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Exploring Statistical Independence for Energy Reconstruction in Calorimeter Systems Operating in Signal Pile-up Conditions

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Abstract

In high event rate detection systems, signal processing must simultaneously provide fast response and robustness against noise. This requirement is particularly critical in high-energy calorimeters operating in modern collider experiments such as those at the LHC. In such condition, the presence of pile-up introduces non-Gaussian components into the noise, degrading the performance of conventional reconstruction algorithms that assume Gaussian statistics. For the non-Gaussian case, an optimal estimation can be obtained using a Maximum Likelihood Estimator (MLE) based on the joint probability distribution of the multivariate noise. However, in practical systems the correct joint distribution is generally unknown and difficult to model. In this work, we propose an approach that circumvents this difficulty by first applying Independent Component Analysis (ICA) as a pre-processing step to pursuit a representation in which the noise mutual information is minimized. In this transformed basis, the joint probability can be factorized into a product of marginal probability density functions, enabling a tractable MLE formulation. The proposed ICA + MLE framework allows the implementation of likelihood-based estimators even in the presence

of strongly non-Gaussian noise. Simulation results using calorimeter-like signals show that the pre-processing step effectively reduces the noise mutual information, leading to performance improvements up to approximately 10% and 50% in terms of estimation error and KL divergence, respectively, with respect to the typical Gaussian MLE approach.

Keywords: Signal Estimation, Statistical Signal Processing, Maximum Likelihood Estimator, Independent Component Analysis, High-Energy Calorimetry

1 Introduction

Modern scientific experiments are commonly designed to cope with high-rate event conditions, where an enormous amount of data is produced in very short time intervals [1–3]. For instance, in the field of particle physics, accelerators generate millions of collisions per second, and systems must rapidly identify meaningful signals hidden in a flood of background events [4, 5]. These complex facilities are comprised of experiments that aim at exploring the structure of the sub-atomic particles, in the search for new particles and physics processes [6, 7], such as the discovery of the Higgs boson, which explains how elementary particles gain their mass [8]. To this end, such experiments are constantly increasing their capacity, pushing both detectors and data-acquisition systems to their limits [9, 10].

One key system present in such complex high-energy physics experiments is the calorimeter [11], where the energy of the particles produced by the collision is absorbed and sampled for further signal processing [12]. These high-energy calorimeter systems are typically highly segmented, comprising thousands of readout channels that produce a response at every particle collision [13, 14].

In high-rate and high-luminosity operation, such as currently seen in the Large Hadron Collider (LHC) facility [5], the calorimeter channel response may be affected by the so-called pile-up, where signals from adjacent collision are collected within the same readout channel. This effect occurs due to the calorimeter response, which is typically shorter in time (roughly 150 ns) than the event period (25 ns, for example, in LHC experiments) [15] and is expected to increase in future LHC operation. As a result, undesired signals are superimposed, introducing nonlinear components to the noise and leading to suboptimal performance of digital energy reconstruction methods, which typically consist of linear filters designed for Gaussian noise [16].

Therefore, these algorithms based on linear filtering handle the noise uncertainties, including the signal pile-up, by using the noise correlation information in the optimization procedure that computes the set of weights to be used for signal estimation (amplitude, phase and pedestal) [17]. Hence, such approaches access only part of the noise information (mean and variance) regardless of whether high order statistics are present or not in the mutual information [18, 19].

In this context, since mutual information captures any kind of dependency, not just simple correlations, this work proposes a pre-processing step based on a linear transformation that aims to minimize the mutual information between the signal time samples

acquired from the calorimeter front-end electronics using the Independent Component Analysis (ICA) method [20, 21]. This is particularly interesting when designing digital filters, as the energy estimation performance increases when the complete noise information is minimized.

Moreover, to perform the energy estimation task, a Maximum Likelihood Estimator (MLE) [22] approach is proposed using signal calorimeter readout time samples pre-processed by the ICA method. Therefore, the goal from this paper is two fold: to minimize the mutual information from the noise and to design an energy estimation method for computing the energy from the pre-processed signals. Furthermore, the proposed combined ICA + MLE approach avoids computationally expensive operations such as evaluating analytical nonlinear functions or performing matrix inversions. For online applications, this is a major aspect to consider, as the energy computation must meet the strong timing constraints typically imposed by the trigger systems [23, 24]. For comparison purposes in terms of energy estimation, the Optimal Filter method [17, 25, 26], which is currently employed in modern calorimeter systems, and a signal deconvolution approach [27] are used, as they have been applied in real collider experiments [28].

In the next section, noise modeling is assessed, envisaging to quantify the non-Gaussian components present in it. In Section 3, the strategy of using the ICA as a pre-processing step followed by a MLE method is described. Section 4 presents the results for simulation data sets comprising different operating conditions, comparing the performance achieved from the proposed approach and typical algorithms currently in use in modern experiments. Finally, Section 5 outlines the final remarks and conclusions, highlighting the main contributions achieved and potential future work.

2 Calorimeter Readout Signals

In order to sample the energy from the particles produced in the collisions, a calorimeter system must be built to collect and process this information. The calorimeter is designed to fully or partially absorb the energy of a given interaction process [11]. For example, to absorb the energy from a charged particle such as an electron, the particles ionize the material (a liquid argon, for instance), producing a measurable electric current, which can be further processed. On the other hand, particles that do not interact in an electromagnetic manner, other approaches may be considered such as scintillating plastic tiles intercalated with iron plates, where the particles produce light proportionally to the energy deposits when crossing the system. The light is then converted into electric signals for further analog processing, such as amplification and shaper steps [12].

