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Conference Paper · January 1997

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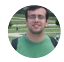

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A Neural Particle Discriminator for Calorimetry in High Energy Physics

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Abstract

A particle discriminator for high energy physics experiments is described. Based on a calorimeter, a detector that measures the energy of incoming particles, a feed-forward neural network performs electron/pion discrimination. The information comes from the energy deposited on each cell of this granular detector and the network is trained by using backpropagation. For 99% pion efficiency, only 2.2% of electrons are misclassified as pions. The discriminating system may be implemented on fast digital signal processor technology for online operation in high-event rate environments.

1 Introduction

In high energy experimental physics, collider experiments are used to test models concerning the structure of matter. Particles are made to collide at high energy in the center of the mass and the resulting reactions are observed from the information readout from detectors placed around the interaction point. In such experiments, many new particles have been discovered, although some models have also been discarded.

For continuing the search of new physics, a new generation of collider machines are being prepared to run in the near future. This is the case of the Large Hadron Collider (LHC), which is being developed at CERN (Switzerland) and is expected to be operational at 2005. This machine features a very high event rate, as the period between collisions is as low as 25 nanoseconds. However, the interesting physics expected to be observed is extremely rare, so that most of the events have to be discarded before being recorded. For building such online validation system, neural network based designs are being proposed to be implemented in digital signal processor technology [1].

Among detectors, calorimeters play an increasing role on modern collider experiments. These detectors measure the energy of incoming particles by total absorption and can achieve very good resolution. Calorimeters are compact detectors which improve energy resolution for higher energy particles. This is valuable for collider experiments, as they experienced a significant increase in the energy of collisions. The LHC should collide protons at 16 TeV at the center of the mass.

Most applications use sampling calorimeters [2]. These calorimeters have a heavy material acting as the energy absorber, so that incoming particles loose their energy when interacting with this material. On the other hand, an active material is used to sample a small fraction of the energy being deposited in the detector, so that energy measurement can be performed by transforming this information into an electrical quantity (current, charge) to be recorded.

Although the main goal is to achieve the best energy resolution, calorimeters are also valuable for particle identification. Due to different energy deposition profiles that can be measured with a calorimeter, particles can be discriminated and this is very useful for validation systems. In fact, due to their good discrimination capacity and to their high speed signal feature, calorimeters generate the main information in which fast validation systems rely on [3].

At LHC, the calorimetry task is split into two detectors. For one possible design, a liquid argon calorimeter is concerned with measurements of electromagnetic (e.m.) interactions. As this type of interactions may be messenger of the interesting physics for LHC, this calorimeter is the main detector for energy measurements. Thus, electrons should have their energy totally absorbed by such e.m. calorimeter.

Placed just after the e.m. calorimeter, the hadronic calorimeter concerns the energy measurements for hadrons. Pions belong to this class of particles. Typically, hadronic calorimeters are much larger (both radially and longitudinally) than e.m. ones. In fact, as particles deposit their energy in the calorimeter by means of generating a shower of particles of decreasing energy in the way they loose energy inside the detector, e.m. particles need much less material to develop their showers. Thus, for absorbing high energy particles, e.m. calorimeters are only a few tens of centimeters long, while hadronic calorimeters need a few meters. At LHC, hadronic calorimetry is being considered to be performed by an iron/scintillating tile sampling calorimeter (Tilecal).

For prototype tests of the calorimeter performance, high energy beams from different particles are used. To this end, high purity in the statistical sample is required, which implies that any undesired particle that is present in the beam line of a given particle and at a given energy should be detected and discarded by the data acquisition system. In this way, the performance to be measured can be realized with the precision required by such high performance detector.

In this paper, an electron/pion discriminator for the Tilecal is described. As the tile calorimeter is more concerned with hadronic measurements, any electron present in a pion beam should be eliminated from the sample.

The reason to use neural processing in this application is two fold. Firstly, neural networks usually have high discrimination capability, so that only a small fraction of electrons may fake the pion trigger for the acquisition system [4]. Secondly, neural network based discriminators may be implemented in hardware for high speed applications. Therefore, an online high performance discriminator can be designed using the neural approach.

In the next section, the main features of the Tilecal are described. In Section 3, the discriminator design is presented and results from experimental data are discussed. Section 4 addresses conclusions.

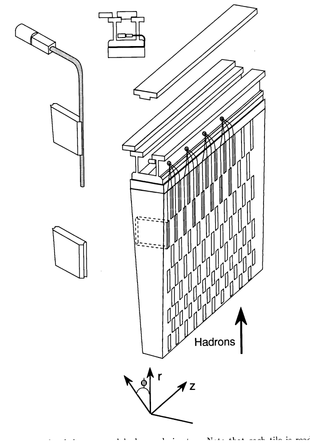

Figure 1. A Tilecal module.

