Neural network based cluster reconstruction in the ATLAS silicon Pixel Detector

This article has been downloaded from IOPscience. Please scroll down to see the full text article.

2013 JINST 8 C04003

(<http://iopscience.iop.org/1748-0221/8/04/C04003>)

View [the table of contents for this issue](#), or go to the [journal homepage](#) for more

Download details:

IP Address: 131.169.3.59

The article was downloaded on 24/04/2013 at 15:32

Please note that [terms and conditions apply](#).

RECEIVED: October 30, 2012

REVISED: January 26, 2013

ACCEPTED: February 11, 2013

PUBLISHED: April 2, 2013

14th INTERNATIONAL WORKSHOP ON RADIATION IMAGING DETECTORS,
1–5 JULY 2012,
FIGUEIRA DA FOZ, PORTUGAL

Neural network based cluster reconstruction in the ATLAS silicon Pixel Detector

T. Pérez Cavalcanti¹

DESY,

Notkestr. 85, Hamburg, Germany

E-mail: Tiago.Perez@desy.de

ABSTRACT: The hit signals read out from pixels on planar semi-conductor sensors are grouped into clusters, to reconstruct the location where a charged particle passed through. The spatial resolution of the pixel detector can be improved significantly using the information from the cluster of adjacent pixels. Such analogue cluster creation techniques have been used by the ATLAS experiment for many years giving an excellent performance. However, in dense environments, such as those inside high-energy jets, it is likely that the charge deposited by two or more close-by tracks merges into one single cluster. A clusterization algorithm based on neural network methods has been developed for the ATLAS Pixel Detector. This can identify the shared clusters, split them if necessary, and estimate the positions of all particles traversing the cluster. The algorithm significantly reduces ambiguities in the assignment of pixel detector measurements to tracks within jets, and improves the positional accuracy with respect to standard interpolation techniques, by the use of the 2-dimensional charge distribution information. The reconstruction using the neural network reduces strongly the number of hits shared by more than one track and improves the resolution of the impact parameter by about 15%.

KEYWORDS: Particle tracking detectors; Pattern recognition, cluster finding, calibration and fitting methods; Particle tracking detectors (Solid-state detectors)

¹On behalf of the ATLAS collaboration.

Contents

1	Introduction	1
2	The neural network algorithm	1
3	Results	2
4	Conclusions	4

1 Introduction

The ATLAS pixel detector determines the position of traversing charged particles. The detector consists of 3 cylindrical layers at 50.5, 88.5 and 122.5 mm around the beam line, the “barrel”, and two sets of 3 disks at each end closing the cylinders, the “end caps”. The nominal pixel size of $50\text{ }\mu\text{m}$ (r - ϕ) and $400\text{ }\mu\text{m}$ (Z) is used throughout most of the detector, although there is also a small percentage of longer pixels [1, 2]. Where Z represents the axis along the beam line, ϕ the azimuth angle, and r the distance to the Z -axis. In the following the polar angle will be denoted by θ and the pseudorapidity by η . The standard clustering algorithm groups fired pixels with a common edge or corner into clusters [2]. The position of the crossing particles is estimated by interpolating the charge deposited on each pixel; the standard algorithm uses a linear interpolation between the first and the last set of pixels in a cluster. In very dense track environment, as in high-energy jets, there is a large probability that the charge deposition of two or more particles overlaps, thus producing large multi-particle clusters. Figure 1 shows how the minimum separation between tracks for jets with p_T higher than 1 TeV in PYTHIA dijet Monte Carlo (MC) events, is smaller than the pixel width in Z direction ($400\text{ }\mu\text{m}$), illustrating the likelihood of merged clusters in such high-momentum jets. MC dijet events were generated using PYTHIA 6 MC program [3], and processed through the ATLAS detector simulation, with a detailed description of the geometry and material of the ATLAS detector, based on GEANT4 [4]. The aim of the neural network algorithm (NN), presented here, is to improve the cluster reconstruction in two ways; first identifying the number of particles that went through each cluster [5]. Secondly producing an accurate estimation of the position, and uncertainty, of each particle.

2 The neural network algorithm

Neural networks (NN) are systems inspired by certain biological systems (like the human brain), composed of a large network of simple computational nodes interconnected in a layer-wise structure. NN are very well suited to solving non-linear statistical correlations and pattern recognition, matching the needs of the cluster identification in the ATLAS Pixel Detector. For the ATLAS cluster recognition, a 4-layer network topology, implemented using JETNET 3.5 [6] was chosen; a

Figure 1. Mean minimum separation between two particles for the innermost layers of the current ATLAS Pixel barrel as a function of jet p_T in PYTHIA dijet MC events [5].

topology that provides a compromise between the performance and the training time. In total the NN cluster recognition uses 10 networks; one that provides the number of particles, another three that calculate the positions of 1, 2 and 3 particles. Six more NN (2 for each position network) are used to produce the estimation of the error both directions.

