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OPTIMAL SIGNAL SELECTION FOR A HIGHLY SEGMENTED DETECTOR

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Abstract

This work presents an extensive study of signal detection against noise for a high-energy calorimeter (energy measurement) in the context of particle collider experiments. We aim at selecting the calorimeter cells (10,000 readout channels available, most of them with no signal) that should be considered for energy reconstruction. Several techniques for the signal detection are employed such as Maximum Likelihood, independent component analysis and neural processing. The results show that the neural network approach for signal detection surpasses the other techniques in terms of both performance and implementation complexity.

Keywords: Signal Detection, Maximum Likelihood, Independent Component Analysis, Neural Networks.

1 Introduction

The experimental high energy physics is often facing problems related to signal detection and estimation in hash conditions. Therefore, advanced techniques of digital signal processing to perform detection for low signal to noise ratio (SNR) events should be used.
In this context, the LHC (Large Hadron Collider) is currently colliding protons at CERN (European Organization for Nuclear Research) aiming to study the particles which are the fundamental building blocks of matter. Two proton beams travel in opposite directions inside

the circular accelerator and collide, with a period of 25 ns, at four points, where dedicated experiments are placed to detect, read out and record the collisions results.

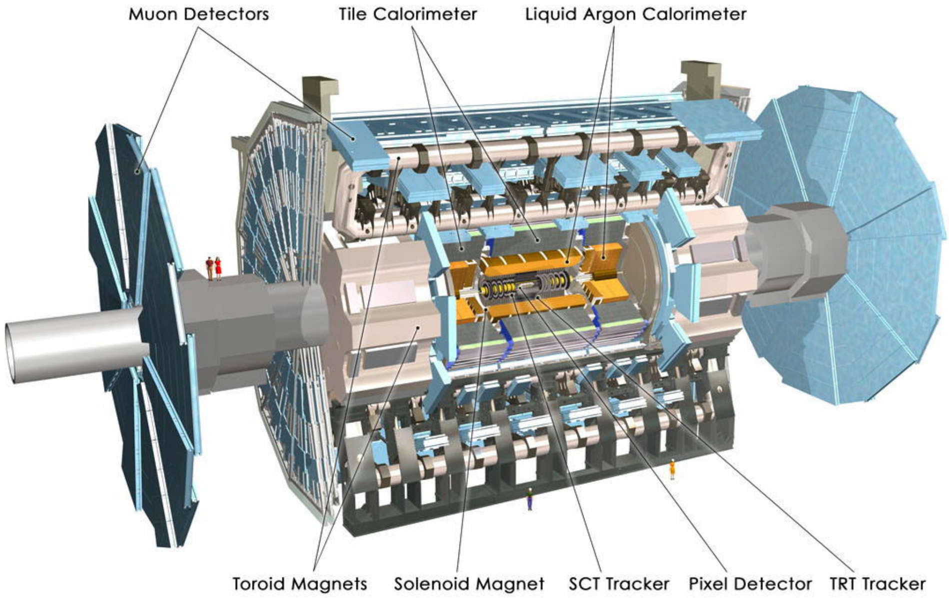


Figure 1 – The ATLAS detector and its subsystems (extracted from *CERN Document Server* – CERN-GE-0803012).

The ATLAS (A Toroidal LHC ApparatuS) is one of two experiments at LHC designed as a general-purpose detector to investigate the widest range of physics possible. ATLAS should record sets of measurements for the particles created in collisions - their paths, arrival times, energies and their identities. The ATLAS experiment is composed of three subsystems that identify particles and measure their momentum and energy. The Inner Detector [1], surrounded by the Solenoidal Magnet, the Electromagnetic [2] and Hadronic [3] calorimeters, and the Muon Spectrometer [5], inside the Toroid Magnets. The detector has a total length of 42 m and radius of 11 m and a schematic representation can be seen in Figure 1.
To perform their tasks, the ATLAS detectors are composed by a large number of channels (electrical signals) that should be read out when a valid event is selected by the complex on-line trigger system. It is important to stress that for some particles and for some channels the signal to noise ratio (SNR) is very low, therefore, it is a difficult task to select channels with signal in this scenario. The correct channel selection has an important impact on the trigger system and the offline analysis.
In this paper, an extensive study of signal detection against noise for the ATLAS Barrel Hadronic calorimeter (TileCal) is presented. The main goal is the selection of the calorimeter channels (around 10,000 channels available) that should be considered for energy reconstruction. Several detection techniques are covered in this work. The first approach used a Maximum Likelihood (ML) detector [6]; the second approach is the use of the Independent Component Analysis (ICA) [7] as a pre-processing for the ML detector; the third one is the use of neural processing [8]. The performances achieved by the proposed methods are evaluated with real data acquired on the experiment and simulated cosmic rays. The next section describes the TileCal detector and Section 3 presents the methods for the TileCal event detection proposed in this paper. Section 4 presents and discusses the achieved performance for each method and finally, in Section 5, some conclusions are derived.

