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Identification of Gamma-Rays and Protons with Feed-Forward Neural Network

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Abstract

The differences of space distributions and time profiles between the gamma ray and proton induced showers in YBJ-ARGO experiment are studied using Monte Carlo simulation data. An artificial neural network algorithm is used to identify the primary gamma ray and hadron induced showers. It is shown that the separation of gamma rays and protons can be achieved with a good efficiency in the energy range of 0.1~10TeV.

1 Introduction:

The search for gamma ray point sources is a popular and important topic in the study of cosmic rays. Many gamma ray sources of HE/VHE have been found by the EGRET experiment on board the Compton Gamma-Ray Observatory covering the 30 MeV to 30 GeV energy region (Gogiel,1996), and by the atmospheric Cherenkov telescopes (ACTs) in ~TeV energy range (Chaman, 1997). But to date, no definite evidence about the existence of the gamma ray point sources above 10 TeV has been observed. One possible reason is that the ground based EAS array can not discriminate the gamma ray showers from the hadronic background. Therefore, if we want to get some meaningful results in the search for gamma ray point sources with the traditional EAS array, we must reduce the threshold energy and increase the detector sensitivity. With much higher detector density (e.g. in the “carpets”) the threshold energy of the EAS array could be lowered to an energy region not far from the present experimental limits in the satellite technology. Efficiently separating the gamma showers from the hadronic showers, which allows to achieve a significant rejection of background events and increase the sensitivity in detecting a gamma signal above the background, is a good approach to increasing the detector sensitivity. This needs both a detector system providing detailed measurements of the air cascades and a good algorithm to discriminate the gamma showers and hadronic showers. The YBJ-ARGO experiment (The ARGO Collabortion, 1997), which will be installed at Yangbajing of China, could give a detailed space-time picture of the shower front and could meet the needs for the above goal.

This article makes a study on the differences of space-time profiles between the gamma showers and the proton showers at the YBJ observation level by means of Monte Carlo simulation. An artificial neural network algorithm is presented to separate the gamma showers from the hadronic ones detected in YBJ-ARGO experiment. The Monte Carlo simulation shows that we could get a good rejection of cosmic ray background in the energy range between 100GeV and 10TeV.

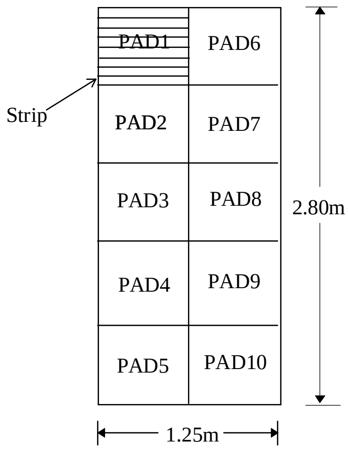

Figure1: The layout of RPC

2 MC Simulation:

The YBJ-ARGO experiment consists of a single layer of RPCs (Resistive Plate Counters) covering an area 5000 m^2 for the first phase of the experiment. Each RPC (125×280cm^2) is equipped with a read-out system made of strips, 6.7cm wide and

62cm long, just as shown in Figure 1. Signals from the strips are OR-ed to get the time of the first particle and the number of particles hitting each 56×62cm^2 PAD. A lead converter of 0.5 cm thick covers uniformly the RPC plane to increase the number of charged particle and to reduce the time spread of the shower front through the shower photon conversion.

Monte Carlo simulations have been performed using the COSMOS code (Kasahara,1995) for the air shower generation and the GEANT code (Brun et al,1991) for the shower particles detection. Primary particles are injected at 0° to 30° zenith angle from the top of the atmosphere, and each secondary particle is followed up to 3MeV or reaching the observation level (a vertical atmospheric depth of 606 g/cm^2). The primary energies are sampled between 100GeV and 10TeV with a power index of -2.7. About 5×10^5 events are generated and used to simulate the detector response with cores uniformly distributed over the YBJ-ARGO RPC carpet. The events selected are following the two conditions:

(1)The number of fired pads: $N_p \geq 50$.

(2)The core position (x_c, y_c) : $|x_c| \leq 25m$ 、 $|y_c| \leq 25m$.

About 1×10^4 simulated γ showers and hadron showers are selected as the sample events.

3 γ/Proton Separation:

Since the YBJ-ARGO experiment can only measure the space-time profile of EAS at limited stages in the shower development, we have to discriminate the gamma showers and proton showers from their lateral distributions. Figure 2 shows the difference between gamma showers and proton showers in their lateral distributions.

