Momentum reconstruction of particles in the forward muon trigger system of the ATLAS detector

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Abstract

We devise a feed forward neural network which identifies the charge and momentum of muons in the forward trigger system of the ATLAS detector. We use second order learning methods to train the network on a set comprising a few thousand simulated events over a wide range of energies and transverse momenta. The network produces an unbiased estimate of the particles' momentum and charge. On a test set, the charge is correctly identified in 94% of the events, and the mean relative error in transverse momentum is about 1.9%.

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1 Introduction

The Large Hadron Collider (LHC) is an accelerator which will bring proton beams into head-on collisions at energies of 14 TeV and luminosity $L = 10^{34}\ cm^{-2}\ s^{-1}$, higher than ever before. The high luminosity produces an event flux of about 1 GHz. In such an environment there is a unique importance to an efficient triggering system operating within the short bunch crossing period of 25 ns. For this purpose the trigger system is organized in three levels, each reducing the rate by several orders of magnitude.

In this work we describe a neural network implementation which may be used as an efficient triggering device. By using standard algorithms the network learns the statistics of the data which is otherwise described by very complicated dynamics.

2 Experimental setting

The muon detection and momentum measurement technique at the ATLAS detector is based on the magnetic deflection of muon tracks in a system of three large superconducting toroid magnets. In this work we focus on triggering with muon hits on three thin-gap chamber (TGC) stations [2, 3, 4] in the end-cap region, $\eta \geq 1.05$, where η is the pseudorapidity $\eta = -\ln\tan(\theta/2)$ and θ is the polar angle. As trigger chambers, the TGC are required to have a good time resolution with fine granularity. The muon that is produced with momentum $\vec{P}$, is Coulomb scattered while traveling through the calorimeter, and its track is being bent by highly non-homogeneous magnetic fields of both the barrel and the end-cap magnets. See Fig. 1 for a general engineering view of the setup. The trigger quality is determined by the momentum resolution that is achieved. Hence we wish to accurately reconstruct the transverse momentum and charge of the muon from the patterns of its hits on the TGCs. This is a highly non-trivial inverse problem.

3 Method

We use a standard feed forward neural network to learn the one to one correspondence between the final direction of the muon track and its charge and initial momentum. For training the network and for testing its performance we use simulated events produced by the DICE program [7] which include all essential features of the detector. We study events with single muon tracks in the range $\eta > 1.05$ which hit the end-cap TGCs. The events include positive or negative muons with transverse momentum (P_T) ranging from 1 to 50 GeV.

Several network architectures were examined, differing from each other by

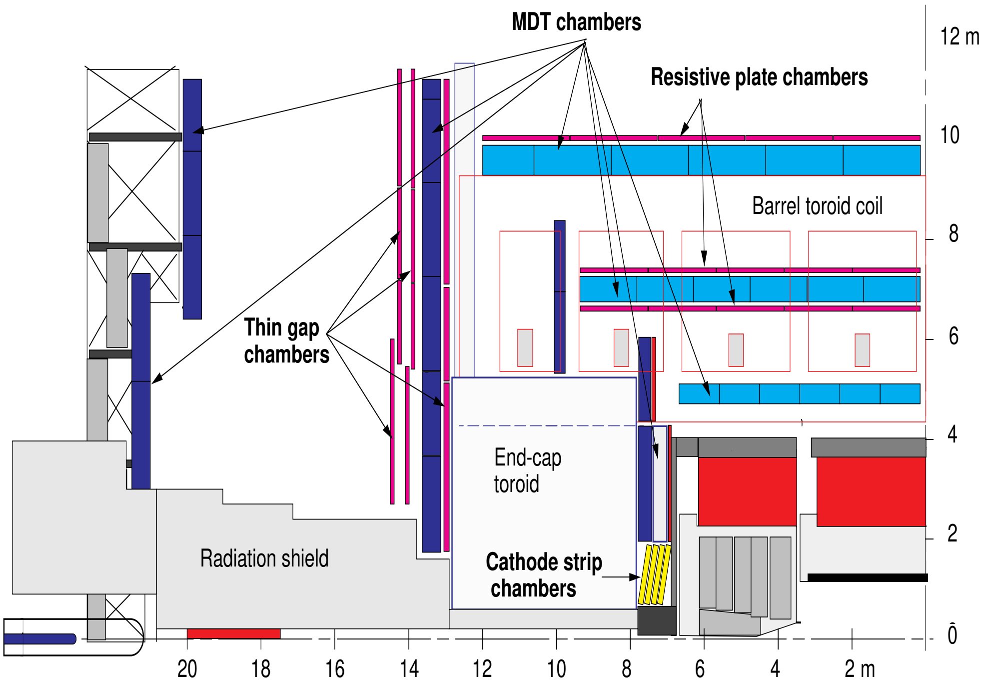

Figure 1: Side view of one quadrant of the ATLAS experiment

the number of hidden layers and the number of neurons within each layer. Each network has four inputs, intermediate layers with sigmoidal transfer functions and four output linear neurons. The input neurons are fed with the slopes and intercepts of the projections of the track of the muon on xz and yz planes, calculated by preprocessing the raw data with the Hough [5] transform. This preprocessing is essential since the raw data consists of missing hits as well as multiple hits where TGC plates overlap. The outputs include the values of the the muon's initial transverse momentum P_T and direction (θ, ϕ) and its electric charge, q. An alternative for hardware implementations is to use a fixed preprocessing neural network dedicated to track identification (e.g. [6]).

Each network was trained using the Levenberg-Marquardt method with 1400 events. Typically, training lasted several thousand epochs. Upon completion of the training phase each network was tested on a test set of 1829 events.

