

# Efficient Level 2 Trigger System Based on Artificial Neural Networks

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The HESS project is a major international experiment currently performed in gamma astronomy. This project relies on a system of four Cherenkov telescopes enabling the observation of cosmic gamma rays. The outstanding performances obtained so far in the HESS experiment has led the research labs involved in this project to improve the existing system: an additional telescope is currently being built and will soon take place within the previous telescope system. This telescope is designed to be more sensitive to the detection of low energy particles than the others, leading to an increase of the number of collected particle images. In this context, which is tightly constrained in terms of latency, physicists have been compelled to design an additional L2 trigger in order to deal with the huge amount of data. This trigger aims to select images of interest (i.e. gamma particles) and reject all other events that are associated to noise. Contrary to classical methods that consist in applying strong cuts based on Hillas parameters, we propose an original approach based on artificial neural networks. In this approach, collected events are first handled by a preprocessing level whose purpose consists in applying transformations on incoming images, thus reducing the dimensionality of the problem. It is based on Zernike moments computation that aims to extract the main features of the images and guarantee image invariance in translation and rotation. Zernike moments have also proved to be reliable in terms of feature representation capability and low noise sensitivity. In a second step, an artificial neural networks ensures the classification of events within two classes (gammas and hadrons, which will also contain muons), indicating whether to keep the image for future processing or to reject it. In this presentation, we will describe the entire L2-Trigger system and provide some results in terms of classification performances. We will discuss the contribution of neural networks in this type of experiments compared with classical solutions.

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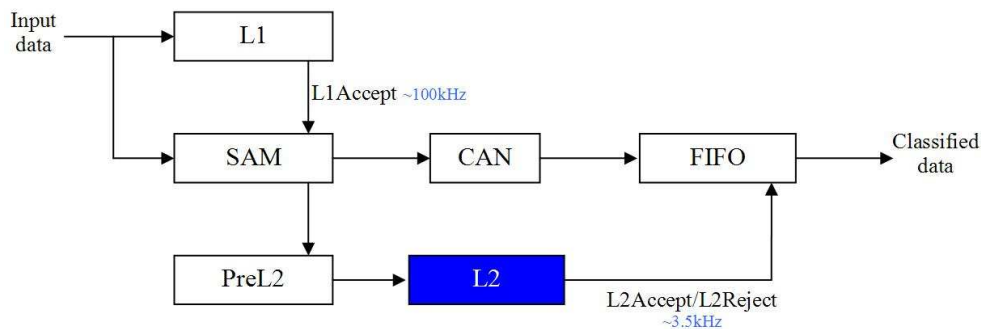
\*Speaker.

## 1. Introduction

A first study dealing with a L2 neural trigger has already been described in [1]. In this paper, we propose to improve the neural solution by adding an efficient preprocessing step in order to help the classifier in its task. The HESS experiment [2] is based on the atmospheric Cherenkov technique that consists in studying Cherenkov light in order to detect gamma-rays. The current HESS system (phase 1) is composed of four imaging Cherenkov telescopes, arranged on a square and is devised for the detection of particles of high energy ( $> 100$  GeV). According to the huge amount of data to be collected, a trigger system composed of two levels is currently integrated in the HESS experiment: a level 1 (L1) and a central trigger. Such a trigger system is useful to keep the relevant events on-line in order to exploit them off-line.

## 2. Second phase of the HESS project

The outstanding performances obtained so far in the HESS system has led the collaboration to improve the existing system: a Very Large Cherenkov telescope (VLCT) will soon take place in the previous system [3]. The HESS2 experiment will upgrade HESS1 by enabling the collection of events of lower energies (from 10 GeV).