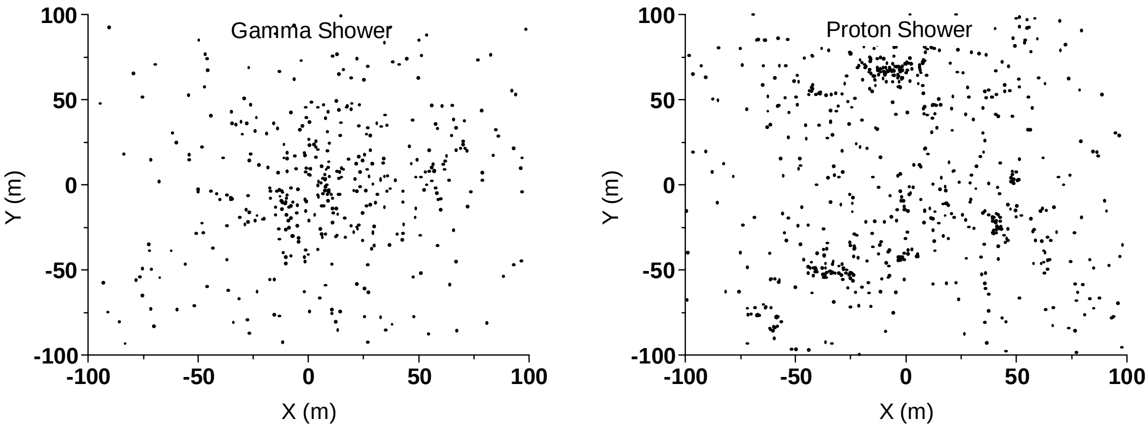

Figure 2: The lateral distribution of a 500 GeV γ and proton induced shower in YBJ-ARGO experiment

In contrast to hadron shower, the core of gamma shower is more concentrated and the particle distribution is much smoother and with less non-uniformity. We can select the following feature parameters to separate gamma showers from proton showers:

(1) total number of fired strips in ARGO: N_h

(2) mean fired strips of all RPCs: $AC = N_c / N_r$, where N_c is the number of total fired strips and N_r is the number of fired RPCs.

(3) mean fluctuations of fired strips over all RPCs: $FC = \sum_{i=1}^{N_r} \frac{|C_i - AC|}{AC} \Big/ N_r$, where C_i is the number of fired strips in ith fired RPC.

(4) mean lateral spread of all fired strips: $R = \sum_{i=1}^{N_h} \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \Big/ N_h$, where (x_i, y_i) is the position of ith fired strip and (x_c, y_c) is the core position.

(5) mean lateral spread of the fired strips over all RPCs: $CR = \sum_{i=1}^{N_r} C_i \sqrt{(x_i' - x_c)^2 + (y_i' - y_c)^2} \Big/ N_r$, where (x_i', y') is the position of the ith fired RPC.

(6) non-uniformity in the lateral distribution.

(7) distance between the core and maximum density position: $d = \sqrt{(x - x_c)^2 + (y - y_c)^2}$, where (x, y) is the position of the maximum density.

(8) the fraction of fired strips near the core: $F_5 = N_5 / N_h$, $F_{10} = N_{10} / N_h$,where N_5 is the number of fired strips within 5m from the core and N_{10} is the number of fired strips within 10m from the core.

By abstracting the 9 feature parameters from the simulation data, we obtain a training sample (3000 showers) and a testing sample (7000 showers). In this work, we use a three layer feed-forward neural network as a classifier. The network contains 9 feature parameters as input neurons, 12 hidden nodes and one output unit. The 9-12-1 network is trained using "Rprop" algorithm (Riedmiler et al, 1993) to give the desired output value 0 for γ and 1 for proton induced showers. The weights in the network are initiated uniformly at random in the range [-0.1,0.1]. The learning rate η and the temperature parameter T are initiated with 0.01 and 1.0 respectively. Figure 3 shows the γ acceptance and proton rejection for the test sample vary with the number of learning epochs and reach a stable state after about 100 training epochs. Figure 4 shows the distribution of the network output for the γ and proton showers of the test sample.