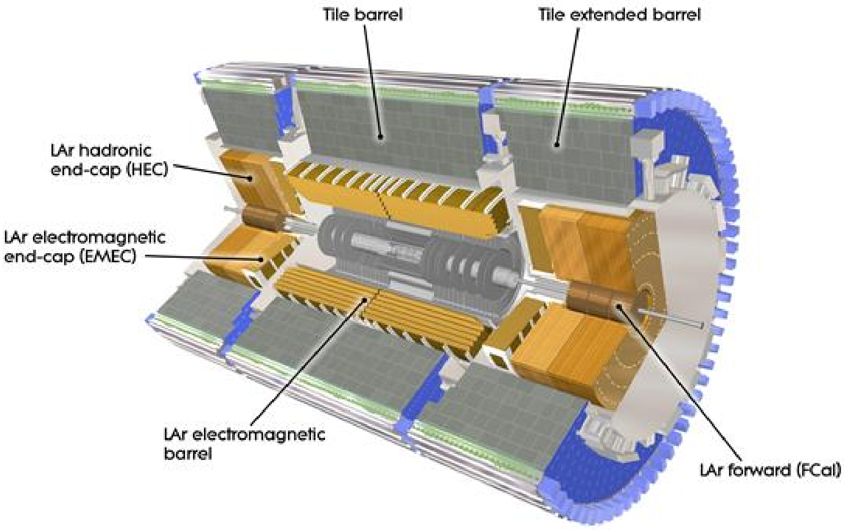


Figure 2 – Calorimetry system of the ATLAS detector (extracted from *CERN Document Server* – CERN-GE-0803015).

2 The Tile Calorimeter

Tilecal is the barrel hadronic calorimeter of ATLAS and is situated behind the electromagnetic calorimeter. It is important for the measurements of jets, hadrons, taus and missing transverse energy. It is a sampling calorimeter with steel as absorber and scintillating tiles as active material.

Tilecal comprises three cylindrical parts: one long barrel divided in two central barrels and two extended barrels. Each part is composed of 64 modules to build the entire cylinder. Each central barrel module and each extended barrel correspond to 22 and 16 cells with double readout, respectively, resulting in almost 10,000 channels (signals). The Tilecal structure can be seen in Figure 2 where the ATLAS calorimetry system is shown.

The Tilecal signal is generated on the scintillating tiles and is transmitted to the outer radius of the module by means of wavelength shift (WLS) fibers that are placed on both sides of the scintillating tiles. Several fibers from the scintillating tiles are grouped together to form the cell in Tilecal. The light signals from these fibers feed a photomultiplier that converts light to a fast electrical signal. The electrical signal is treated by an analog shaper before its digitization with a sampling frequency of 40 MHz [3]. Figure 3 shows a typical Tilecal signal pulse before its digitization.

The digitized signals with 7 samples spaced by 25 ns are received by the ReadOut Drivers (ROD) boards [9] where the energy deposited in each TileCal readout channel is estimated. The estimated energy is sent to the ROD only if the event has been selected by the online trigger system.

It is important to stress that when the energy deposition is low in one calorimeter cell (ionizing muons for example) it is difficult to select this particular cell among many others with noise. Figure 4 shows the 7 samples of a muon signal pulse (left) and a case of noise (right). It is clear that in such a situation the discrimination between signal and noise is hard.

