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Muon energy reconstruction in the ANTARES detector

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ABSTRACT

The energy reconstruction of both neutrino-induced muons from neutrino interactions in the vicinity of the detector and of muons from cosmic ray air showers contributes indispensable information for a broad range of physics analyses, e.g. by increasing the sensitivity in neutrino point source searches or in offering access to observables such as the atmospheric neutrino spectrum. Currently, four energy reconstruction methods are implemented in the ANTARES data analysis framework, ranging from estimates based on photon counting and the total charge deposited in the detector to methods based on probability density functions and Artificial Neural Networks. These four methods, their performance and systematic studies of the energy resolution capabilities of the ANTARES detector are presented.

1. Energy-related analysis in ANTARES

Energy reconstruction of neutrino-induced muons is in the core of ultra-high-energy neutrino astronomy. Large-volume neutrino experiments face the challenge of distinguishing cosmogenic neutrinos from a comparatively large background of neutrinos produced by air showers in the atmosphere, in order to increase the statistical significance of discoveries of cosmic point sources. Generally, cosmogenic neutrinos are expected to have a harder spectrum than atmospheric neutrinos, exceeding their flux in the ultra-high energy region, which makes event selection through energy reconstruction an essential task. On the other hand, the measurement of the diffuse cosmogenic neutrino flux can give a hint toward production mechanisms of ultra-high-energy cosmic rays.

In the ANTARES neutrino telescope, Cherenkov photons from muons produced by charged-current interactions of neutrinos are detected. The detector is located in the Mediterranean Sea, about 40 km off the French coast at a depth of 2500 m. It consists of 885 Optical Modules (OMs), installed in groups of three on 12 vertical lines. These lines have an instrumented length of 350 m each, covering a total area of 0.1 km^2. Single photons are measured using the charge induced in photomultiplier tubes within the OMs which are digitized by two Analogue Ring Samplers (ARSs). The readout of a triggered ARS, which is called a 'hit', provides a measurement of the arrival time and the amount of photons arriving at the OM within the integration window of the ARS. Photon arrival time and the charge of these hits are the basic information available for muon energy reconstruction, and are used in various ways in the reconstruction methods developed by the ANTARES collaboration.

2. Muon energy loss

Muon energy estimates cannot be obtained by direct measurement but are dependent on the characteristics of the energy loss of the particle traversing the medium. At all energies, ionization causes a fairly constant and homogeneous energy loss of the muon, while radiative processes like bremsstrahlung, pair production and photonuclear processes emerge and become dominant above the muon critical energy of several hundred GeV, where their contribution to energy loss increases linearly with energy [3]. They add a strongly stochastic fluctuation to energy losses, as they cause electromagnetic and hadronic particle cascades along the muon track, in which a substantial fraction of the muon energy is deposited. Therefore, energy loss can only be calculated by statistical approximation of the mean muon energy loss per unit length, which is given by

$$\left\langle \frac{dE}{dx} \right\rangle = a(E) + b(E)E \tag{1}$$

where $a(E)$ describes the ionization loss and $b(E)$ contains the effect of all radiative processes.

This implies two possibilities to reconstruct the muon energy. In the low-energy region with dominant ionization loss, the total length of the track can be used to estimate the energy, if the track ends or is contained within the detector volume. In the case of

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ANTARES, tracks up to about 100 GeV can be contained within the detector, although the limited size of the detector poses a challenge to the identification of tracks at 100 GeV. For particles with energies above the muon critical energy, the onset of radiative processes can serve to reconstruct particle energy, as cascades cause additional photons through Cherenkov emission of the constituents of the cascade, which arrive at the photomultiplier tubes delayed in comparison to direct Cherenkov emission of the muon due to their diverging emission angle and due to scattering. This delay is called the time residual of a photon $t_{res} = t_{hit} - t_{Cherenkov}$. The time residual and number of photons are therefore the basic observables for muon energy reconstruction in the high energy region. In this region, energy reconstruction has to deal with the highly stochastic nature of muon energy loss, which leaves a comparatively large uncertainty in the reconstruction of the single muon energy which cannot be overcome by technical means.