Regardless of the approach chosen, the information from a particle interaction with the calorimeter is commonly processed in a way that the signal output is stable and presents a well defined shape. The amplitude of the shaped pulse (unipolar or bipolar) is supposed to be proportional to the energy deposited within the calorimeter readout channel [29–31]. The stability of such pulses may also be affected by electronics aging or miscalibration, which can cause phase shifts and deformation of the original shaped pulse. Additionally, although the width of the shaped pulse is defined in order

to minimize the signal pile-up on the tails of preceding pulses, the signal pile-up becomes unavoidable in the case of high-event rate and high luminosity experiments. Finally, the fast analog signals are converted into digital samples with a given sampling frequency, and a window of a certain number of time samples representing the entire pulse (or partially) is read out for every event. These samples are used to estimate the parameters of interest, such as the amplitude and time of the incoming digital signals for a given calorimeter readout channel. These parameters are propagated to complex trigger systems that select the signals to be stored for offline event reconstruction which comprises the physics analysis.

In high rate and high luminosity experiments, the calorimeter signal processing chain can be affected by multiple pulses arriving at the same readout cell within short time intervals. In the case where the event period is smaller than the time required to produce the complete response signal, a same readout cell can receive multiple signals that originate from different collision events, distorting the readout pulse shape. As a result, apart from the typical Gaussian noise from the electronics components, the adjacent signals introduce non-Gaussian components to the noise, degrading the performance of linear methods that estimate the amplitude and time of the response signal [16]. The signal pile-up effect is illustrated in Figure 1, where an additional signal is read out 50 ns after the event of interest.

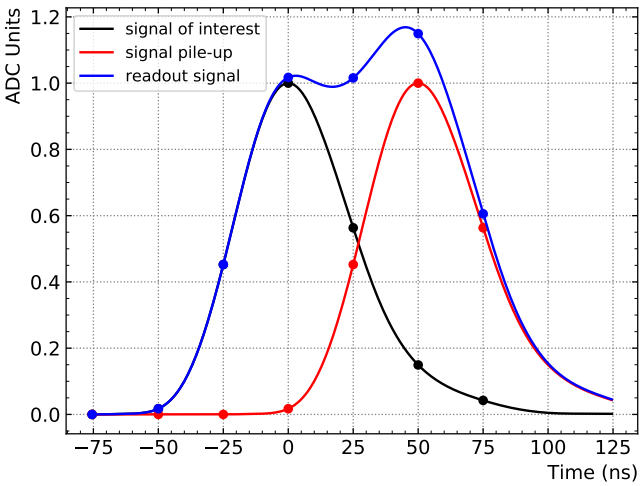


Fig. 1: Example of signal pile-up effect, where an additional pulse (in red) coming from another collision is read out within a same window of the signal of interest (in black), producing the distorted signal (in blue). Extracted from [16].

3 Proposed Methodology

In the next sections, some preliminary concepts regarding the MLE approach, mutual information, and ICA, are described. These concepts are fundamental to finally develop the proposed method, presented in Section 3.4.

3.1 MLE approach

MLE is based on estimators that use maximization of certain probability functions to estimate the parameter of interest. The function is chosen according to the problem that needs to be solved and the data that must be analyzed. Once one has the related distribution, various methodologies can be applied in order to achieve the maximization and estimate the value of the interest parameter that provides it.

Mathematically, this reasoning can be written starting by the likelihood function, as in Equation (1):

$$L(\mathbf{X}|\theta) = P(\theta|\mathbf{x} = \mathbf{X}), \tag{1}$$

where L is the likelihood function and θ is the interest parameter, which must be estimated considering the case where $\mathbf{x} = \mathbf{X}$.

To perform this estimation, Equation (1) is maximized, using any suitable method.

In the context where the signal of interest is being corrupted with only Gaussian noise, a special MLE version can be tested. In this case, MLE is implemented using the multivariate Gaussian PDF, since the problem considered here is multi-dimensional. The multivariate Gaussian PDF is given by Equation (2),

$$p(\mathbf{x}) = \frac{1}{|\mathbf{C}|^{\frac{1}{2}}(2\pi)^{\frac{N}{2}}} \exp\left[-\frac{(\mathbf{x}-\boldsymbol{\mu})^{\top}\mathbf{C}^{-1}(\mathbf{x}-\boldsymbol{\mu})}{2}\right], \tag{2}$$

where N is the dimension of the problem, $\mathbf{x}$ is the vector of random variables that describe the process ($N \times 1$), $\mathbf{C}$ is the data covariance matrix ($N \times N$), and $\boldsymbol{\mu}$ is the mean of the data ($N \times 1$).

In this work, the vector $\mathbf{x}$ is the noise, given by $\mathbf{n} = \mathbf{r} - A\mathbf{s}$, where $\mathbf{r}$ is the received signal, A is the amplitude of the signal of interest and $\mathbf{s}$ is the reference pulse, related to the electronic. To maximize the Equation (2), a derivative process was implemented. After the derivation, the obtained equation was set to zero and the amplitude A was isolated, culminating in Equation (3).

$$\hat{A}_{\text{gauss}} = \frac{\mathbf{r}^{\top}\mathbf{C}^{-1}\mathbf{s}}{\mathbf{s}^{\top}\mathbf{C}^{-1}\mathbf{s}}. \tag{3}$$

Therefore, using Gaussian MLE it is possible to estimate the amplitude directly from a closed-form equation which results in a set of N coefficients that can be implemented as a linear filter, suitable for online implementation as it presents low computational cost and fast response.

3.2 Mutual Information

Mutual Information is a well-known and useful method to calculate the statistical dependence between two random variables. This measure provides the amount of information one variable contains about the other, i.e., how much information the two variables share. The MI also determines how similar the joint probability is to the product of the marginal probabilities.