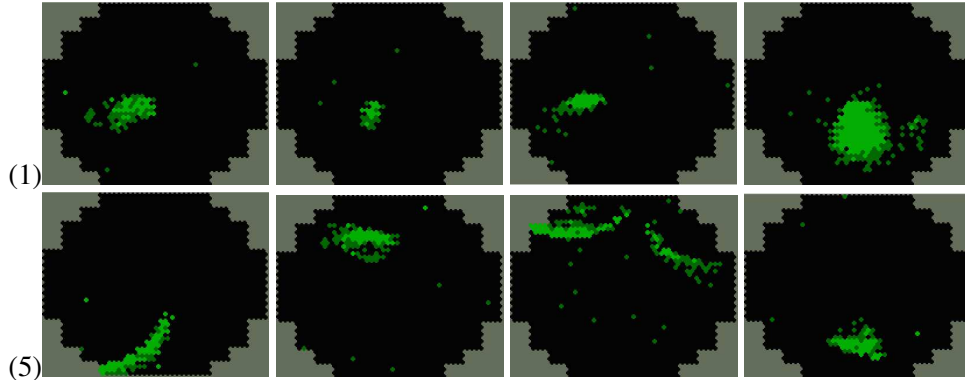
**Figure 1:** Trigger system in HESS-II

In this new context, the quantity of data to be collected by the VLCT will drastically increase. The huge amount of data to be processed on line (240 GBauds in approximately  $10 \mu s$ ) has led the collaboration to propose a new efficient trigger scheme composed of three levels: two trigger levels (L1 and L2) and a central trigger. The figure 1 describes the global trigger system.

Data coming from the camera are stored in an analog memory (SAM). In parallel, they are sent to the L1 which has the same structure as in HESS1. It generates a binary signal at a mean rate of 100 KHz indicating whether an event has to be kept (L1Accept) or rejected (L1Reject). If the L1Accept occurs, the image is digitally converted and stored in a FIFO until a L2Accept/Reject (mean rate: 5 kHz) from the L2 trigger occurs. In parallel data are sent to the PreL2 for thresholding at three energy levels. The image is then sent to the L2 trigger.

### 3. A pattern recognition issue

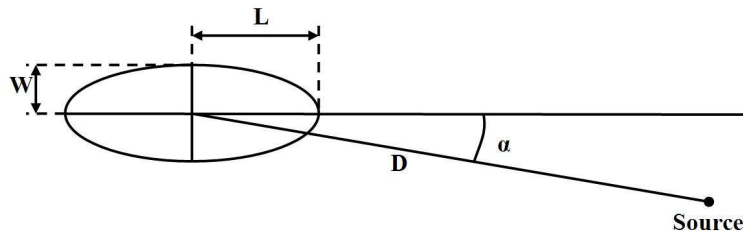
In the HESS2 experiment, the incoming images consist of the signatures of hadronic or electromagnetic showers on the telescope. Three types of particles have to be discriminated: gammas, muons and protons. In this context, the interesting particle type is gamma. Muons and protons may be considered as observation noise and do not need to be recorded. The nature of images differs according to the incident energies and to the impact distance. Examples of particles' signatures are depicted in figure 2.



**Figure 2:** Gamma (1-4), muon (5-6) and proton (7-8) images of different energies.

#### 3.1 Classical approach

Astrophysicists generally perform thresholds on the images according to physical characteristics in order to isolate interesting events. They usually compute Hillas parameters [4] and apply cuts on the obtained results. The idea of this algorithm is to adjust a bi-dimensional ellipse on the image according to the particle signature (see figure 3). Parameters such as the center of gravity (CoG), length, width, surface, area and the  $\alpha$  angle are computed. According to the parameters values, the particles are classified in three different classes: gammas, muons and protons.

