A Hybrid Training Method for Neural Energy Estimation in Calorimetry

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Abstract. A neural mapping is developed to improve the overall performance of Tilecal, which is the hadronic calorimeter of the ATLAS detector. Feeding the input nodes of a multilayer feedforward neural network with the energy values sampled by the calorimeter cells in beam tests, it is shown that the original energy scale of pion beams is reconstructed over a wide energy range and linearity is significantly improved. As it happens for classical methods, a compromise between nonlinearity correction and the optimization of the energy resolution of the detector has to be accomplished. A hybrid training method for the neural mapping is proposed to achieve this design goal. Using the back-propagation algorithm, the method intercalates an epoch of training steps, for which the neural mapping mainly focus on linearity correction, with another block of training steps, in which the original energy resolution obtained by linearly combining the calorimeter cells becomes the main target.

INTRODUCTION

For the LHC experiment, the ATLAS detector is currently being developed at CERN. Among its subdetectors, calorimeters play an important role, as they measure accurately the energy of the incoming particles and provide a detailed energy deposition profile.

The hadronic calorimetry in ATLAS is performed by the scintillating tile calorimeter (Tilecal), which comprises three sections: one barrel and two extended barrels (1). Each section is made of 64 modules and the whole calorimeter system has more than ten thousand readout channels.

In a practical calorimeter design, nonlinearities typically arise (6). Therefore, a sort of nonlinearity compensation scheme has to be provided and multiparameter functions are usually employed for this purpose. However, very often an improvement on linearity is followed by a deterioration of the energy resolution of the detector, so that a compromise between these two design parameters has to be accomplished. Moreover, the multiparameter function approach typically results in energy dependent parameters, which makes the compensation algorithm rather complex.

The approximation of a mathematical function using examples of its action on experimental data points appears in many different areas of basic science and engineering. Neural networks have proved to be valuable in many of such problems, as their nonlinear processing capability usually provides a good solution even for complex mapping problems. In particular, feature-based networks, like multilayer networks trained by means of backpropagation (2), can implement an input/output mapping as a result of the supervised learning process, which modifies the synaptic weights of the network. During the training phase, the mapping is continuously modified according to the patterns fed into the input nodes of the network and their respective target values, which represent the knowledge of the action of the mapping on such input patterns (3).

This work aims at developing a neural mapping for estimating the actual energy being deposited in the Tilecal. Recent studies (5) shown that a multilayer neural network tends to correct effectively the linearity response of the Tilecal for a wide energy range, but the energy resolution suffers from deterioration, as for the classical approach. Thus, for achieving both good linearity and high energy resolution, a hybrid training method for the multilayer neural mapping is proposed in this paper.

THE EXPERIMENTAL SETUP

The Tilecal is a three-layer segmented hadronic calorimeter. A calorimeter module (see Figure 1) consists of iron (to absorb the energy of the interacting par-

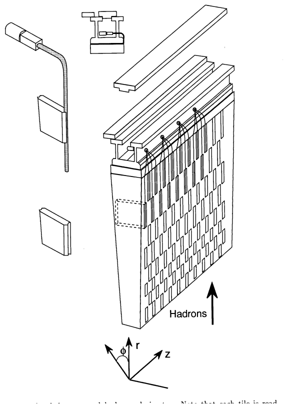

FIGURE 1. A calorimeter module.

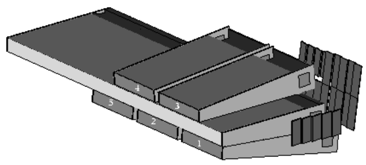

FIGURE 2. Experimental setup.

ticles), scintillating tiles (for sampling the energy being deposited in the detector), and optical fibers (to carry the light produced in the tiles towards the outer part of the detector). Groups of fibers are optically coupled to a photomultiplier, defining the detector segmentations.

The development of the neural estimator used experimental pion data from a last generation (Module 0) prototype. The experimental arrangement is shown on Figure 2. In these tests, one half (right side) of the Module 0 prototype of the barrel section was instrumented, producing 46 readout channels. To compensate for the unavoidable energy leakage, which results from the use of such reduced (single module) calorimeter system in the tests, five modules from a previous generation of prototypes were placed around the Module 0 (two above and three below), representing additional 200 channels to be readout. These five modules also simulate the information of neighboring modules in the actual arrangement for LHC operation. For all data used in this paper, the pion beam was aligned to enter at the center of the instrumented part of Module 0 prototype.

The performance of the Tilecal prototype and its neural estimator for pions was evaluated from tests for which ten nominal beam energies were selected, ranging from 10 to 400 GeV. On average, 6000 events were accumulated for each nominal energy value.

The Tilecal provides very good calorimeter performance. If its original response is evaluated by linearly adding the raw data (digitized energy values from analog-to-digital converters with pedestal subtraction) from calorimeter cells for each event (without any attempt for corrections that have been shown possible to be made (1)), some nonlinearities can be observed. As expected, Gaussian distributions are obtained, although some energy leakage effect can be noted (above 100 GeV) in the form of lower-energy tails.

