

Composition studies based on the muon content of the showers measured by the UMD

T_b – **X**_{max} correlation analysis

Varada Varma Kizakke Covilakam Supervisors : A. D. Supanitsky, R. Engel DDAp/DDEIT and HIRSAP Annual Meeting 21 November 2023

Recap

Eur. Phys. J. C manuscript No. (will be inserted by the editor)

Reconstruction of air shower muon lateral distribution functions using integrator and binary modes of underground muon detectors

V.V Kizakke Covilakam^{a,1,2}, A.D. Supanitsky¹, D. Ravignani¹

¹Instituto de Tecnologías en Detección y Astroparticulas (CNEA, CONICET, UNSAM), Av. General Paz 1499, San Martín, B1650KNA, Buenos Aires, Argentina *Astrohen Institut für Technolorie. Institut für Kernnhvsik. Hermann-von-Helmholtz-Platz 1. Essenstein-Leonoldshafen. 76344.

"Karlsruher Institut f
ür Technologie, Institut f
ür Kernphysik, Hermann-von-Helmholtz-Platz 1, Eggenstein-Leopoldshafen, 76344, Baden-W
ürttemberg, Germany.

Received: date / Accepted: date

Abstract The investigation of cosmic rays holds significant importance in the realm of particle physics, enabling us to expand our understanding beyond atomic confines. However, the origin and characteristics of ultra-high-energy cosmic rays remain elusive, making them a crucial topic of exploration in the field of astroparticle physics. Currently, our examination of these cosmic rays relies on studying the extensive air showers (EAS) generated as they interact with atmospheric nuclei during their passage through Earth's atmosphere. Accurate comprehension of cosmic ray composition is vital in determining their source. Notably, the muon content of EAS and the atmospheric depth of the shower maximum serve as the most significant indicators of primary mass composition. In this study, we present two novel methods for reconstructing particle densities based on muon counts obtained from underground muon detectors (UMDs) at varying distances to the shower axis. Our methods were analyzed using Monte Carlo air shower simulations. To demonstrate these techniques, we utilized the muon content measurements from the UMD of the Pierre Auger cosmic ray Observatory, an array of detectors dedicated to measuring extensive air showers. Our newly developed reconstruction methods, employed with two distinct UMD data acquisition modes, showcased minimal bias and standard deviation. Furthermore, we conducted a comparative analysis of our approaches against previously established methodologies documented in existing literature

1 Introduction

Cosmic rays constitute a population of highly energetic elementary particles and nuclei with an unknown origin that descend upon Earth from outer space. Their spectrum

"e-mail: varada.varma@iteda.cnea.gov.ar(corresponding author)

approximately 109 eV to 1020 eV [1]. Direct measurement of primary cosmic rays with sufficient flux, which occurs at low energies, is feasible through experiments conducted in space. Nevertheless, for energies surpassing approximately 1015 eV, the flux weakens, necessitating reliance on the interactions between primary particles and atmospheric molecules to generate secondary particles called extensive air showers (EAS) [2]. These showers can be observed during their progression in the atmosphere, either on the Earth's surface or underground. The Pierre Auger Observatory, positioned in the southern hemisphere [3], encompasses detectors capable of investigating cosmic ray showers at all three levels: during their development in the atmosphere, on the surface, and underground. Consequently, these showers are reconstructed to examine the primary particles' three principal observables: energy spectrum, arrival direction, and chemical composition. Notably, the Pierre Auger Observatory employs Underground Muon Detectors (UMD) to directly measure the muon content of the showers. High-energy muons exhibit superior penetration capabilities compared to other secondary particles. Subterranean experiments have demonstrated that the density of muons serve as indications of the primary cosmic ray nuclei's chemical composition and energy spectrum. However, this sensitivity is constrained by a threshold imposed by the thickness of the soil covering. Muons possess a unique sensitivity to composition due to a phenomenon where lighter particles (e.g., protons) exhibit lower efficiency in producing multiple muons when compared to heavier nuclei. Although underground detectors cannot determine the energy and specific type of primary particles on an event-to-event basis, it is possible to derive information about the mass composition by comparing the measured distributions of muon multiplicities with those calculated

follows a nearly power law distribution, spanning from

Submitted to EPJC

Under 2nd review

Goal and Motivation

- Statistical correlation r (X_{max},Y) where Y \rightarrow observable dependent on the muon density from the UMD.
- Provide a measure of the spread of masses in the primary beam → Mixed composition or pure compositions?
- High energy HIM?
- Minimize the effect of the muon deficit and use a parameter similar to the number of muons.
- Reduces the dependency on the High energy HIM used.

Mass sensitive observable T_b for the UMD

• For each event with N stations,

$$T_{b} = \sum_{i=1}^{N} \left[\rho_{i} \times \left(\frac{r_{i}}{r_{0}} \right)^{b} \right] \text{ in } \text{m}^{-2} \qquad r_{0} = 450 \text{ m}$$
$$\rho = \frac{N_{\mu}}{A \cos \theta}$$

- Uses the muon density from the UMD
- Does not require a fit for the muon lateral distribution function (MLDF)

Merit factor

Separation of proton and iron showers with $T_{\mbox{\tiny b},}$

M F =
$$\frac{|E[T_{b,fe}] - E[T_{b,pr}]|}{\sqrt{Var[T_{b,fe}] + Var[T_{b,pr}]}}$$

MDSDSSD standard applications used to simulate and reconstruct events.