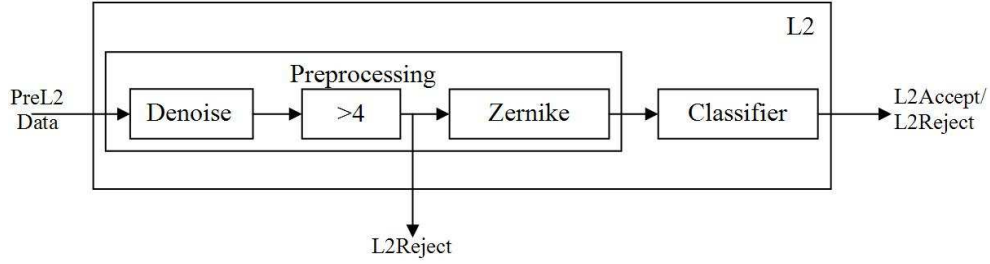


**Figure 3:** Overview of Hillas parameters

Since Hillas parameters constitute an efficient way of discriminating between particles, it has seemed appropriate to extend these concepts by considering non linear systems that are also known as effective classifier and that have shown rather impressive results in quite similar problems. A new trigger system based on a neural architecture has then been envisaged.

### 3.2 Neural solution

The neural scheme (figure 4) consists in a neural classifier and its associated preprocessing.



**Figure 4:** Level 2 trigger system

#### 3.2.1 Preprocessing

The main role of preprocessing is to reduce the dimensionality of the problem by extracting significant information from the input data and thus simplify the neural network structure. Nevertheless, a drawback of such preprocessing relies in its relative complexity and a compromise between the complexity of the neural network and its associated preprocessing must be performed.

The envisaged preprocessing is divided into three steps: A first step aims to remove the isolated pixels that do not bring any information. These pixels have to be removed in order to obtain the most representative image of the particles.

The second step consists in rejecting data that are not relevant. In fact, some of the biggest clusters in the images are smaller than 4 pixels. Since a classifier can not make a decision with such a poor information, these clusters have to be automatically rejected.

The final step strives to extract the most interesting features of the image. In this step, two algorithms have been studied. The first is based on the utilization of the Hillas parameters (see section 3.1). The second makes use of Zernike moments [6].

**Zernike moments** In this case, the role of preprocessing is to implement rotation and translation invariance in order to reduce the number of parameters describing the images. The Zernike moments are proved to be efficient in terms of feature representation capability and low noise sensitivity. They are based on the orthogonal Zernike polynomials  $R_{p,q}$ .

$$R_{p,q}(r) = \sum_{s=0}^{(p-|q|)/2} (-1)^s \frac{(p-s)!}{s! \left(\frac{p-2s+|q|}{2}\right)! \left(\frac{p-2s-|q|}{2}\right)!} r^{p-2s} \quad (3.1)$$

The expression of the Zernike moments  $Z_{p,q}$  of order  $p$  and repetition  $q$  is:

$$Z_{p,q} = \frac{(p+1)}{\pi} \sum_{x=1}^N \sum_{y=1}^N R_{p,q}(r) e^{iq\theta} f(x,y) \quad \text{with } r = \frac{(x^2 + y^2)^{1/2}}{N} \quad \text{and } \theta = \tan(y/x) \quad (3.2)$$

Since HESS2 images have a poor resolution (52 by 48 pixels coded on 2 bits), the order of the Zernike moments to use can be low. In our study, it has been found that Zernike moments of order 8 (25 moments) are sufficient to describe the incoming images.

### 3.2.2 Neural network

The structure of the neural network is a simple multi-layer perceptron (MLP) with 5 or 25 inputs, according to the type of preprocessing to be considered. The proposed network is composed of 1 hidden layer and 3 outputs corresponding to the three types of particles to identify (gammas, muons and protons). Each output neuron features a TanH activation function that ranges between -1 (rejected) and 1 (accepted). Since outputs are continuous, only the maximum of the three values is retained in order to make a decision according to the nature of the particle.

The selected image patterns that have been used for the learning phase of the neural network are respectively composed of 2000 gammas, 2000 muons and 2000 protons distributed in all ranges of energies. The remaining data have been distributed between the testing and the validation base (1600 events for each particle and each set).

