An alternative method for the TileCal signal detection and amplitude estimation

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Abstract. The Tile Barrel Calorimeter (TileCal) is the central section of the hadronic calorimeter of ATLAS. It is a key detector for the reconstruction of hadrons, jets, taus and missing transverse energy and it assists the muon measurements due to a low signal-to-noise ratio. The energy deposited in each cell is read out by two electronic channels for redundancy and is estimated by reconstructing the amplitude of the digitized signal pulse sampled every 25 ns. This work presents an alternative approach for TileCal signal detection and amplitude estimation under low signal-to-noise ratio (SNR) conditions, exploring the applicability of a Matched Filter. The proposed method is compared to the Optimal Filter algorithm, that is currently being used at TileCal for energy reconstruction. The results for a simulated data set showed that for conditions where the signal pedestal could be considered stationary, the proposed method achieves a better SNR performance than the Optimal Filter technique.

1. Introduction

Experimental high energy physics often faces problems related to signal detection and reconstruction in harsh conditions. Therefore, advanced techniques of digital signal processing should be used in order to reconstruct signatures with low signal-to-noise ratio (SNR). The ATLAS (A Toroidal LHC ApparatuS) is a general purpose detector built for probing proton-proton collisions and heavy ion collisions at the Large Hadron Collider (LHC). It is composed of six different subsystems: The Inner Detector [1], the Solenoidal Magnet that surrounds the inner detector, the Electromagnetic [2] and Hadronic [3] calorimeters, the Toroid Magnets [4] and the Muon Spectrometer [5], as illustrated in figure 1. The detector has a total length of 42 m and radius of 11 m.

The ATLAS detectors comprise a large number of channels that should be read out when a valid event is selected by the complex online trigger system [6]. Besides selecting the valid events, those systems should perform substantial operations such as estimating the correct energy and time of the events. This process should be carried out online, and for this reason, their algorithms must be fast. It is worth mentioning that many channels are likely to have low energy deposition which impacts on the SNR level. Due to this fact, they could be discarded during event reconstruction. The correct channel selection selection impacts on the trigger system and the offline analysis.

In this paper, a Matched Filter (MF) to perform both the signal detection and the amplitude estimation for the ATLAS Hadronic calorimeter (TileCal) is presented. The Matched Filter technique is known to be the optimal signal detector in terms of the SNR for cases where the received signal could be described as a known signal (deterministic) corrupted by Additive White Gaussian (AWG) noise [7]. The main goal of the proposed technique is the selection of the calorimeter cells (around 5,000) that should be used for energy reconstruction. As each calorimeter cell has two associated readout channels, this work also

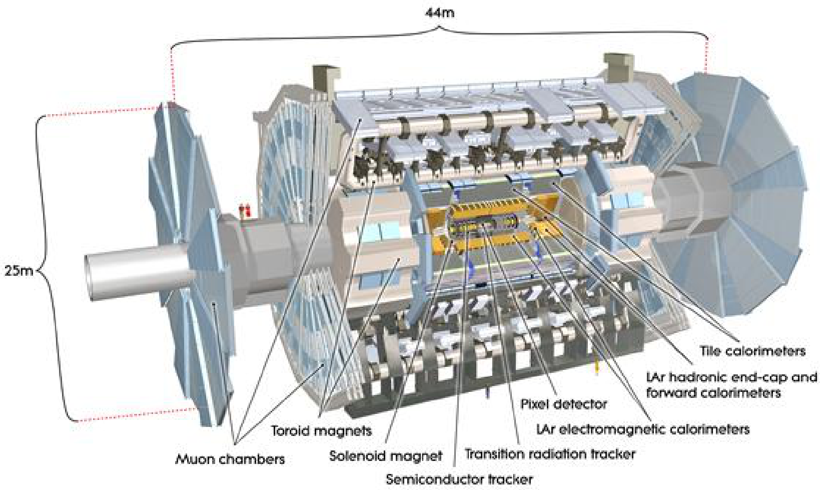


Figure 1. The ATLAS detector and its subsystems (extracted from CERN Document Server CERN-GE-0803012 01).

analyzes the impact on signal detection when these signals are summed before the energy estimation. The performance achieved by each of the methods is evaluated using experimental noise acquired on the ATLAS experiment and simulated TileCal pulses based on its reference pulse shape corrupted by the experimental noise.