4 Results

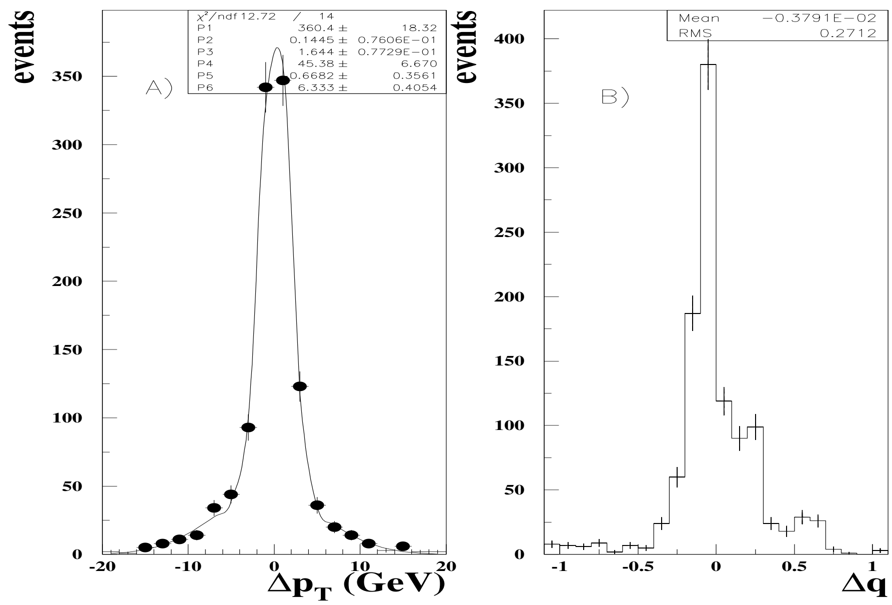

Figure 2: The errors of the network estimte of A) the muon's transverse momentum and B) the track charge. A double Gaussian is being used to fit the Δp_T distribution. P1-P3 (P4-P6) are the constant, mean and width of the first (second) Gaussian. Also shown are the mean and RMS of Δq.

The network with the least sum-squared errors over the test set has two intermediate layers with seven neurons each. The training phase of this network consisted of 2000 epochs. Figure 2 shows the test set distribution of the deviation of the network estimate of the transverse momentum and charge. The widths of both histograms in Fig. 2 stems primarily from real stochasticity of the data due to Coulomb scatterings, and the finite width of the interaction region.

We calculate the mean relative error of transverse momentum separately for several pseudorapidity bins. The distribution of errors within each bin is approximately gaussian. The mean as well as the width of the distribution are depicted in Fig. 3. The poorer resolution in the range $\eta < 1.8$ stems from the highly non-homogeneous magnetic field in this region, produced by a superposition of the magnetic fields of the end-cap and barrel toroid coils [1].

Identifying the muon's charge is somewhat more robust, due to its discrete nature. In total, charge is identified correctly in 95.8% of the events. Most

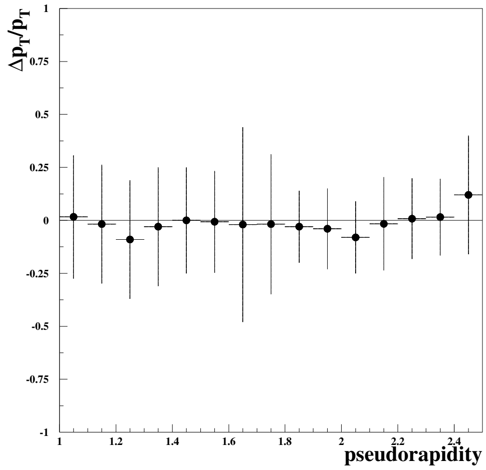

Figure 3: The mean relative error in transverse momentum as a function of η. The error bars are RMS of gaussian fit of $\Delta P_T/P_T$. The larger widths in the region $\eta < 1.8$ mark poorer transverse momentum resolution in this region due to highly non-homogeneous field.

of the misclassifications occur at high momentum, where the bending of the trajectory due to the magnetic field is smallest. This tendency is demonstrated in Fig. 4, where we plot the mean of the network error of the charge q, viewed as a real number.

5 Summary

We presented a feed forward neural network which is capable of estimating the charge and momentum of a muon. The data is intrinsically stochastic, giving rise to an approximately gaussian distributions of network errors. The stochasticity of the data is the major source of network errors. The simplicity of the network enables to realize it with nanosecond technology hardware, thus making it appropriate for second level triggering.

Acknowledgment

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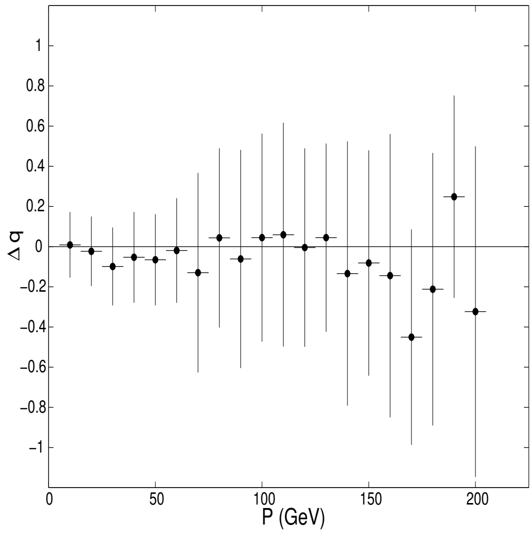

Figure 4: The mean error in charge estimate Δq as a function of the total momentum P. The error bars denote standard deviations of Δq within each momentum bin. Since the final estimate for the charge is just the sign of q, charge misclassifications are actually quite rare (totally $\approx 6\%$).

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