For an n-dimensional problem where $n > 2$, the Mutual Information may be calculated considering two variables at a time. In this sense, MI between two variables X and Y is formally defined as shown in Equation (4), where $p(x, y)$ is the joint probability between X and Y, while $p(x)$ and $p(y)$ are the marginal probabilities.

$$\mathrm{MI}(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}, \tag{4}$$

Once the MI for all variables was computed two by two, a mutual information matrix can be assembled. Using the information from this matrix, it is possible to compute the total Mutual Information in the data from Equation (5).

$$\mathrm{MI}_{\mathrm{total}} = \frac{\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \mathrm{MI}_{i,j}}{\sum_{i=1}^{N} \sum_{j=1}^{i} \mathrm{MI}_{i,j}}, \tag{5}$$

with i and j denoting the rows and columns of the matrix, respectively.

3.3 Independent Component Analysis (ICA)

Independent Component Analysis is a method used to minimize mutual information and correlation between highly correlated data. This approach seeks a transformation that can separate the sources presented in the data, knowing that achieving zero mutual information is not always possible. Initially, a linear model is defined as

$$\mathbf{x} = \mathbf{M}\mathbf{s} + \mathbf{n} \tag{6}$$

and the aim is to estimate the matrix $\mathbf{M}$ (which is rectangular and has fewer columns than rows) and the vector of interest $\mathbf{s}$ using the vector of observations $\mathbf{x}$.

Since the presence of noise within the data often renders the full estimation of $\mathbf{s}$ impossible, the problem is reformulated using a contrast function $\mathbf{F}$ and a vector $\mathbf{z}$, whose independent components lead to the maximization of $\mathbf{F}$. The Equation (7) describes this process.

$$\mathbf{x} = \mathbf{F}\mathbf{z} \tag{7}$$

Therefore, the problem becomes maximizing a contrast function, which happens when the components of $\mathbf{z}$ are independent.

There are some algorithms to solve the ICA problem. In this work, FastICA was chosen. It is one of the most popular and uses a linear transformation to minimize the correlation in data, from some iterative steps. This method operates using a transformation consisting of q variables to estimate q weight vectors that maximize the non-Gaussianity of the expression $\mathbf{w}_i^T\mathbf{x}$, for $i = 1, 2, ..., q$. The complete procedure can be found in [32].

3.4 Combining ICA and MLE

For the present work, the Gaussian PDF was used as the likelihood function, as an initial guess, to estimate the signal amplitude. This strategy is interesting for high energy calorimeter systems, as it results in a linear, simple, and fast response digital FIR filter which can be employed for online applications, despite operating in suboptimal condition when in pile-up scenarios. A derivative procedure was used to maximize the Gaussian PDF as follows in the next section.

Furthermore, a source separation technique based on ICA was implemented as a pre-processing step, aiming to minimize the mutual information introduced by both electronic noise and the pile-up. To this end a data set comprising only noise (electronic plus pile-up) is needed. As the ICA output provides independent variables regarding the noise, the joint probability function can be computed by multiplying the individual marginal probabilities associated to each variable, which can be performed by using a look-up-table search.

Since the calorimeter pulse shape is known (from the shaper circuit), a given parameter can be tested (amplitude, in this case) by subtracting the known pulse from the incoming signal and computing the joint probability function. The parameter that provides the greatest probability is chosen. Figure 2 shows the proposed strategy for computing the joint probability, where the blocks P_1, P_2, P_3 and P_N correspond to the individual marginal probabilities estimated by the ICA method.

It is worth mentioning that during the FastICA step some parameters can be adjusted. It is important to note that, in the present work, two of them were set: `tanh` was used as the activation function and the dimensionality was preserved, therefore N components were retained.

Based on Figure 2, the steps to compute the signal amplitude using ICA are the following:

1. Compute the separation matrix applying ICA to noise dataset;
2. Define a test value for the pulse amplitude A_{ica}, using the one estimated by Gaussian MLE as a reference;
3. Subtract the model from the received signal in order to obtain the noise: $\mathbf{n} = \mathbf{r} - A_{ica}\mathbf{s}$;
4. Project the obtained noise into the independent component basis using the separation matrix estimated by ICA (T_{ICA});
5. Construct the PDFs from histograms experimentally computed using the noise distributions;
6. Estimate the marginal probabilities using the obtained $\mathbf{n}$ for each PDF;

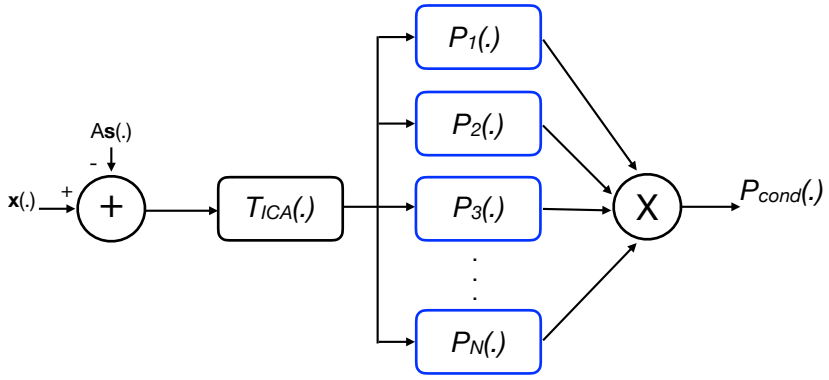


Fig. 2: Steps applied to compute the joint probability P_{cond} for a given incoming signal $\mathbf{x}$.