Next section describes the TileCal environment and section 3 presents the alternative method for the TileCal signal detection and amplitude estimation. Section 4 presents the achieved performance for both methods and a comparison between them is carried out. Finally, in section 5, some discussions and conclusions are outlined.

2. The TileCal calorimeter

The ATLAS Hadronic Tile Calorimeter (TileCal) is a sampling calorimeter made of steel and plastic scintillating tiles. It comprises three cylindrical parts: one central barrel and two extended barrels. Each cylindrical part is composed of 64 modules. Each central (extended) barrel module is divided into 23 (16) cells with double readout, resulting in almost 10,000 channels (electronic signals). The TileCal structure can be seen in figure 2 where the ATLAS calorimeter system is shown.

The deposited energy in a particular TileCal cell is sampled by a group of scintillating tiles and transmitted through wavelength shifting fibers, connected on both sides of the scintillating tiles, up to the photo-multipliers where the light is converted into an electrical signal. Therefore, for each TileCal cell two electronic signals (channels) are available.

The fast electronic pulse generated at the photo-multiplier is conditioned by a shaper circuit which provides an electronic pulse for each channel, with 50 ns Full Width at Half Height (FWHH) and the amplitude proportional to the deposited energy. Therefore, the TileCal pulse shape can be considered almost invariant from channel to channel and the energy deposited by the particle at a given cell can be retrieved by the corrected estimation of the TileCal pulse amplitude. Figure 3 illustrates the analog TileCal reference pulse.

The TileCal analog signals are converted to digital signals with 40 MHz sampling frequency at the digitizer board and a window with 7 samples (150 ns) is enough represent the entire pulse. Then, the seven samples from each TileCal channel are transmitted through optical fibers up to the readout drivers (ROD), where the energy estimation is performed online.

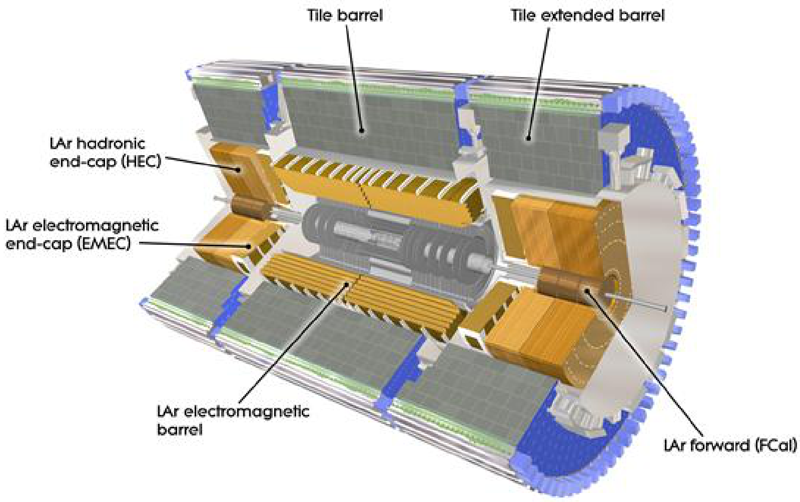


Figure 2. The ATLAS calorimetry system (extracted from CERN Document Server CERN-GE-0803015 01).

