, the neural network is different. Essentially, a network represents a collection of models, and the training is actually finding the most appropriate one from the collection. This means the method is more comprehensive and can
Figure 7: Position resolution in the Y direction. (a) shows 6 towers in row 1, while (b) in row 2(b). Different markers represent the results of different reconstruction methods.

Figure 8: Position resolution in the X direction. Different markers are from different reconstruction methods.

Fig. 8 shows the resolution in the X direction. The position scanning step in the X direction is only 2 mm, which is less than 5 mm in the Y direction, so the scanning only spans 3 towers. It is the same that two rows of towers are scanned in the experiment, but since the rules of resolution are basically the same, only the results of the 1st row are shown in the plot. It can be seen that the position resolution in the X direction is slightly better than
Y. This is because in the scanning of position, the smaller step size makes the calibration of the real position more accurate, reducing the uncertainty.

All the results shown above are obtained when the beam energy is fixed at 1.6 GeV. However, the position resolution is highly related with the beam energy, because the energy determines the distribution and fluctuation of the electromagnetic shower. Showers would strongly affect the energy deposition in towers and thus the position accuracy. Fig.9 shows that the resolution gets improved with beam energy and is nearly proportional to \(1/\sqrt{E}\). The position resolution is under 3 mm when the energy reaches 2 GeV. As before, CNN achieves the smallest resolution and then the center of gravity method with bin correction and finally, with two 1D corrections.

![Figure 9: Position resolution with respect to the beam energy](image)

5 Conclusions

This paper carefully studies the position resolution of the ECal detector designed for the MPD experiment at NICA. The analysis is based on a beam test in DESY, and the results are well explained. The reconstruction method of charge center of gravity and some accompanying nonlinear corrections are described in detail. A new method based on deep learning and neural networks are also proposed and implemented to further improve the position resolution. It has been proved by the experiment that the position resolution is around 3.5~3.8 mm for 1.6 GeV electron beam, while less than 3 mm for 2 GeV electrons. These results meet the requirements of the MPD experiment, and are of great significance to the further study of the detector.
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