7. Assuming statistical independence, calculate the joint probability using a product of the marginal probabilities.

The procedure consists of conducting an exhaustive search around the amplitude estimated by Gaussian MLE in order to identify the value of A that maximizes the joint probability.

4 Results

In this section, the data set is described, and results from two proposed forms of analysis are presented: firstly, on the noise modeling and mutual information suppression, and, subsequently, on the energy reconstruction efficiency.

4.1 Dataset

For signal production, a stand-alone tool was used to generate energy deposits within a generic calorimeter readout system [33]. This simulation package is integrated within the Lorenzetti Simulator [34], a general high-energy calorimeter framework developed to assess new signal processing techniques in triggering and energy reconstruction tasks.

In the simulation framework, an usual unipolar pulse signal from a typical RCCR shaper circuit was considered, adopted similarly in previous work [35, 36]. Therefore, signals were superimposed using a given occupancy percentage factor, ranging from 10 to 80%. In order to simulate real operating conditions, the pile-up pulses were produced using an exponential distribution, reproducing the typical energy of low

pT collisions in modern high event rate experiments, as also reported in previous studies [37]. Additionally, other noise sources were also taken into account as follows: electronic distortions in each time sample due to the electronic aging process was modeled by a random Gaussian variable with a standard deviation of ± 1 ADC; a random phase shift between ± 10 ns; and finally, additive Gaussian noise of zero mean and standard deviation equal to 1.5 ADC, simulating typical electronic noise. Readout windows of seven time samples containing this pile-up noise are recorded, with the samples digitized every 25 ns.

Regarding the target signals, an exponential distribution was used. Afterwards, these target signals were combined with the previously described noise conditions to emulate the complete received signal corresponding to the calorimeter response. To assess the statistical aspects of the efficiency analysis, a k-fold cross-validation strategy was applied as follows. Initially, for each occupancy level, a set comprising 2,000,000 noise samples was generated. This data set was then partitioned into ten subsets (folds), and the amplitude estimation (energy reconstruction) for the target signals was performed by each method individually for every subset.

4.2 Noise characteristics

The main approach to the estimation methods studied in this work is based on noise modeling, which comprises both the typical electronic noise and the signal pile-up. This means that the efficiency of the methods is intrinsically associated with an accurate modeling of the noise distribution.

In this sense, analysis regarding the noise modeling was conducted with the aim of evaluating the Gaussian distribution's capability to describe de noise. The Gaussian was chosen because the MLE is applied together with the Gaussian PDF to estimate the signal amplitude. Figure 3 shows **(a)** the fit of Gaussian distribution to the noise data considering 50% occupancy and **(b)** the values of KS Statistic and Kurtosis for all the range of occupancies.

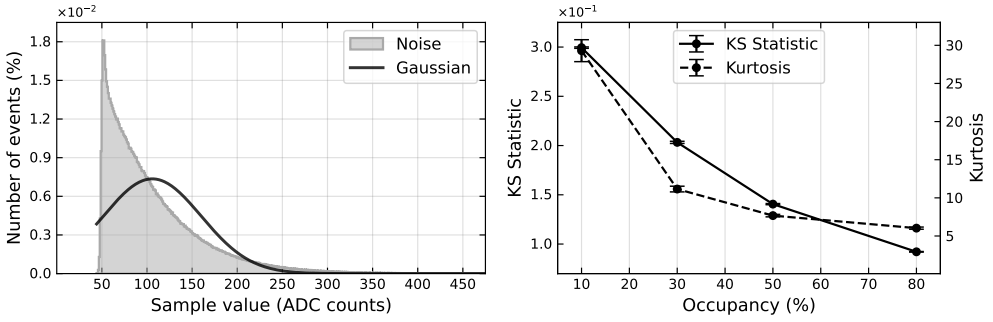


Fig. 3: (**a**) Gaussian fit to noise data for 50% occupancy. (**b**) KS Statistic considering Gaussian fits and Kurtosis for all occupancies

From Figure 3(a), it is possible to observe the difficulty faced by the Gaussian function in fitting the data. Such behavior is expected due to the intrinsic nonlinearity identified in the noise data. Similar patterns are detected for all ranges of occupancies and Figure 3(b) aims to show two well-known metrics that corroborate the analyzes.

KS Statistic measures the difference between two distributions. Among other uses, it is useful to evaluate the similarity between two distributions: if two distributions are exactly the same, the values of KS Statistic are zero, just as very distinct distributions lead to high KS values. Simultaneously, Kurtosis provides information about the Gaussianity of distributions. For the analyses performed in this paper, Kurtosis of 3 indicates a Gaussian distribution, while smaller than 3 denotes a flatter distribution, with shorter tails (platykurtic), and higher than 3 corresponds to a sharper distribution, with longer tails (leptokurtic).

Analyzing the KS Statistic, Figure 3(b) presents significant values, especially for lower occupancies. It is expected since, from a given level, the Central Limit Theorem (CLT) begins to be observed and the distributions start to converge towards a Gaussian distribution [38]. Even with the decrease, all range of occupancies shows results indicating the difficulty of the Gaussian distribution in describing the noise data.

The analyzes for Kurtosis, shown in the same plot, present results consistent with the values of KS Statistic. For lower occupancies, the noise distribution has higher values of Kurtosis, indicating the presence of long tails combined with sharper distributions. As the occupancy increases, the Kurtosis decreases, demonstrating that the distribution is becoming more Gaussian, once again alluding to CLT.

From these graphs, one can notice that even when occupancy increases and the distributions approach a Gaussian shape, the values of KS Statistic and Kurtosis are still significant. It shows the difficulty that the Gaussian distribution has to fit the data.