2 The Detector

Scintillating tile calorimeters are widely used in high energy physics due to their good performance and fast signal features. In typical designs, the tiles are oriented about normal to the particle trajectories and are readout by means of wavelength shifting optical fibers. When a particle interacts with the detector, it excites the scintillating material and light is produced. The light is then transported by the fibers to the output of the detector.

Specifically designed for matching LHC requirements, the Tilecal has the scintillator tiles and iron absorber plates aligned with the direction of the primary particles. Coupling to the edges of the tiles, fibers run in longitudinal direction in order to carry the light information. Figure 1 shows a module of such detector [5].

The light signals are converted into electrical signals by means of photomultiplier tubes that readout specific groups of fibers. This allows for radial and longitudinal segmentations for each module. Thus, a module of such calorimeter consists of five cells (towers) in the radial direction (1 meter long) and four sampling layers in depth (2 meters long). Considering that both sides of each segment are readout by fibers, 40 signals are provided by a single module.

The data used in this paper concern experimental tests performed in a five module prototype

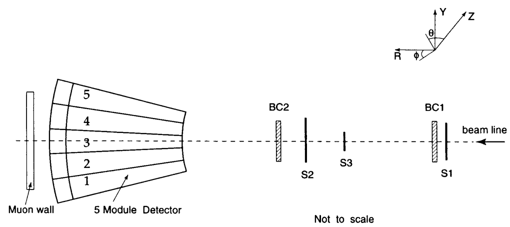

Figure 2. The experimental setup.

[5]. The experimental setup can be seen in Figure 2. Auxiliary detectors are used by the data acquisition system to measure the accuracy and purity of the beam line. To this end, beam chambers (BC1 and BC2) supply information concerning the impact point of the particle beam line in the detector. For analysing the performance of the detector to high energy electrons and pions, a muon wall allows to reject muons from the data sample. The scintillating counters (S1-S3) provide the triggering signal for the data acquisition system, so that signals are recorded when a coincidence signal of the counters is achieved. The calorimeter signals are recorded by means of charge analog-to-digital converters (ADCs), which are available for each group of fibers that form a calorimeter segment. Thus, a total of 200 signals are provided by the full detector for each event being recorded.

In order to cope with the wide dynamic range of the calorimeter measurements, the photomultiplier signals are split into two signal paths with gains of 1 and 10. Both signal paths are concurrently acquired by means of the ADCs. The switching between the two signal path readouts is set in the offline analysis program. Low charge signals are preferably readout from the ADCs associated to the higher gain path, while higher charge signals may be preferably readout from the ADCs which record the unit gain line, in order to avoid saturation.

3 Neural Discriminator

For designing a neural electron/pion discriminator for the Tilecal, pions and electrons of 100 GeV were acquired by the acquisition system described above. The data sample was validated by an offline analysis of the auxiliary detector information. Therefore, muons that fake the low energy spectrum for pions were rejected. Beam chamber information allowed to retain events inside a beam spot not greater than 2 cm, with respect to the calorimeter center (middle point of module # 3). This is important to avoid energy leakage that may result due to the restricted dimensions of the prototype under test (with respect to the final design which will feature 10 000 readout channels).

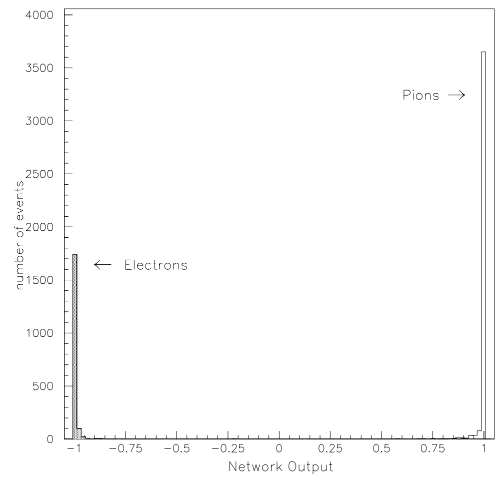

Figure 3. The network output for electrons and pions of 100 GeV.

The valid data sample included 3218 electrons and 7982 pions, and was split into two sets, forming the training and test sets required for network design. The training phase of the network was performed on events belonging to the training sets and discriminator efficiencies were evaluated by considering the network response to the testing set, so that generalization could be tested.

In this work, the neural network had a feedforward fully-connected topology and was trained by using the standard backpropagation learning procedure. Network simulations were performed using JETNET 2.0 package [6] and the hyperbolic tangent was used as the neuron activation function.

The grained information of the calorimeter was fed into the network, which represented a 200 component input data vector. The energy deposited on each segment was normalized by the total energy absorbed by the calorimeter for each event. A network with 40 nodes in the hidden layer and having a single output node was the topology used.

