

Muon and Neutrino Energy Reconstruction for KM3NeT

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KM3NeT is a European deep-sea research infrastructure that will host a neutrino telescope with a volume of several cubic kilometers at the Mediterranean Sea. The telescope will search for galactic and extragalactic neutrinos from distant astrophysical sources. In large water Cherenkov detectors the reconstructed muon is used to approximate the neutrino direction and energy. Muon energy estimation is also critical for the differentiation of muons from neutrinos originating from astrophysical sources from muons and neutrinos generated in the atmosphere which constitute the detector background. We describe a method to determine the muon and neutrino energy employing a Neural Network. An energy resolution of approximately 0.26 has been achieved for muons at the TeV range.

XVI International Workshop on Neutrino Telescopes, 2-6 March 2015 Palazzo Franchetti – Istituto Veneto, Venice, Italy

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1. Introduction

KM3NeT collaboration aims to deploy a neutrino telescope of several cubic kilometers at the bottom of the Mediterranean Sea in order to search for neutrinos of galactic and extragalactic origin. Each detection unit hosts 18 optical modules (OMs) vertically aligned on a string. Each optical module consists of a 17 inches glass sphere with 31 photomultipliers (PMTs). These PMTs will detect the Cherenkov light emitted by charged particles which are produced during the neutrino interactions with the Earth or the sea water. The present analysis focuses on v_{μ} and the muons produced during the charged current interactions of v_{μ} . The detector background consists of atmospheric v_{μ} and μ events which are induced by cosmic ray interactions in the atmosphere and travel through the detector volume leaving signatures similar to astrophysical v_{μ} .

A sample of CC v_{μ} events was simulated and then split in two different subsamples to prevent from adding bias to the results. The first event subsample was used to train and test the Neural Network while the second subsample was used to evaluate the network performance. Isotropic atmospheric v_{μ} flux (by Bartol) [1] was assumed with neutrino energy ranging from 10² GeV to 10⁸ GeV. Neutrinos have been generated with an energy spectrum $E^{-1.4}$. A random background rate of 5 kHz was assumed for each PMT, including dark current, ⁴⁰K decays and bioluminescence. In addition to random coincidences, a coincidence of 500 Hz due to genuine coincidences from ⁴⁰K decay has also taken into account. The simulated events were reconstructed using the KM3NeT track reconstruction package.

2. Energy Reconstruction

Muons lose energy via ionization and by stochastic processes, such as bremsstrahlung, pair production, and photonuclear interactions. The total average energy loss of the muon is:

$$-\frac{dE}{dx} = a(E) + b(E)E_{\mu}$$

where $a \simeq 0.274 \text{ GeV m}^{-1}$ accounts for the energy loss due to ionization and $b \simeq 0.000349 \text{m}^{-1}$ is due to the stochastic energy loss. Muons with $E_{\mu} > 1$ TeV lose energy stochastically, while for lower energies ionization dominates. We describe a method to derive muon (and consequently neutrino) energy from the light collected along its passage through the detector volume.

2.1 Neural Network

This analysis is based on the employment of an artificial neural network, and specifically, a Multi-Layer Percepton (MLP) Neural Network which is part of the TMVA package included in ROOT [2]. The first layer holds the input variables, the intermediate layers are the hidden layers of the neural network and the output layer holds the output variable, the neural network estimator. A weight is associated to each directional connection between the output of one neuron and the input of another neuron. The neuron activation function used was the hyperbolic tangent while the weights were adjusted with the use of the Broyden–Fletcher–Goldfarb–Shannon (BFGS) method [2].



Figure 1: The median of the logarithm of the reconstructed energy to the MC muon energy with respect to the MC muon energy with 68% and 90% quantiles is illustrated.



Figure 2: The distribution of $log_{10}(E_{reco}/E_{\mu})$ for events with $E_{\mu} \ge 1$ TeV is illustrated and a Gaussian fit was applied.

2.2 Event Selection and Description of the Neural Network Input Variables for the Energy Reconstruction

Since the determination of muon energy is based on the collection of light in PMTs, muons should have traveled an adequate distance inside the volume of the detector before an attempt to evaluate their energy is made. This minimum expected muon path (MEP) depends on the reconstructed muon zenith angle as the optical modules (OMs) in the detector configuration are not homogeneously distributed in space (OMs in a string are placed at less than half of the distance between neighboring strings). The minimum expected muon path (MEP) for horizontal muons is the detector radius, while for vertical muons it is half of the height of the string. If the distance between the first and the last PMT position along the track is more than 30% of the MEP the events are accepted.

The quantities that have a strong dependence on the muon and neutrino energy and are used as input variables to feed the Neural Network are:

i. The number of OMs used in the reconstruction. A weight was used to take into account that muons with lower energies travel shorter distances inside the detector volume.

ii. The number of PMTs that have pulses and were used in the reconstruction weighted according to the vertical distance from the track.

iii. The ratio of the total number of PMTs that have pulses and were used in the reconstruction to the number of PMTs that could be hit according to the track and the PMT direction (under Cherenkov hypothesis) but have not recorded any pulses.

iv. The Total Time over Threshold of all PMTs (as a measure of charge) used in the reconstruction.

2.3 Results on Muon and Neutrino Energy Reconstruction

Once the weights of the inter-neuron connections of the NN have been produced, the different subsample of v_{μ} events is used for the estimation of muon and neutrino energy.

As a measure of the quality of this energy estimator, the median of the logarithm of the ratio of the reconstructed muon energy to the MC muon energy with 68% and 90% quantiles with respect





Figure 3: The ratio of the events for which the energy is estimated to the number of events that cross the detector volume with respect to the MC muon energy.

to the logarithm of the MC muon energy is depicted in Fig. 1. The median reaches $\simeq 0.3$ for muons with $E_{\mu} = 1$ TeV while it decreases to $\simeq -0.05$ for muons with $E_{\mu} \ge 10$ TeV. The distribution of $\log_{10}(E_{reco}/E_{\mu})$ for events for which the energy was estimated is shown in Fig. 2. The energy resolution is $\simeq 0.26$ for 1 TeV $\le E_{\mu} \le 100$ PeV.

The efficiency of this energy estimator is investigated for all reconstructed muons that cross the detector volume and have survived the MEP selection criteria and is depicted in Fig. 3. A very high efficiency of 99% is achieved for the whole energy range while for muons with energies $E_{\mu} > 10$ PeV the efficiency decreases. The direction of muons at this high energy range can be reconstructed even if they cross the borders of the detector; however they do not deposit their energy inside the instrumented volume and their energy cannot be reliably reconstructed.

3. Conclusions

A new method for the muon and neutrino energy reconstruction using a Multi-Layer Percepton Neural Network with appropriate input variables was presented. The performance of the energy estimator is very good resulting to an energy resolution $\simeq 0.26$ in $\log_{10} E_{\mu}$ for muon energy at 1 TeV $\leq E_{\mu} \leq 100$ PeV.

Acknowledgements

The presented work has been partially financed by the European Social Fund (NSRF 2007-2013) under the Thalis initiative GRBNeT project-MIS 360381. One of the authors (E.D.) would like to thank Christos Markou and Ekaterini Tzamariudaki for their invaluable assistance during the supervision of the present work.

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