4.3 Mutual Information

The mutual information was estimated using the signal time samples two by two, and then using the Equation (5) for the computation of total mutual information.

The first figure of merit that is worth analyzing is the mutual information matrix. Figure 4 presents these matrices before and after ICA for 50% and 80% occupancy levels. Since lighter colors represent a greater amount of information, the color scales show that the shared information between variables is reduced after the ICA method is applied to the data.

The principal diagonal of the matrix has high values because it refers to self mutual information of the random variables. Additionally, the closest variables share a greater amount of information with each other, which leads to lighter colors in the superdiagonal and the subdiagonal.

While these matrices are meaningful, it is still worth quantifying the total mutual information at each occupancy level. Such results are shown in Figure 5, where one can see the reduction in this quantity after the use of ICA. For 10% occupancy, ICA has more difficulty to minimize the mutual information in the data, mainly because of the high non-Gaussianity of the distribution. When the occupancy increases, the distribution becomes more Gaussian due to the central limit theorem, although it still

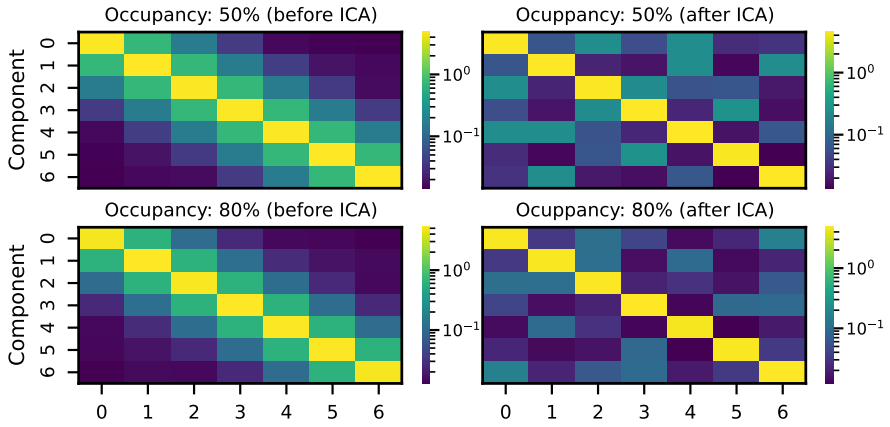


Fig. 4: Mutual information matrix before and after the use of ICA for 50% and 80% occupancies

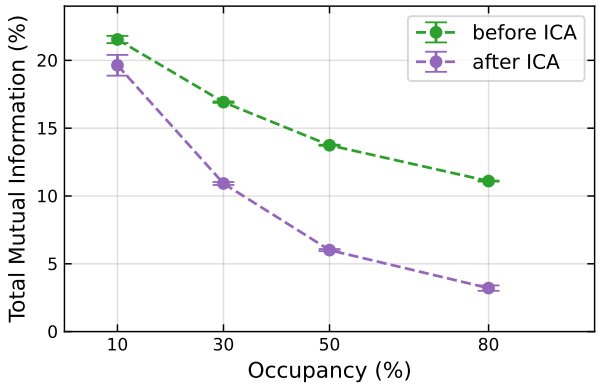


Fig. 5: Total Mutual Information before and after the use of ICA for all occupancies

presents large mutual information values. In that sense, the impact of using the ICA is more pronounced as occupancy increases.

4.4 Efficiency Analysis

Regarding the energy estimation efficiency analyzes, the studies begin looking at the distributions of errors taking into account the four methods employed: OF, MAE, Gaussian MLE and MLE + ICA. The first three are linear and well-known methods in the literature, while the last one is the method proposed in this work. The idea is to use source separation, via ICA, to improve the Gaussian MLE efficiency.

The efficiency was first implemented using Gaussian MLE. Once these amplitude values were obtained, they were used as input for the MLE + ICA method. Firstly, the FastICA was applied to the noise samples and then the amplitude was estimated by performing the multiplication of the marginal probabilities in a range through an

table search. For clarity, the Algorithm 1 shows a schematic to estimate the amplitude using the proposed MLE + ICA strategy.

Algorithm 1 MLE + ICA estimation strategy using the amplitude estimated by Gaussian MLE as a basis

Initialize:
$\hat{A}_{ica} \leftarrow \hat{A}_{gauss}$
$p_{ica} \leftarrow -1$
for $A = \hat{A}_{gauss} - 100$ to $\hat{A}_{gauss} + 100$ **do**
  for $i = 1$ to $ndim$ **do**
    $p_i \leftarrow$ marginal probability for independent component i using amplitude A
  end for
  $p_{total} \leftarrow$ product of marginal probabilities p
  if $p_{total} > p_{ica}$ **then**
    $\hat{A}_{ica} \leftarrow A$
    $p_{ica} \leftarrow p_{total}$
  end if
end for

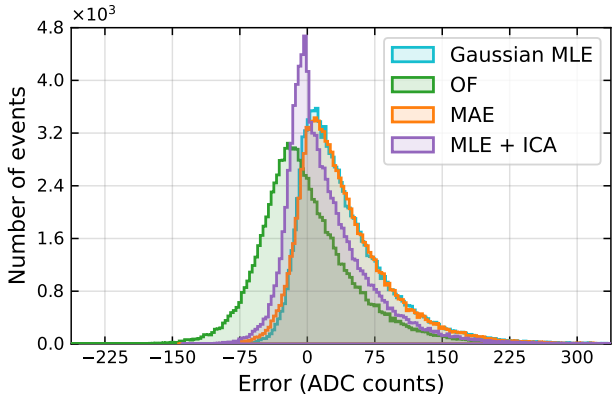
Figure 6(a) presents the histogram of errors for an occupancy level of 80%, considering the four methods. From the distributions, one can see that the MLE + ICA method seems to have an error more centered at zero and less dispersed around zero. These two characteristics are desired when evaluating error distributions, as the goal is to obtain errors as close to zero as possible.