2.1. Systematic studies of energy loss phenomenology

In order to investigate the stochastic error induced by the energy-loss phenomenology, a dedicated Monte Carlo study is in progress, of which some first results will be presented here. The Monte Carlo simulation [1] of the ANTARES detector response to passing muons was performed for muons tracks which were uniformly and isotropically distributed in the detector. For each track, various discrete energies for the complete sensitive energy range of ANTARES were assumed, and the track simulation repeated 500 times for each energy. In the first step, basic reconstruction parameters like the total charge of the ARS readout and the average time residuals for hits in each event were investigated. In the second step, the energy was reconstructed for each event to estimate the performance of the energy reconstruction methods for a given track.

As ANTARES is optimized for the detection of muon tracks emerging from below the detector, the best reconstruction quality can be expected for tracks with a zenith-angle $\theta = 180^\circ$ (upgoing tracks). In order to analyse the energy resolution obtained from the basic parameters mentioned above, the total charge of the OM readouts per simulated track and the mean time residual per event are plotted for various upgoing tracks in Figs. 1 and 2. The total charge is here corrected for the varying detector efficiency towards the individual track while the same correction was not necessary for the average time residual. This shows that the number of photons can serve as a good measure for energy loss,

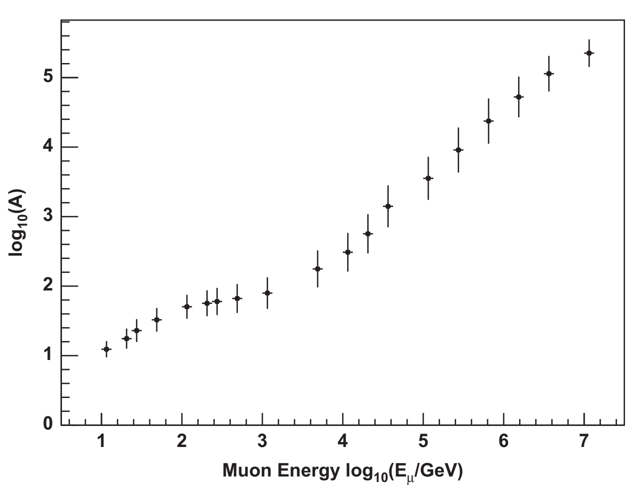

Fig. 1. Integrated charge A measured in ANTARES for repeated simulations of upgoing muon tracks ($\theta = 180^\circ$) at discrete energies.

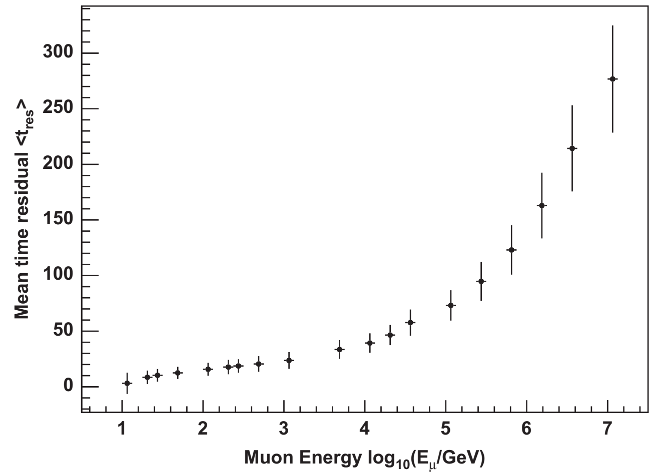

Fig. 2. Average time residual of all hits per event for repeated simulations of upgoing muon tracks at discrete energies.

but has to be corrected for detector effects and efficiency. As the number of photons is also dependent on the length of the track in the detector, the number of photons can also be used for reconstruction of muon energies below 100 GeV.