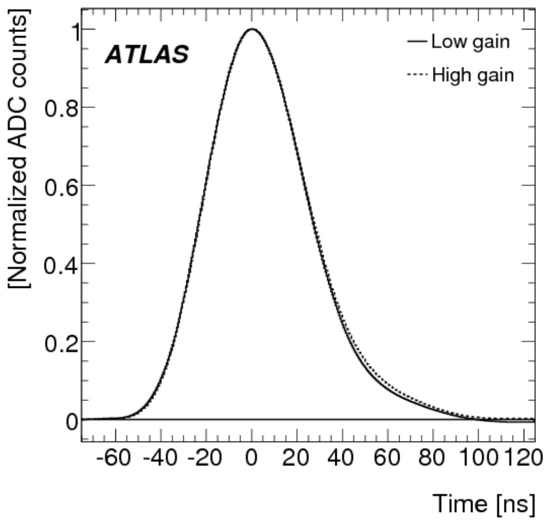


Figure 3. TileCal reference pulse shape.

The Optimal Filtering (OF) method [8] is the currently used algorithm to reconstruct the energy and the time at the ROD level during detector operation. It makes use of a weighted linear combination of the signal samples to obtain the amplitude, time and pedestal (baseline offset) of the pulse.

In this paper, an alternative study of signal detection and amplitude estimation for TileCal is presented and its performance is compared to the current method used in TileCal.

3. An alternative method for TileCal signal detection and amplitude estimation

This section briefly introduces the theory of signal detection and describes the proposed method to perform the signal detection and amplitude estimation for TileCal.

3.1. Signal detection

For a given discrete signal $s[k]$, where k represents the samples, which is transmitted through a channel that introduces an additive noise $n[k]$, with a received signal expressed by $r[k] = s[k]+n[k]$, it is desired to detect, with maximum efficiency, the presence of $s[k]$ in $r[k]$. In other words, a processing should be performed on the received signal in order to optimize the decision among two possible hypothesis:

- Hypothesis H_0: Only noise.
- Hypothesis H_1: Signal plus noise.

Thus, the detection problem can be described as a function of the received signal, as follows:

$$\begin{array}{ll} H_0 : r[k] = n[k] & k = 0, 1, 2, ..., N-1 \\ H_1 : r[k] = s[k] + n[k] & k = 0, 1, 2, ..., N-1 \end{array} \quad (1)$$

By representing the sequence $r[k]$ as an array $\mathbf{r}$ and considering $\mathbf{R}$ a given outcome at the receiver, it can be demonstrated [7] that the relationship which maximizes the detection efficiency is given by the maximum likelihood ratio, as follows:

$$L(\mathbf{r};\mathbf{R}) = \frac{f_{\mathbf{R}|H_1}(\mathbf{r}|H_1)}{f_{\mathbf{R}|H_0}(\mathbf{r}|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \quad (2)$$

The terms $f_{\mathbf{R}|H_0}$ and $f_{\mathbf{R}|H_1}$ are the probability density functions of the received signal $\mathbf{R}$, given that H_0 (noise) and H_1 (signal plus noise) occurred, respectively, and γ is the detection threshold. The idea is to decide in favor of hypothesis H_0 if the probability of the received signal given that noise was transmitted is greater than the probability of the received signal given that signal was transmitted and in favor of H_1 if the opposite occurs. In such way, the maximum likelihood ratio maximizes the detection probability and minimizes the detection error probability.

The probability density functions are usually unknown for the majority of the real detection problems, therefore, the detection algorithms consist mainly in estimating $f_{\mathbf{R}|H_0}$ and $f_{\mathbf{R}|H_1}$ from a set of data where each event is known in advance.

3.2. The matched filter method

In the case where the probability density functions of the noise samples are Gaussian with covariance matrix $\mathbf{C}$ and the signal of interest $s[k]$ is deterministic, the maximum likelihood ratio reduces to

$$L(\mathbf{r}) = \frac{\frac{1}{\sqrt{2\pi \det(\mathbf{C})}} exp\{-\frac{(\mathbf{r}-\mathbf{s})^T\mathbf{C}^{-1}(\mathbf{r}-\mathbf{s})}{2}\}}{\frac{1}{\sqrt{2\pi \det(\mathbf{C})}} exp\{-\frac{\mathbf{r}^T\mathbf{C}^{-1}\mathbf{r}}{2}\}} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \quad (3)$$

By performing some mathematical operations on Equation (3), the optimum detector results in:

$$\sum_{k=0}^{N-1} r_k s_k^{'} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma' \quad (4)$$

where $\mathbf{s}^{'} = \mathbf{C}^{-1}\mathbf{s}$.