The Optimal Filtering (OF) method [10, 11] is the default algorithm used to reconstruct the energy and the time in the ROD during the operation of the detector. It makes use of

weighted linear combinations of the signal samples to obtain the amplitude, time, pedestal (baseline of the signal) and quality of the reconstruction of the pulse.
In this paper, an extensive study of signal detection for TileCal is performed. The proposed methods presented here could be used for offline signal reconstruction algorithm or possibly implemented at the ROD level to improve its performance in terms of signal detection.

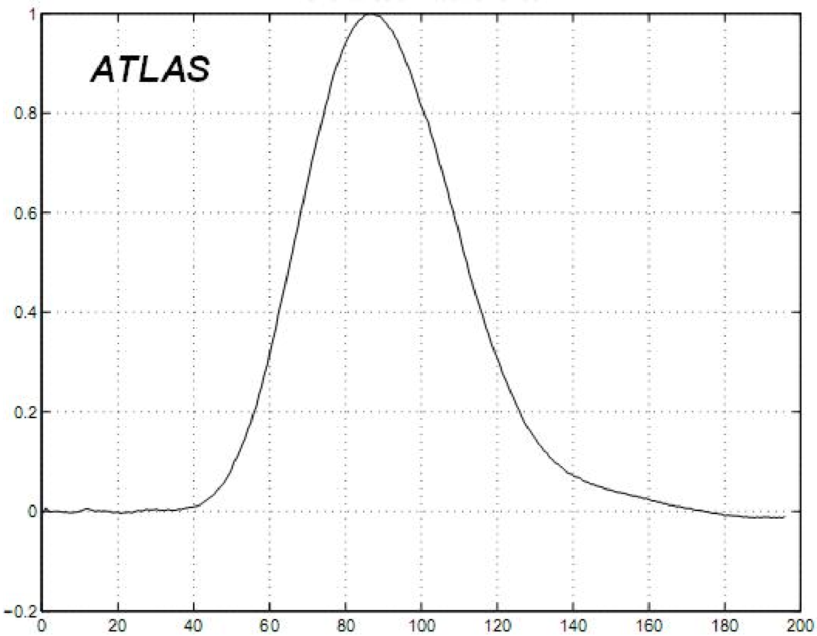


Figure 3 – Simulation of a typical Tilecal signal. The horizontal axis is time in nanoseconds and the vertical axis is the normalized amplitude.

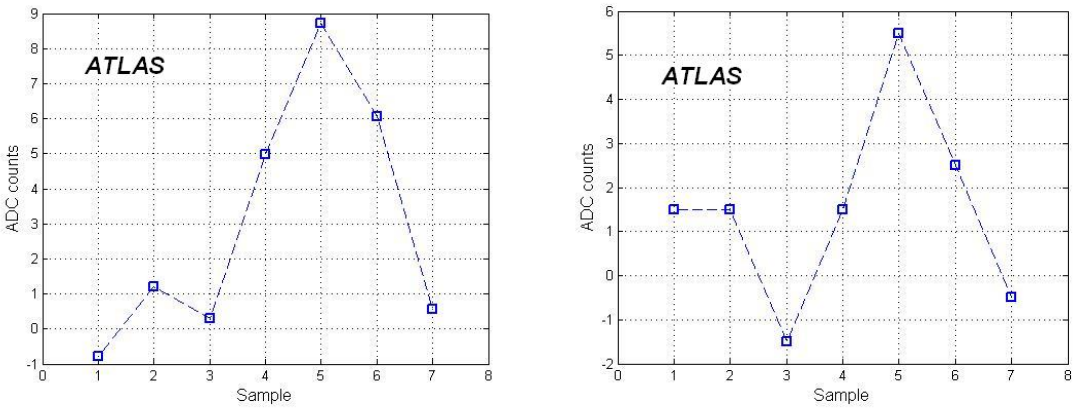


Figure 4 – A simulated event signal on the left and a simulated noise signal on the right.