The neural networks are fed with the following data:

- The charge of each pixel in an area of 7×7 pixels around the cluster centre, calculated as the centre of gravity of the fired pixels.
- A vector of the pixel size in the Z - η direction.
- Estimated direction (θ , ϕ) of the traversing particles (if no tracking information is available, the θ , ϕ angles between the interaction point and the cluster centre are used).

The training of the NN was performed using a mixture of $t\bar{t}$ MC events and high p_T PYTHIA dijet MC events ($140 < \text{jet } p_T < 560 \text{ GeV}$). Figure 2 illustrates the performance of the neural network algorithm. The figure shows a cluster produced by the charge deposition of the two particles, with the outcome of the position NN displayed by the blue markers. These are very close to the true positions of the crossing particles (pink markers). The probability of the number of crossing particles is depicted by the numbers at the bottom.

3 Results

In a dense track environment there is a significant probability that clusters are produced from the charge deposited by more than one particle, hence our tracking algorithms may associate these clusters to more than one track. Using the NN clustering, the number of shared clusters is greatly reduced. Figure 3 shows the reduction of shared clusters in the innermost barrel layer ($R = 50.5 \text{ mm}$).

Figure 2. A cluster produced by two particles. The pink and red markers depict the true particles position and direction. The blue stars show the positions calculated by the NN. The numbers on the bottom show the probability of the number of particles [5].

Figure 3. Shared hits on-track in the innermost barrel layer for track with $p_T > 100$ GeV from $t\bar{t}$ samples [5].

As this layer is the closest to the interaction point, the separation between tracks is expected to be the minimum and therefore the largest performance gain is anticipated. Figure 4 shows the cluster residuals (difference between the crossing positions calculated by the cluster algorithms and the extrapolation of the tracks) for 4-pixel clusters. Using the standard clustering, a two-peak structure is visible, that disappears when using the NN clustering. Clusters of this size are mainly produced by delta rays. Using the linear interpolation, these will pull the cluster's centre away from the actual crossing point. The refined treatment of the data performed by the NN greatly improves the estimation of the particles crossing point. This is also visible for other cluster sizes, and in the Z residuals. While linear interpolation can be calibrated on data [2], the NN relies on simulations for training. Nevertheless its application to data shows improvements similar to the one observed in simulations. The NN also greatly improves the impact parameter determination, as shown in

Figure 4. Cluster residual in the r - ϕ direction for 4-pixel clusters from $t\bar{t}$ events, reconstructed with standard interpolation and the NN algorithms [5].

Figure 5. Longitudinal impact parameter resolution for tracks with $p_T > 100$ GeV from $t\bar{t}$ events [5].

figure 5. A similar gain is also noticeable for the transverse direction. These improvements in the impact parameter resolution have a direct effect on the primary and secondary vertex reconstruction, greatly improving the performance of heavy flavour tagging.

4 Conclusions

The NN clustering algorithm provides a great improvement on the pixel cluster resolution. This is especially visible for dense environments in the innermost pixel layer. The NN approach will be crucial and will need further optimization with the planned increase in luminosity at the LHC and the addition of a pixel layer in 2013, the IBL [7].

References

- [1] ATLAS collaboration, *The ATLAS experiment at the CERN Large Hadron Collider*, 2008 *JINST* **3** S08003.
- [2] G. Aad et al., *ATLAS pixel detector electronics and sensors*, 2008 *JINST* **3** P07007.
- [3] T. Sjöstrand, S. Mrenna and P.Z. Skands, *PYTHIA 6.4 physics and manual*, *JHEP* **05** (2006) 026 [[hep-ph/0603175](#)].
- [4] GEANT4 collaboration, S. Agostinelli et al., *Geant4 — a simulation toolkit*, *Nucl. Instrum. Meth. A* **506** (2003) 250.
- [5] ATLAS collaboration, *Neural Network cluster reconstruction in the pixel detector*, ATL-COM-PHYS-2012-476, <http://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/IDTRACKING/PublicPlots/ATL-COM-PHYS-2012-476>.
- [6] C. Peterson, T. Rönngvaldsson and L. Lönnblad, *JETNET 3.0 — a versatile artificial neural network package*, *Comput. Phys. Commun.* **81** (1994) 185.
- [7] ATLAS collaboration, *ATLAS insertable B-layer technical design report*, CERN-LHCC-2010-013, ATLAS-TDR-019 (2010).