The new detection threshold γ' relates to the old threshold γ according to

$$\gamma' = ln(\gamma) + \frac{\mathbf{s}\mathbf{C}^{-1}\mathbf{s}^T}{2} \quad (5)$$

Hence, Equation (4) shows that the decision between two hypothesis H_0 and H_1 is optimized through the inner product between the received signal and a replica of the deterministic signal of interest $s[k]$ after pre-whitening. Therefore, the decision between two classes can be optimized by filtering the received signal by its matched filter, whose impulse response $h[k]$ is given by [7]:

$$h[k] = s^{'}[-k + N] \tag{6}$$

For TileCal, the electronic noise readout during nominal TileCal operation has been shown to be Gaussian-like [9]. The pulse shape of an incoming signal is rather similar to the TileCal reference pulse shape as the latter was acquired and studied over an intense calibration period [10]. Therefore, even working under sub-optimum conditions, the MF approach may achieve good results for TileCal. For this, optimal TileCal signal detection is approximately performed by using the reference signal pulse shape. Since this corresponds to using seven samples, MF implements a fast finite impulse response (FIR) [11] filter according to Equation 6, which is appropriate for online applications.

3.3. Amplitude estimation through the matched filter

The acquired TileCal signal could be described by the components shown in Equation (7), where $r[k]$ is the received signal, ped is the baseline offset, $n[k]$ is the electronic noise, A is the amplitude and $s_{ref}[k]$ is the TileCal reference pulse:

$$r[k] = ped + n[k] + A \cdot s_{ref}[k] \tag{7}$$

By performing the inner product between the received signal and the TileCal reference pulse after pre-whitening, the amplitude of the incoming signal can be estimated. Equation (8) shows the inner product operation and Equation (9) shows the expression for the estimated amplitude:

$$y = \sum\nolimits_{k=0}^{N-1} r[k]s^{'}[k] \tag{8}$$

$$A = \frac{y - ped \sum_{k=0}^{N-1} s^{'}[k]}{\sum_{k=0}^{N-1} s_{ref}[k]s^{'}[k]} \tag{9}$$

4. Results

Both MF and OF methods were implemented in software and their detection efficiencies under low SNR conditions are evaluated below. Two different analysis are performed, at single channel and cell level.

4.1. Database

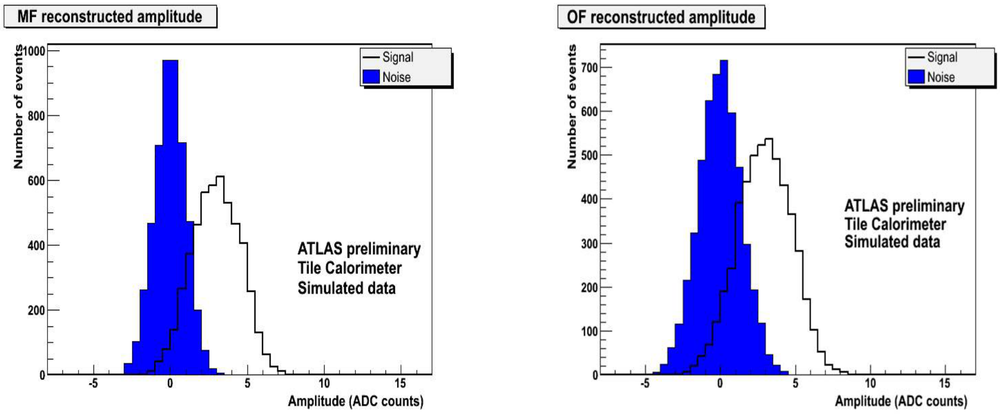
The database used comprises two classes with 5,016 events each: the noise data set, which is composed of noisy signals taken from a pedestal run during nominal TileCal operation, and the signal data set, which is constructed from TileCal reference pulse shape with added noise. In order to simulate realistic low SNR conditions, both amplitude and time shifting distributions were taken into account to generate the signal data set.