3 Proposed Methods for the Tilecal Signal Detection

A baseline approach for event detection is to calculate the energy deposited by the signal and to define a threshold, where any signal energy above the threshold level is classified as a signal event. Since noise signals are likely to have sometimes similar amount of energy

deposited as the low energy event signals, it becomes interesting to perform a pre-selection of signals before calculating the energy itself, envisaging the increase of the detection performance.
In this work, we propose three different methods to carry out the pre-selection of cells for TileCal and to avoid performing calculations for events that are mostly compatible with noise. As mentioned in Section 1, the first approach uses a ML detector, the second makes use of the ICA as a pre-processing phase for the ML detector and the third one is about the use of a neural processing. It is worth mentioning that all of them make use of the digitized time signals sampling the pulse from each calorimeter cell.

3.1 Maximum Likelihood Detector

In this section, the first two approaches for event detection is presented based on the use of a ML detector. The ML detector will be designed using the digitized time signal sampled from each calorimeter cell (one digitized signal per PMT), using the Tilecal analog-to-digital converter. For each triggered event, 7 samples of each PMT time signal (the pulse shape) are recorded, using a 40 MHz sampling rate.
The ML approach is based on a hypothesis test. In other words, the detection system has to decide between two possible hypotheses: only noise (H_0) or signal and additive noise are present in the receiving end of the detection system (H_1). The decision rule can be summarized by the likelihood equation:

$$\frac{f_{L|H_1}(l \mid H_1)}{f_{L|H_0}(l \mid H_0)} \underset{H_0}{\overset{H_1}{\lessgtr}} \gamma \qquad (1)$$

where $f_L|H_1(l|H_1)$ and $f_L|H_0(l|H_0)$ are the conditional Probability Density Functions (PDF) for a given outcome **L** of N samples, depending whether the valid hypothesis is either H_1 or H_0, respectively. Thus, for each calorimeter cell, H_1 (cell selected) is chosen if the likelihood ratio is above γ, otherwise H_0 is considered corrected (noisy cell). The constant γ can vary, depending on weight assigned to a decision between one of the two hypotheses.

3.1.1 PDF Estimation

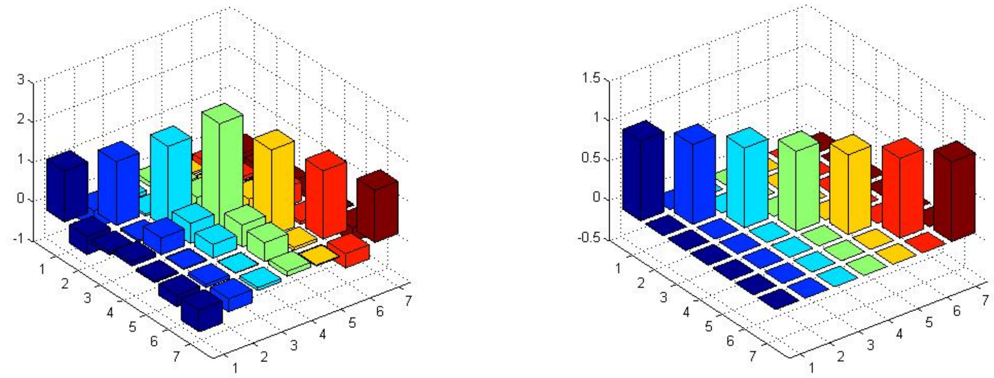
As a first PDF estimation approach, the samples will be statistically independent. In this way, the PDF will be the product of individual probability distributions. Even though statistical independence may not be a realistic assumption here, this simple ML approach produces satisfactory detection efficiency results, as will be shown in Section 4. Further improvements can be achieved by performing some preprocessing techniques, where the samples become either statistically independents or, at least, uncorrelated (see Section 3.1.3).

3.1.2 Noise Whitening

For the ML detector design, the additive noise should be white [12]. Figure 5a, shows the covariance matrix for the TileCal digital noise samples, where one can see some correlation among neighbor samples. Figure 5b shows the same data set after noise whitening transformation [12].