To quantify the dispersion of the error data, Figure 6(b) shows the standard deviation taken from the estimation errors for all occupancy ranges. It can be depicted that the standard deviation values increase as the occupancy also increases. For lower occupancies, i.e., 10% and 30%, there is no significant improvement compared to Gaussian MLE, since the results are too close for both. In contrast, for 50% and 80%, the use of ICA brings better outcomes. For 80%, even the MAE method is outperformed.

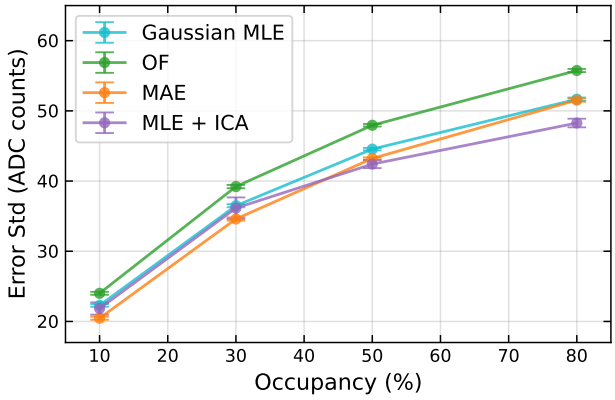
Since the error distributions are not symmetric, an additional metric used for performance analysis is the Kullback-Leibler (KL) divergence [39], which quantifies the difference between two distributions: if they are identical, KL is equal to zero, while it is 1 when they are completely distinct. In other words, it provides the amount of information that is lost when the true amplitude is approximated by the estimated amplitude. Figure 7 shows the values of Kullback-Leibler (KL) Divergence for all methods in the entire range of occupancies.

From the curves, one observes that the MLE + ICA method presents smaller values for this metric, with respect to the other methods. Even considering the uncertainties, the amplitude estimated by MLE + ICA seems to be better adjusted to the true amplitude than the amplitude spectrum estimated by the other methods.

The last analysis conducted in this paper regards the performance of the methods when all energy ranges are considered. To this end, the standard deviation of errors was estimated for amplitude intervals between 0 and 1023 ADC counts. Figure 8 shows



(a)



(b)

Fig. 6: (**a**) Histogram of errors for 80% occupancy. (**b**) Standard Deviation of errors for all occupancies.

these results considering the four methods considered. It can be observed that the MLE + ICA method presents smaller values for the standard deviation in all ranges of amplitudes. For initial intervals, it is even more efficient, when compared to the other methods.

5 Conclusions

This paper addressed the signal processing task of estimating the high-energy calorimeter response at channel level in different signal pile-up conditions. The pile-up is a consequence of the high rate and high luminosity conditions which modern experiments face, such as the LHC experiments. In the search for rare physics processes, particle colliders increase their luminosity as it increases the number of interactions per collision and, therefore, the number of signals produced at each collision. In the

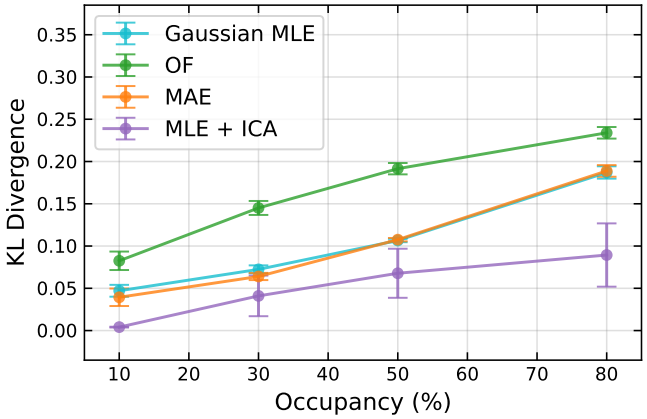


Fig. 7: KL Divergence between the estimated and reference amplitudes for all occupancies.

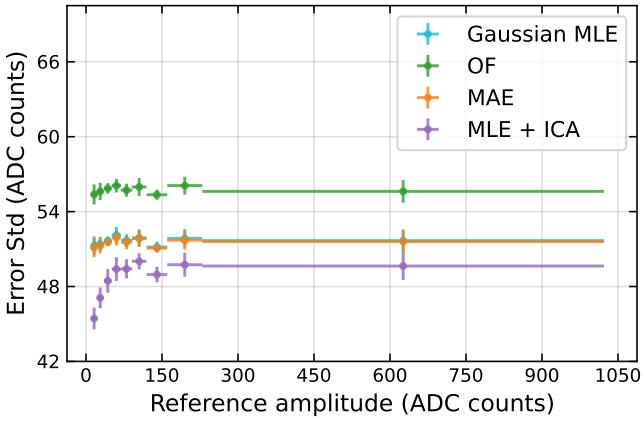


Fig. 8: Standard Deviation of errors considering the range of values of the reference amplitude for 80% occupancy.

other hand, the readout systems, like the calorimeter, must cope with such hash conditions that result in the pile-up effect, where the signal of interest overlaps with signals that belong to adjacent collisions. This undesirable effect degrades the performance of digital filters that reconstruct the signal energy by estimating the amplitude of the readout pulse.