Figure 3 shows the network output for the testing set. During the training phase, the target value was assumed to be -1 for electrons and 1 for pions. The network performance achieved

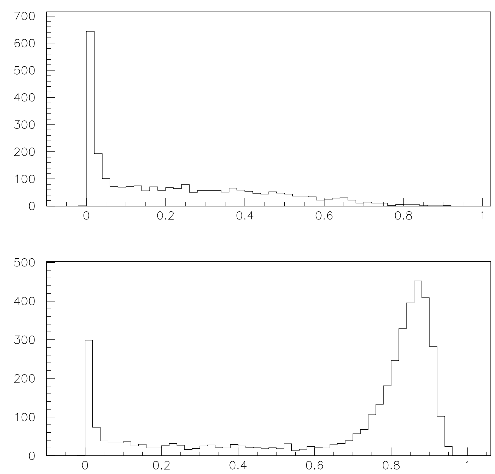

Figure 4. Fraction of the energy deposited in the first sampling layer for pions (top) and electrons (bottom).

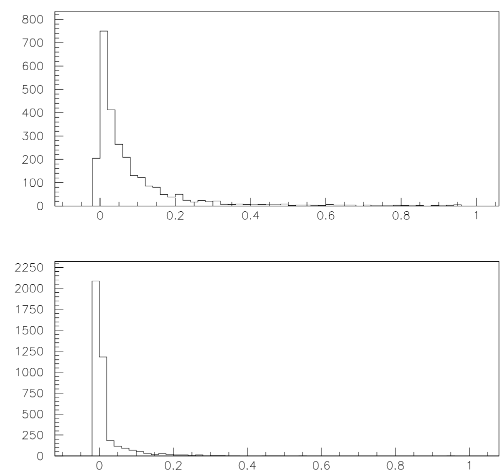

Figure 5. Fraction of the energy deposited in the fourth sampling layer for pions (top) and electrons (bottom).

99% pion efficiency with 2.2% of electrons being misclassified as pions.

In order to compare the performance of the neural network based discriminator to a classical discrimination procedure, the energy deposition profile for the four detector's sampling layer was studied. This information is commonly used in calorimetry for electron/pion separation.

As mentioned before, electrons should deposit their energy in the first layers of the detector, so that the fourth layer should sample energy only for pions. On the other hand, pions typically enter much deeper in the calorimeter before depositing a significant part of their energy. Therefore, the first sampling layer should see a small fraction of pions' total energy, As electrons start to interact almost immediately with the detector, the first sampling layer do see a good fraction of their total energy. Figures 4 and 5 show, respectively, the distributions for the fraction of energy deposited in the first and the fourth sampling layers for both particles.

The distributions for the fist layer are much broader than the ones for the fourth, so that the discrimination based on the information of the last layer should perform better than the one based on the first layer. Just requiring for a particle a minimum deposition of 1% of the total energy in the fourth layer in order to be identified as a pion, 75.6% of pions are correctly classified, and the classification error for electrons amounts to 21.6%. If the first layer information is added, so that a particle to be identified as a pion needs more than 1% of the total energy in the fourth layer, or less than 40% of the total energy in the first layer, the discrimination performance slightly improves. Doing so, 87.5% of pions are correctly classified and 25.1% of electrons are misclassified as pions. Therefore, these discrimination methods can not compete with neural networks in which performance is concerned.

It should be mentioned that the poor efficiency achieved by the discrimination method based on the sampling layer information reflects the coarse granularity of this detector. In fact, hadronic calorimeters do not need fine grained cells, as e.m. calorimeters do. Therefore, the differences in the energy deposition for pions and electrons are not very well detailed for hadronic calorimeters, when these detectors are compared to their e.m. counterparts. In fact, more precise electron/pion separation at LHC conditions needs additional information stored in the e.m. section of the calorimeter system.

4 Conclusions

For a scintillating tile calorimeter, electron/pion discrimination was addressed by neural processing. Using the energy deposited by the incoming particle in each segment of a five module calorimeter prototype, a pion efficiency of 99% was achieved with 2.2% of electrons being misclassified as pions. The discrimination performance of the neural network based discriminator proved to be significantly better than a discrimination method based on the energy deposited longitudinally on each sampling layer of the calorimeter.

Besides good performance, the neural discriminating system allows to address online system operation, so that detector performance can be obtained by means of a refined pion sample (free of electron contamination). To this end, digital signal processor (DSP) technology exhibit quite adequate features. Today, fast DSPs are available in the market [7] and they can run C language codes that easily can describe the production phase of the neural discriminator. This implementation is under development.

Acknowledgments

We are thankful for the support that has been provided to this work by CNPq and FUJB (Brazil) and CERN (Geneva, Switzerland). We would like to thank the Tilecal Collaboration for providing the experimental data sets.

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