Using the bootstrap method to calculate the errors,

T_b for fixed energies



T_b for continuous energies



7

T_b for continuous energies



Discrimination power of T_{1.5}



Mean of T_{1.5}



10

\mathbf{X}_{\max}

- X_{max} atmospheric depth where the number of particles in the air shower reaches a maximum value.
- Difficult to simulate Offline MD FD hybrid events
- Work around $\rightarrow X_{max}$ taken directly from the shower and fluctuate it with a Gaussian of mean = 0 and a standard deviation from ICRC 2017.
- X_{max} resolution as a function of energy for standard FD,

$$\sigma[X_{\text{max}}] = 14.78 + 3.4 \times (\log E - 19.6)^2$$
 in g/cm²

X_{max} vs $T_{1.5}$



Correlation factor for a composition mixture



 $C_p = \frac{N_p}{N_p + N_{fe}}$

Statistical uncertainty



Correlation coefficient for a proton-iron composition mixture for different HIM



15

Comparison between single use and reused showers⁶



⁶A.D. Supanitsky, et al., Effect of multiple reusing of simulated air showers in detector simulations, Astropart. Phys. 30 (2008) 264–269

Outlook and conclusions

- A new mass sensitive observable **T**_b was defined for the UMD.
- A value of **b** \approx **1.5** was found to give T_b the optimum separation power.
- The correlation parameters τ and r_G were found to be unaffected by outliers and the most efficient in terms of low standard deviation.
- Next step → consider a composition model with the four different mass fractions (p, He, N and Fe) from Auger data and apply the analysis to study its capability to distinguish between pure and mixed composition scenarios.
- Future work → Apply the method to data when we have enough statistics

Thank you

Backup

Thesis outline

4	Comparison of the muon content of UMD data and simu L1 CORSIKA shower library simulation and event libra Calculation of the muon density at 450 m from the sh the average muon LDF 4.2.1 From data 4.2.2 From simulations Computation of a z-scale Compare the shape of the MLDF obtained from simu S Results	tions 9 Per axis obtained from 9 Per axis
5	5 Composition studies based on the muon content of the UMD 5.1. Mare concitive observable from UMD Ti	owers measured by the
	5.1.1 Merit factor against b 5.1.2 Discrimination power of T _b 5.1.3 Optimizing T _b	
	5.2 (Δ) method to reconstruct X _{max} from the surface det 5.3 Correlation parameter 5.4 Dependence of the correlation parameter on high energiable	w hadronic interaction
	5.5 Distinguishing between mixed composition and pur 5.6 Summary	ompositions 11
6	6 Reconstruction of air shower muon lateral distribution binary modes of the UMD	nctions using ADC and
	6.1 Characterization of the ADC output	
	6.2 Simulation	
	6.3 Likelihoods and the reconstruction methods 6.3.1 Comparison of the Gaussian likelihood with	e compound likelihood 13
	ix	
		Completed
		completed
x	x	CONTENTS
	6.4 Performance of the reconstruction methods 6.4.1 Study of the effect of the inhibition window binary mode	the saturation of the
	6.5 Summary	

20

Comparison of the muon content of the UMD data and simulations

- Muon density at 450 m from the shower axis obtained from the average muon LDF
 - Calculate the muon density from data
 - Calculate the muon density from simulations
 - Define the z-scale
 - Compare different z values
- Analysis on muon LDF
 - Compare the shape of the muon LDF obtained from simulations and data
 - Analyze how the shape depends on the parameters

Simulations

- Monte Carlo shower library used : infill library in the KIT cluster ¹
- Low Energy Hadronic Interaction model UrQMD
- High Energy Hadronic Interaction Models EPOS-LHC and QGSJetII-04
- Primaries Iron, proton, Helium, Nitrogen
- Uniform distribution \in 16.8 $\leq \log(E/eV) \leq 18.7$
- Isotropic distribution of zenith angles $0^{\circ} \le \theta \le 48^{\circ}$

Offline UMD reconstruction strategies

- MLDF reconstruction strategy Original likelihood ¹
- Counting strategy Inhibition strategy (GAP 2022-001)
- Pattern finding strategy Consecutive in window strategy (constant window consecutive-rows-of-ones criteria).
- Bias parametrization applied outside Offline²,

$$N_{\mu corr} = \frac{N_{\mu rec}}{1 + f_{bias}}$$

1 A.D.Supanitsky, et al., Underground muon counters as a tool for composition analyses, Astropart. Phys. 29, Issue 6 (2008) 461-470

Comparison of bias parametrizations



24

Pearson Product moment correlation coefficient (r)

$$r = \frac{cov(X, Y)}{\sigma(X)\sigma(Y)}$$

Spearman's Rank Correlation coefficient (rs)

For a sample of size n, the n raw scores X_i , Y_i are converted to ranks $R(X_i)$ and $R(Y_i)$,

$$r_s = \frac{cov(R(X), R(Y))}{\sigma(R(X))\sigma(R(Y))}$$

Kendall Rank Correlation Coefficient (τ)

 $\tau = \frac{\text{number of concordant pairs} - \text{number of discordant pairs}}{\text{Total number of pairs}}$ **concordant** \rightarrow **ranks agree in terms of their order**

discordant \rightarrow ranks disagree in terms of their order

Gideon and Hollister Rank Correlation Coefficient (r_G)

$$d_i^- = \sum_{j=1}^i I(\mathcal{R}(y_i) < N+1-i) \qquad d_i^+ = \sum_{j=1}^i I(i < \mathcal{R}(y_i))$$
$$r_G = (max\{d_i^-\}maxd_i^+)/[N/2]$$