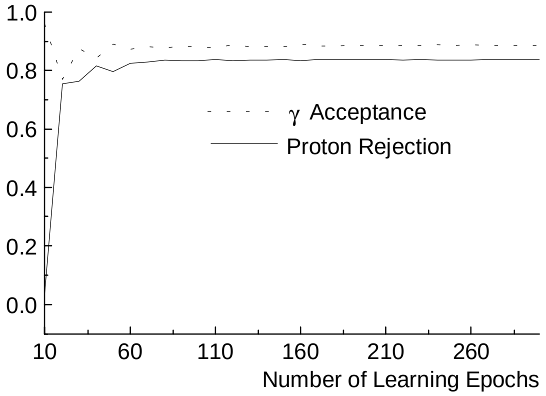

Figure 3: The γ acceptance and proton rejection vs learning cycles for the test samples

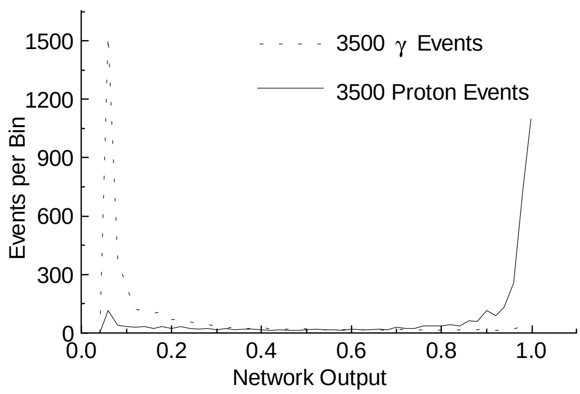

Figure 4: The distribution of the network output for the test samples

4 Results and Discussions:

7000 MC events are tested after training the network. It is found that the network is able to correctly select 86.3% of testing samples (the γ acceptance is 88.9% and the proton rejection is 83.7%) and the identification power increases with the number of fired pads. The detailed results are summarized in Table 1.

Table 1: γ/proton identification dependence on hit pads number

Number of fired pads	50-80	80-150	150-300	>300
γ acceptance	85.9%	89.8%	90.6%	91.9%
Proton rejection	79.5%	83.1%	87.2%	90.2%
Right identification	82.7%	86.4%	88.9%	91.1%

The main aim of γ and proton separation is to increase the signal-to-noise ratio. This ratio can be described by:

$$S/\sqrt{B} \propto E^{-\gamma_s} AT\varepsilon_\gamma \Big/ \sqrt{E^{-\gamma} AT(\Delta\varphi)^2(1-\varepsilon_{had})} = E^{\frac{\gamma}{2}-\gamma_s}\sqrt{AT}\frac{1}{\Delta\varphi}Q$$

where A is the detector area, T is exposure time, $\Delta\varphi$ is angular resolution, Q is the γ/proton separation quality factor, defined as: $Q = \varepsilon_\gamma / \sqrt{1-\varepsilon_{had}}$, here ε_γ is the γ acceptance, ε_{had} is the hadron rejection.

Proton rejection and gamma acceptance depend on the cut value ξ in the network output. To find the optimal value of ξ, it is necessary to maximize the quality factor with respect to ξ. Figure 5 shows the quality factor as a function of the cut value in the network output. When the net cut value ξ is 0.15, a maximum Q value of 2.59 (92.8% rejection of protons and 69.5% acceptance of γ-rays) is attained. Therefore, all events producing a value $\geq$ 0.15 are classified as γ-rays while those with value < 0.15 are considered to be proton background.

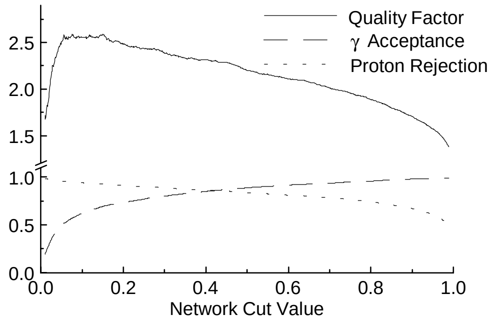

Figure 5: The quality factor Q as a function of the cut ξ in the network output

The core position play a very important role in the discrimination of γ/proton. We assume the reconstructed cores obey a Gaussian distribution, and use the same sample of events of the previous analysis, only the real position of the core is replaced by the reconstructed core. The identification power is affected by the uncertainties in the core determination, just as it is shown in the following Table 2.

Table 2: The identification power for γ and proton, when the uncertainties in the core determination are taken into account

σ_x, σ_y	0m	1m	2m	3m	4m	5m	6m
γ acceptance	88.9%	88.9%	87.6%	85.7%	85.3%	85.4%	83.1%
Proton rejection	83.7%	83.0%	80.8%	80.2%	78.5%	75.8%	74.1%
Right identification	86.3%	85.9%	84.2%	83.0%	81.9%	80.6%	78.6%
Quality factor	2.20	2.16	2.00	1.93	1.84	1.74	1.63

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