4.2. Amplitude estimation

In order to evaluate the energy estimated by both methods, the amplitude of the signals were estimated. The amplitude distributions estimated by the MF and OF methods are shown in figures 4(a) and 4(b), respectively. The constant ped in Equation (9) was estimated by taking the mean value of the first sample of the incoming signals.

As was mentioned in section 2, the TileCal has double readout, therefore, Two channels are associated with each TileCal cell. Currently in TileCal, the energy is estimated per channel and summed up to form the final cell energy used for offline analysis.

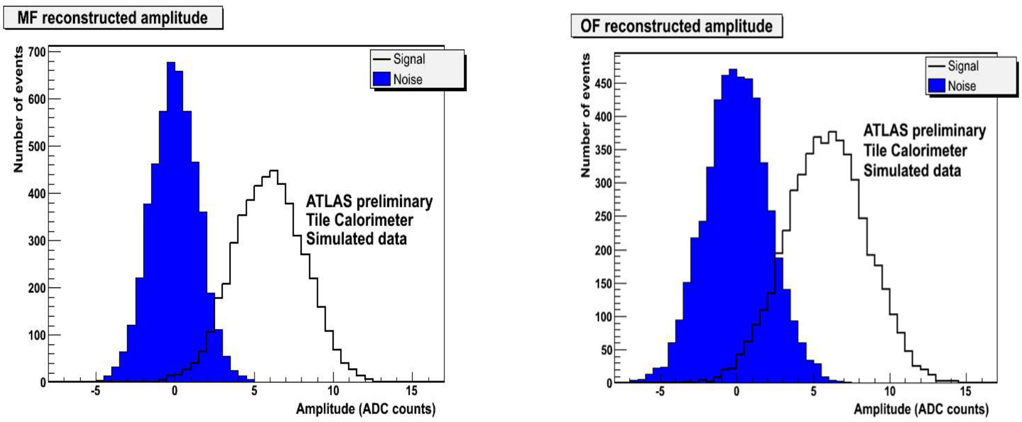
Supposing that the noise between channels of the same cell is uncorrelated and the signals are summed before estimating the amplitude, the noise standard deviation of the resultant signal would be increased



(a) (b)

Figure 4. Amplitude reconstructed by MF (a) and OF (b) for TileCal single channel.

approximately by a factor of $\sqrt{2}$ [12]. Figures 5(a) and 5(b) show the distributions of the estimated amplitude for the MF and OF approaches, respectively, considering the sum of the TileCal channels for a given cell.



(a) (b)

Figure 5. Amplitude reconstructed by MF (a) and OF (b) for TileCal cell.

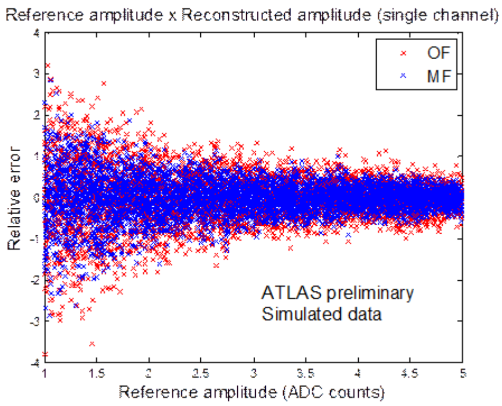
On both approaches, it can be seen that the MF method shows a better separation between signal and noise.

Since the standard deviation of the noise distribution is the error estimate in the measurement of the signal amplitude, table 1 summarizes this result for both types of analysis performed.

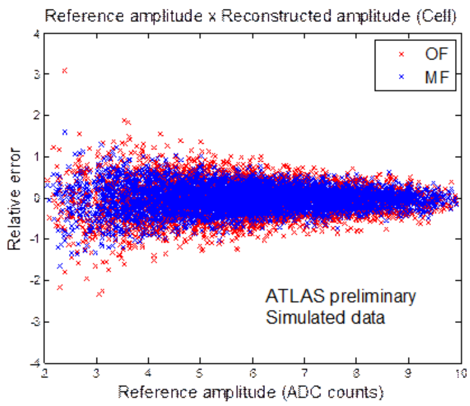
Table 1. Error estimate normalised to the mean signal ADC count.