Using a validated simulation environment, the results showed that the pile-up changes the noise characteristics, and the mutual information between the time samples comprises not only linear correlations, but additional higher order statistical moments. Using the ICA method as a pre-processing step, the noise mutual information is reduced for all channel occupancy levels, with a maximum improvement around 10% considering a channel occupancy of 80%. As a result, the spread of the estimation

error is also decreased with respect to the MLE for Gaussian noise, particularly in the low signal-to-noise ratio range. Additionally, the estimated energy with the proposed MLE + ICA method obtained better KL divergence scores when compared to the currently used strategies, showing a better estimation performance as this quantity compares the amplitude distributions between the simulated energy spectrum and the estimated one.

The presented results indicate that using ICA as a refinement technique for the Gaussian MLE may be a suitable option, as it yields good outcomes and builds upon a well-established linear method widely used in practical applications. Furthermore, since ICA operates on Gaussian MLE estimates, it is expected to provide improved performance.

In light of the promising results achieved, the proposed MLE + ICA strategy will be tested with real data collected in a real high-energy calorimeter system operating under high-luminosity conditions. Furthermore, since the ICA method did not totally suppress the noise mutual information, this step could be replaced by another approach to further decrease this quantity and potentially increase the MLE performance. Additionally, in view of the good performance of the ICA, the exhaustive search, used to estimate the signal amplitude and initially adopted as proof of concept, will be replaced by a more efficient technique.

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References

[1] Hayrapetyan, A., *et al.*: Performance of the CMS high-level trigger during LHC Run 2. Journal of Instrumentation **19**(11), 11021 (2024) https://doi.org/10.1088/1748-0221/19/11/P11021

[2] Cruz, I.H.: The Belle II experiment: fundamental physics at the flavor frontier. Journal of Physics: Conference Series **761**(1), 012017 (2016) https://doi.org/10.1088/1742-6596/761/1/012017

[3] Palomares, C., DUNE Collaboration: DUNE Physics Program and Status. Journal of Physics: Conference Series **2156**(1), 012107 (2021) https://doi.org/10.1088/1742-6596/2156/1/012107

[4] Gray, H.M.: Future colliders for the high-energy frontier. Reviews in Physics **6**, 22 (2021) https://doi.org/10.1016/j.revip.2021.100053

[5] Evans, L., Bryant, P.: LHC Machine. Journal of Instrumentation **3**, 08001 (2008)

[6] The ATLAS Collaboration: The ATLAS Experiment at the CERN Large Hadron Collider. Journal of Instrumentation **14**(8), 08003 (2019)

[7] The CMS Collaboration: The CMS Experiment at the CERN LHC. Journal of Instrumentation **3**, 08004 (2008)

[8] The ATLAS Collaboration: Observation of a new particle in the search for the Standard Model Higgs boson with the ATLAS detector at the LHC. Physics Letters B **716**(1), 1–29 (2012)

[9] Leo, W.R.: Techniques for Nuclear and Particle Physics Experiments, 2nd edn. Springer, Berlin, Germany (1994)

[10] Ruggiero, F.: LHC accelerator R&D and upgrade scenarios. The European Physical Journal C - Particles and Fields **34**, 433–442 (2004) https://doi.org/10.1140/epjcd/s2004-04-047-1

[11] Wigmans, R.: Calorimetry: Energy Measurement in Particle Physics, 2nd edn. Oxford University Press, Oxford - UK (2017). https://doi.org/10.1093/oso/9780198786351.001.0001 . https://doi.org/10.1093/oso/9780198786351.001.0001

[12] Knoll, G.F.: Radiation Detection and Measurement. Wiley, New York, NY (2010). https://cds.cern.ch/record/1300754

[13] Guz, Y.: The LHCb Calorimeter system: design, performance and upgrade. Journal of Instrumentation **12**(07), 07024 (2017) https://doi.org/10.1088/1748-0221/12/07/C07024

[14] Kreße, T., ATLAS Liquid Argon Calorimeter Group: Current and future challenges when operating the ATLAS Liquid Argon Calorimeter. Journal of Instrumentation **19**(02), 02061 (2024) https://doi.org/10.1088/1748-0221/19/02/C02061

[15] Anderson, K., Gupta, A., Merritt, F., Oreglia, M., Pilcher, J., Sanders, H., Shochet, M., Tang, F., Teuscher, R., Wu, H., *et al.*: Design of the front-end analog electronics for the ATLAS tile calorimeter. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment **551**(2-3), 469–476 (2005)

[16] Gonçalves, G.I., Peralva, B.S.-M., Seixas, J.M., Andrade Filho, L.M., Cerqueira, A.S.: Performance of Optimal Linear Filtering Methods for Signal Estimation in High-Energy Calorimetry. Journal of Control, Automation and Electrical Systems (2022) https://doi.org/10.1007/s40313-022-00907-0

[17] Fullana, E., Castelo, J., Castillo, V., Cuenca, C., Ferrer, A., Higon, E., Iglesias, C.,

Munar, A., Poveda, J., Ruiz-Martinez, A., Salvachua, B., Solans, C., Teuscher, R., Valls, J.: Digital Signal Reconstruction in the ATLAS Hadronic Tile Calorimeter. IEEE Transactions on Nuclear Science **53**(4), 2139–2143 (2006) https://doi.org/10.1109/TNS.2006.877267

[18] Lii, K.-S.: Nonlinear systems and higher-order statistics with applications. Signal Processing **53**, 165–177 (1996) https://doi.org/10.1016/0165-1684(96)00084-9

[19] Cover, T.M., Thomas, J.A.: Elements of Information Theory, 2nd edn. Wiley, Hoboken, NJ (2006)

[20] HyvÄrinen, A., Oja, E.: Independent component analysis: algorithms and applications. Neural Networks **13**, 411–430 (2000) https://doi.org/10.1016/S0893-6080(00)00026-5