3.1.3 Feature Extraction (PCA)

Once the whitening matrix is extracted and the noise samples are uncorrelated, the Principal Component Analysis (PCA) [13] technique can be applied over the data set (from event signals). PCA projects the distributions onto an orthogonal base, composed by the eigenvectors of the data set covariance matrix. The variances of the new distributions will be the correspondent eigenvalues. In Figure 6, the eigenvalues of the covariance matrix for the events (muons) are plotted and sorted out by amplitude. One can notice that the signal energy is mostly concentrated on the two first components. Thus, this transformation allows a dimensional reduction from 7 to 2 components, without losing significant information. Besides, since PCA is just an orthogonal transformation (rotation), the noise will still be white in this new base.



(a) (b)

Figure 5 – Covariance matrix for the noise set before the whitening transformation (a) and after the whitening transformation (b).

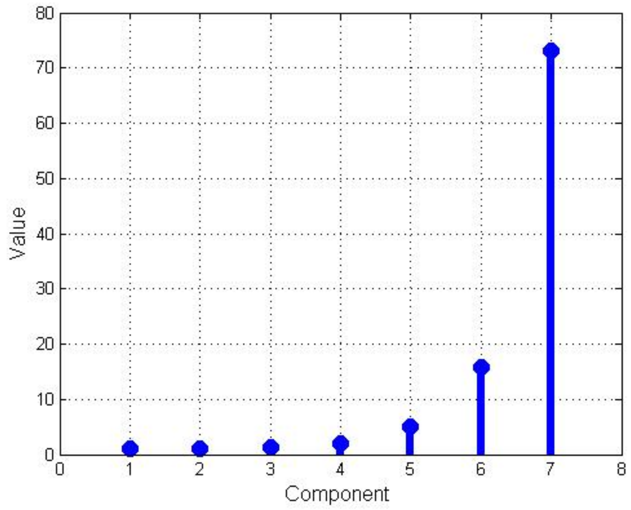


Figure 6 – Eigenvalues of the covariance matrix of the simulated event signals.

3.1.4 Feature Extraction (ICA)

Since the whitening transformation does not achieve statistical independence, Independence Component Analysis (ICA) should be considered. In that way, the PDF estimation for the ML detector could lead to better results than using PCA. ICA is based on the central limit theorem [14], therefore, it tries to maximize the nongaussianity of the components to find the independent components. In this work, the FastICA algorithm [7] was used.

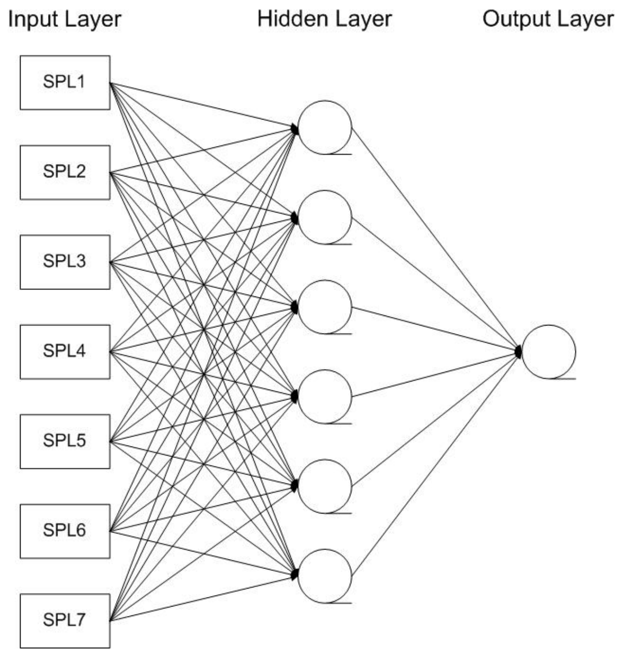


Figure 7 – Configuration of the neural network proposed.

3.2 Neural Network

The third method proposed in this work makes use of a neural network to perform the event detection. The 7 samples are presented directly to the neural network as its input parameters. The neural network output informs whether the signal is an event or noise.

The proposed neural network uses a supervised training algorithm, therefore, the first step is to take several signals of both event and noise and divide this set in two, the training set and the test set. The training set is used for the synaptic weights update, while the test set is used only for performance evaluation. It is worth mentioning that both sets contain the same number of signals, envisaging an efficient detection.