For evaluating linearity, a least squares straight line fitting was performed on the data points and the maximum relative deviation with respect to the fitting was measured.

To compute the energy resolution, a model based on a linear combination of scaling and constant factors was employed (6):

$$\frac{\sigma}{E} = \frac{a}{\sqrt{E}} + b \tag{1}$$

The scaling factor a dominates the energy resolution at higher energy values, where the constant term b becomes dominant. From raw experimental data (no corrections), a maximum non-linearity of 8.5% and an energy resolution of $\frac{39.6\%}{\sqrt{E}} + 5.0\%$ were measured (see Figure 3).

NEURAL ESTIMATION

The feedforward neural network used to perform the desired energy estimation was fed with the energy sampled by each calorimeter cell (246 input nodes). The network had 20 neurons in the hidden layer. For all such neurons, a sigmoidal activation function was used. A single linear neuron in the output layer then provided the desired linear reconstruction of the energy scale.

First, the network was fully trained with backpropagation method. The experimental data sets were equally split into two for building the required training and testing sets. The input data were normalized by a constant factor, which was obtained (mean value plus one sigma) from a distribution of all cell energies for the various nominal beam energies. As neuronal saturation has been observed to play an important role for the energy resolution of the neural estimator (4), the temperature factor of the sigmoids were controlled to guarantee proper operation of the hidden neurons. Normalized nominal beam energies defined the target values of the training phase.

The nonlinearity of the original response was pretty well compensated for. However, the energy resolution was worse, and the model from equation (1) did not describe the behavior of the estimator. As was mentioned, this is in agreement with recent studies on the development of the neural mapping for the Tilecal (5).

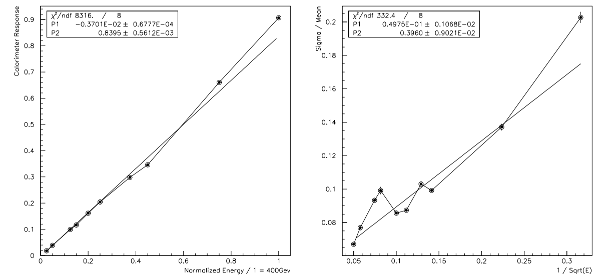

FIGURE 3. Linearity (left) and energy resolution (right) from the original calorimeter response (linear combination of cells).

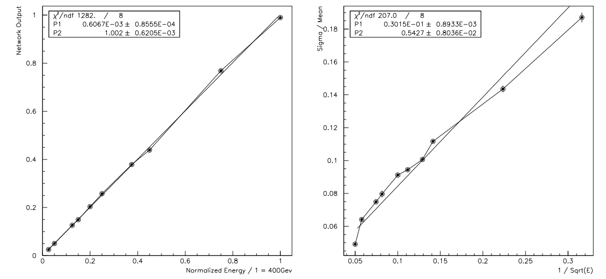

FIGURE 4. Linearity (left) and energy resolution (right) from the neural estimator and hybrid training.

In order to improve the performance of the neural estimator, it would be desirable to retain the proven ability of the estimator for nonlinearity compensation, but introduce a way to reduce the deterioration on energy resolution, recovering, at least, the original response that is obtained when a linear combination of cells is performed.

To achieve this goal, a hybrid method was developed for the training phase of the network. Thus, using backpropagation, the neural network was trained mixing a bunch of training steps, in which the target values were set as nominal beam energies (main focus on nonlinearity compensation), with a set of training steps, for which the network tries to follow the original calorimeter response (focusing on achieving a good energy resolution), and the target values being the total energy obtained from the linear combination of calorimeter cells.

The determination of the number of cycles of each training phase of the proposed method deserved some attention. It should be observed how long it would take for the network to learn the original calorimeter response and switch from one phase to another. Thus, 30000 training steps were used in the phase the network follows the nominal beam energy targets, and 7500 training steps were required to learn the original calorimeter response.

The performance for this training approach can be evaluated from Figure 4, representing a linearity better than 2.8% and an energy resolution of $\frac{54.3\%}{\sqrt{E}} + 3.0\%$. It can be depicted from this figure that the behavior of the energy resolution of the estimator tends to align with the model of equation (1), in this case.

CONCLUSIONS

A neural mapping for compensating for nonlinearities that may arise from raw data analysis over the experimental response of the Tilecal was presented. In order to achieve a significant improvement on the linearity of the original calorimeter response and keep the original good energy resolution of the detector, a hybrid training method for the neural estimator was developed using the standard backpropagation algorithm. The method successfully learns the original calorimeter response as a way to keep in track the energy resolution figure, while correcting for the observed nonlinearities.

As the neural estimator generally exhibits a different behavior for low and high energy ranges, a multiple neural network estimator is being also developed. Combining networks that would be able to learn in more detail the energy deposition profiles for different energy ranges may improve the overall estimation performance.

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