[21] Comon, P.: Independent component analysis, A new concept? Signal Processing **36**, 287–314 (1994) https://doi.org/10.1016/0165-1684(94)90029-9

[22] Kay, S.M.: Fundamentals of Statistical Processing, Volume I: Estimation Theory. Prentice-Hall Inc, New Jersey (1993)

[23] The ATLAS Collaboration: The atlas trigger system for lhc run 3 and trigger performance in 2022. Journal of Instrumentation **19**(06), 06029 (2024) https://doi.org/10.1088/1748-0221/19/06/P06029

[24] Das, P., CMS Collaboration: An overview of the trigger system at the cms experiment. Physica Scripta **97**(5), 054008 (2022) https://doi.org/10.1088/1402-4896/ac6302

[25] Cleland, W.E., Stern, E.G.: Signal processing considerations for liquid ionization calorimeters in a high rate environment. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment **338**(2), 467–497 (1994) https://doi.org/10.1016/0168-9002(94)91332-3

[26] Peralva, B.S.-M.: Signal Reconstruction in ATLAS Tile Calorimeter using Run 3 Real Data and Perspectives for the Phase-II Operation. In: 2023 IEEE Nuclear Science Symposium, Medical Imaging Conference and International Symposium on Room-Temperature Semiconductor Detectors (NSS MIC RTSD), pp. 1–2 (2023). https://doi.org/10.1109/NSSMICRTSD49126.2023.10338330

[27] A. Filho, L., Peralva, B.S., Seixas, J., Cerqueira, A.S.: Calorimeter Response Deconvolution for Energy Estimation in High-Luminosity Conditions. IEEE Transactions on Nuclear Science **62**(6), 3265–3273 (2015) https://doi.org/10.1109/TNS.2015.2481714

[28] Marin, J.L.: Energy Reconstruction Performance in the ATLAS Tile Calorimeter

Operating at High Event Rate Conditions Using LHC Collision Data. In: 2020 International Conference on Systems, Signals and Image Processing (IWSSIP), pp. 361–366 (2020). https://doi.org/10.1109/IWSSIP48289.2020.9145451

[29] Caldwell, A., Gialas, I., Mishra, S., Parsons, J., Ritz, S., Sciulli, F., Sippach, W., Smith, W., Hervas, L., Kötz, U., Klanner, R.: Design and implementation of a high precision readout system for the zeus calorimeter. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment **321**(1), 356–364 (1992) https://doi.org/10.1016/0168-9002(92)90413-X

[30] Muller, H., Budnikov, D., Ippolitov, M., Li, Q., Manko, V., Pimenta, R., Rohrich, D., Sibiryak, I., Skaali, B., Vinogradov, A.: Front-end electronics for pwo-based phos calorimeter of alice. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment **567**(1), 264–267 (2006) https://doi.org/10.1016/j.nima.2006.05.104 . Proceedings of the 4th International Conference on New Developments in Photodetection

[31] Tylmad, M.: Pulse shapes for signal reconstruction in the atlas tile calorimeter. In: 2009 16th IEEE-NPSS Real Time Conference, pp. 543–547 (2009). https://doi.org/10.1109/RTC.2009.5321656

[32] HyvÄrinen, A., Oja, E.: Independent component analysis: algorithms and applications. Neural Networks **13**, 411–430 (2000) https://doi.org/10.1016/S0893-6080(00)00026-5

[33] Gonçalves, G.I.: CPS — Calorimetry Pulse Simulator. https://github.com/ingoncalves/calorimetry-pulse-simulator. Accessed: 2026-01-17 (2022)

[34] Araújo, M.V., Begalli, M., Freund, W.S., Gonçalves, G.I., Khandoga, M., Laforge, B., Leopold, A., Marin, J.L., Peralva, B.S.-M., Pinto, J.V.F., Santos, M.S., Seixas, J.M., Simas Filho, E.F., Souza, E.E.P.: Lorenzetti showers - a general-purpose framework for supporting signal reconstruction and triggering with calorimeters. Computer Physics Communications **286**, 108671 (2023) https://doi.org/10.1016/j.cpc.2023.108671

[35] Rimes, S.M., Peralva, B.S.-M., Libotte, G.B., Paschoalin, T.C.A., Andrade Filho, L.M., Seixas, J.M.: A maximum likelihood approach for signal estimation and data quality assessment for high-energy calorimeter systems. IEEE Transactions on Nuclear Science **72**(12), 3801–3808 (2025) https://doi.org/10.1109/TNS.2025.3630987

[36] Duarte, J.P.B.S., Filho, L.M.d.A., Filho, E.F.d.S., Farias, P.C.M.A., Seixas, J.M.: Online energy reconstruction for calorimeters under high pile-up conditions using deconvolutional techniques. Journal of Instrumentation **14**(12), 12017 (2019) https://doi.org/10.1088/1748-0221/14/12/P12017

[37] Banerjee, S.: Cms simulation software. Journal of Physics: Conference Series **396**(2), 022003 (2012) https://doi.org/10.1088/1742-6596/396/2/022003

[38] Darling, D.A.: Review: B. V. Gnedenko and A. N. Kolmogorov, Limit distributions for sums of independent random variables. Bull. Amer. Math. Soc. **62**, 50–52 (1956) https://doi.org/10.1090/S0002-9904-1956-09978-1

[39] Belov, D.I., Armstrong, R.D.: Distributions of the Kullback–Leibler divergence with applications. British Journal of Mathematical and Statistical Psychology **64**(2), 291–309 (2011) https://doi.org/10.1348/000711010X522227