	Single channel	Cell
OF	1.4149	1.0417
MF	1.0116	0.7458

For the purpose of illustrating the estimation quality of both methods, figures 6(a) and 6(b) show the relative error estimation with respect to the reference amplitude for single channel and cell analysis, respectively. In addition to that, it can be seen that both methods have similar performance in estimating the signal amplitude.



(a)



(b)

Figure 6. Relative error for single channel (a) and cell (b) analysis.

4.3. Signal detection

In order to evaluate the performance of each method for signal detection, the associated threshold (eg γ' for the MF method) were varied and the Receiver Operating Curve (ROC) [13] could be constructed for each scenario. Such curves can be seen in figure 7. It can be noticed that the best detection efficiency is achieved by the MF method with summed signals.

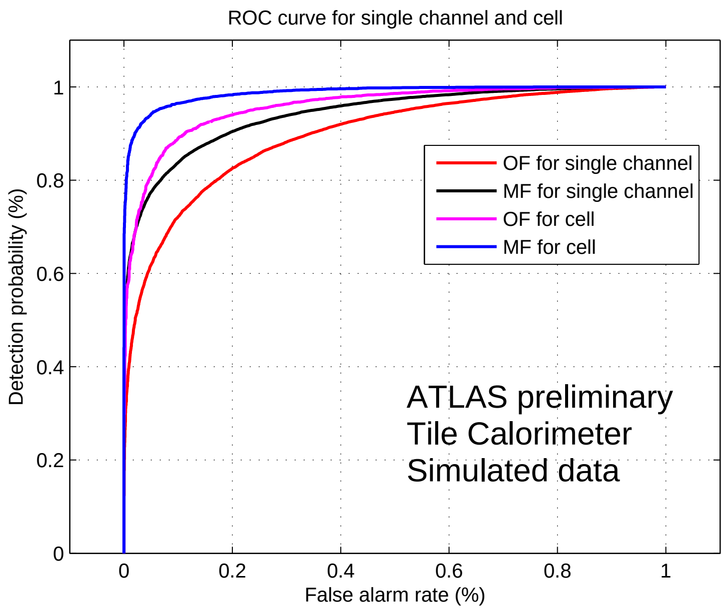


Figure 7. Detection efficiency against false alarm rate for all four analysis.

In order to quantify the results shown in figure 7, for a false alarm rate of 0.01%, the MF achieved 66.23% and 86.30% of probability of detection for single channel and cell analysis, respectively. For the same false alarm rate, the OF method attained 43.36% and 60.55% of probability of detection for single channel and cell analysis, respectively.

These results can be reproduced for experimental data in scenarios where the pedestal and the signal shape remain constant or with low variation rate, which is the case for the current LHC data taking setup.

5. Conclusions

In this paper, an alternative method for TileCal signal detection and amplitude estimation was presented. Differently from the current algorithm that performs this task, the proposed method makes use of an estimate of the signal pedestal whereas this parameter does not affect the performance of the current method. In conditions where the pedestal can be considered stationary, the MF approach has been shown to surpass the OF method in terms of detection efficiency. Besides that, since the MF method implements a FIR filter, it could be simply employed in the TileCal digital signal processors since these devices are suitable to carry out such fast multiply-accumulates (MACs) operations.

Concerning future studies, a pre-processing step has been implemented aiming to decorrelate the signals of the channels from the same cell before adding them up. In addition to that, other approaches to improve the pedestal estimation, such as adaptive filters, are under consideration. In scenarios with high pile-up (high luminosity) such methods could be very useful.

Acknowledgements

We are thankful to CNPq, CAPES and FAPEMIG (Brazil) for the financial support to this work. We also would like to thank many colleagues from the ATLAS collaboration for the fruitful discussions concerning this work.

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