In order to improve the generalization of the neural network and to avoid overtraining, the criteria of stop the training is the efficiency on the test set.

A multilayer feed forward neural network is used for detection with the resilient back-propagation as a training algorithm. The activation function is the hyperbolic tangent for all neurons. The number of hidden layers and neurons are defined by optimizing several times the neural network with different topologies, choosing the one with best performance. The configuration which best fits the application has one hidden layer with 6 neurons, and a single neuron at the output, as shown in Figure 7.

The signal at the neural network input is considered noise if the neural network output is negative, otherwise, the signal is considered as an event.

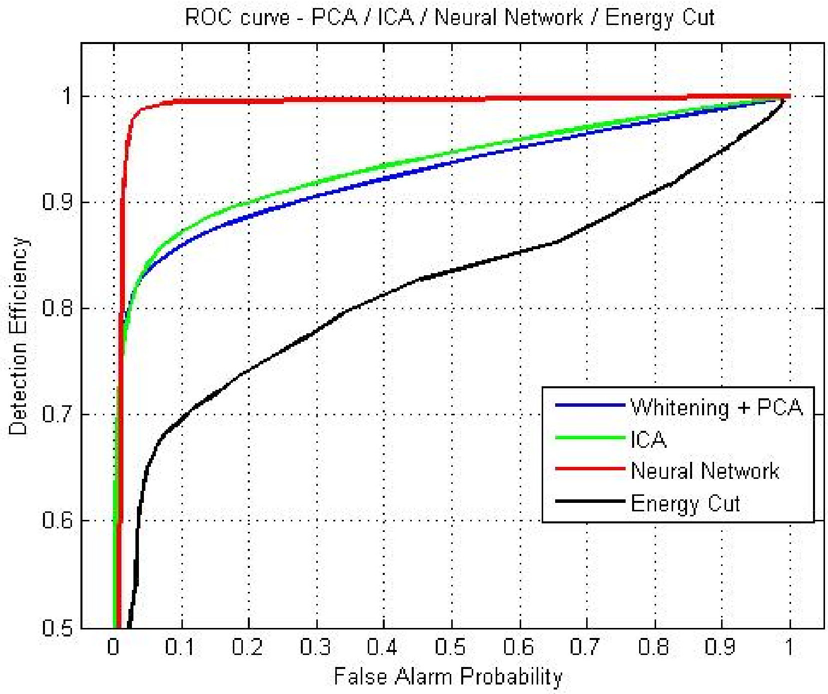


Figure 8 – Detection efficiency vs. false alarm of the proposed methods using simulated data.

4 Results

In this section, the proposed methods are implemented by software and their performances are evaluated with simulated data. For comparison effect, it was also implemented a method based on energy cut where the energy of the signal is reconstructed through a fitting method [15].

4.1.1 Dataset

The dataset is composed of two sets, one with 240.000 low SNR event signals and another with 240.000 noise signals. The noise set was obtained from specific Tilecal noise acquisitions while the event signal set was based on cosmic ray simulations [16].
For both PCA and ICA, half of the data sets were used for PDF estimation as well as for training the neural network. The other half of the data set was used to validate the methods by evaluating its detection efficiency.

4.1.2 Performance Evaluation

The performance evaluation of the proposed methods is presented in terms of its ROC (Receiver Operating Characteristics) curve [12]. For that, the same validation data set was used. Figure 8 shows all curves including the energy cut based method, used here for comparison. It can be seen that the ICA curve slightly surpasses the PCA curve as expected. However, since the ICA method is linear, it does not make the noise signal samples totally independent, which explains the superior performance of the neural network approach, which has the ability to cope with nonlinearities.

5 Conclusions

In this paper, different approaches for detection of low SNR events in Tilecal were presented and evaluated. It can be concluded from that all three proposed methods have higher detection efficiency when compared to another one based only on energy cut, which is commonly used in Tilecal.
The neural network approach is the one that separates best event signals from noise, but further analysis should be performed in order to guarantee no biasing for this method.
All methods could be either intended for the offline energy reconstruction algorithm or possibly for integration to the RODs (hardware), both cases aiming to provide a better signal selection for the Tilecal cells with low energy level deposition.

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