## 4. Results

Results are expressed in terms of gammas' recognition rate and muons or protons rejection rate. The applied thresholds for the Hillas approach follow this procedure: (i) if  $\text{CoG} < t$  then the event is recognized as a gamma particle, (ii) if  $\text{CoG} \geq t$  and  $\alpha < 20$  deg then the event is recognized as a gamma, (iii) otherwise the event is rejected. This parameter  $t$  has been chosen in order to accept the maximum number of gammas while rejecting the maximum number of muons and protons. It has been fixed to 0.5. The obtained results (see table 1) show that the neural solution performs a

	Gamma	Muon	Proton
Hillas filter	60%	56%	37%
NN with Hillas	71%	84%	82%
NN with Zernike	95%	58%	41%

**Table 1:** Recognition rates of a neural network with 3 outputs

better classification than the classical Hillas algorithm. Since the main objective of the system is to identify most of gamma events, the neural network with a Zernike-based preprocessing seems to represent the most efficient solution. Nevertheless, the Hillas-based network provides better rejection of noise at the expense of a lower gamma's recognition rate.

	Gamma recognized	Muon and proton recognized
NN with Hillas	76%	80%
NN with Zernike	85%	70%
NN with Hillas + Zernike	82%	84%

**Table 2:** Recognition rates of a neural network with 2 outputs

A second study has been performed in order to merge both muons and protons classes onto a single class (see table 2). Gamma's recognition rate is slightly reduced in the case of the Zernike based network but the rejection of muons and protons is considerably improved. Both approaches

have been combined in the last line of the table: both neural networks have been computed separately and the best outcome has been retained for the final decision. This solution permits a better recognition of muons and protons. Nevertheless, in the case of gamma's recognition, the neural network associated with Zernike moments still provides better results.

## 5. Conclusion

The classical Hillas approach is often utilized by astrophysicists as a trigger solution. Unfortunately, the cuts performed on the results often reject too many gamma particles. The neural approach, which has already shown efficient results in other physics experiments as [7], constitutes an interesting solution. Moreover, this type of algorithms may be easily implemented on hardware and in real-time as shown in [8],[9]. This seems particularly interesting since the processing time in the HESS2 experiment is tightly constrained : only 10  $\mu$ s are available to make a decision at L2. In this context, an efficient algorithm has been described. Zernike moments have shown to be an efficient preprocessing in the L2 trigger of HESS. Although far more complex than neural networks in terms of hardware computations, it may be envisaged to implement such algorithms within classical reconfigurable circuits.

## References

- [1] S. Khatchadourian, J.-C. Prévotet and L. Kessal, *A Neural Solution for the Level 2 Trigger in Gamma Ray Astronomy*, Proc. 11<sup>th</sup> ACAT, Amsterdam, Netherlands, 2007.
- [2] W. Hofmann, *The H.E.S.S. Project*, Proc. Symposium The Universe Viewed in Gamma-Rays, 2002.
- [3] P. Vincent, H.E.S.S. collaboration, *H.E.S.S. Phase II*, Proc. 29<sup>th</sup> ICRC, Pune, India
- [4] A.M. Hillas, Proc. 19<sup>th</sup> ICRC, La Jolla 3, 1985.
- [5] C.M. Bishop, *Neural networks for pattern recognition*, Oxford University Press, 1996.
- [6] R. Mukundan and K.R. Ramakrishnan, *Moment functions in image analysis: theory and applications*, World Scientific, 1998.
- [7] C. Kiesling *The H1 Neural Network Trigger Project*, Proc. 7<sup>th</sup> ACAT, Batavia, Illinois, USA, 2000.
- [8] J.-C. Prévotet et al., *Moving NN Triggers to Level-1 at LHC Rates*, Nuclear Instruments and Methods in Physics Research A, 2003.
- [9] N. Ramanan, S. Khatchadourian, J.-C. Prévotet and L. Kessal, *Neural Network Hardware Architecture for Pattern Recognition in the HESS2 Project*, Proc. 16<sup>th</sup> ESANN, Bruges, Belgium, 2008.