The average time residual, on the other hand, needs no correction for detector effects, as it simply measures the excess of late photons over direct Cherenkov photons from the muon. As a drawback, this parameter cannot be used in the low energy range, as it only reflects the contribution of radiative processes to the energy loss.

3. Energy reconstruction in ANTARES

Two basic approaches to single muon energy reconstruction are pursued within ANTARES. Either the energy is obtained by fitting the distribution of an energy-correlated parameter over the simulated spectrum, or energy-loss patterns are modelled using a wide range of parameters. Reconstruction methods using the first approach are the *dE/dx-Estimator* and the *R-Estimator*, while modelling based on probability density functions (PDFs) is used for the *Maximum Likelihood* approach and within *Artificial Neural Networks*. These four methods will briefly be described here.

3.1. The dE/dx-estimator

The total number of photons caused by the muon is the basic quantity to be used for muon energy reconstruction, but it has to be corrected for the detector efficiency ε towards a given track, which considers the attenuation length λ_{att} of the medium and the angular acceptance α of each OM. It is given by

$$\varepsilon = \sum_{N_{OM}} \frac{e^{d/\lambda_{att}} \alpha}{d} \tag{2}$$

where d is the distance between the muon track and the OM for photons emitted with the Cherenkov angle. The total number of photons is also dependent on the track length within the detector, therefore, the energy loss has to be corrected for the path length L of the muon in the detector. This disqualifies the estimator for energy reconstruction in the low energy range, but can increase accuracy in the regime of radiative losses. The estimate for dE/dx is therefore given by the correlated parameter

$$\rho = \frac{1}{N_{\rm hits}} \frac{\sum A}{L_{\rm eff} \varepsilon} \tag{3}$$

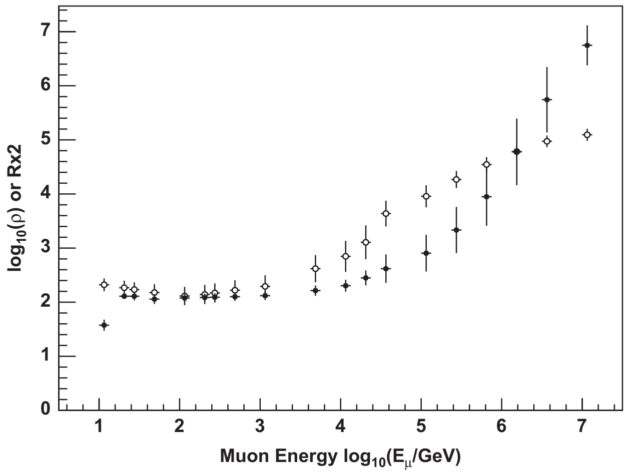

Fig. 3. *R*-value (black markers) and ρ of the dE/dx-Estimate (white markers) for repeated simulations of upgoing muon tracks at discrete energies.

where A is the total amplitude of the ARS readouts and N_{hits} the number of hits associated with the event. For upgoing muons, average values for ρ are plotted in Fig. 3. A polynomial fit of ρ to simulated data is used to obtain dE/dx and thus the mean energy for this energy loss.

3.2. The R-estimator

The larger time residual of Cherenkov photons of muon-induced cascades is reflected in the number of hits at a given OM. In the case of several photons arriving at the OM, the two ARSs in each OM are triggered consecutively and undergo a deadtime of 250 ns before they can be triggered again. For this estimator, only hits within 500 ns of the estimated arrival time of Cherenkov photons are selected. Therefore, only two consecutive readouts of both ARSs are analysed and a maximum of four hits can be recorded at one OM. This is used to define the *R*-parameter, which is given by the average number of hits per OM with at least one hit divided by the total number of OMs with hits

$$R = \sum_{N_{OM}} \frac{N_{hits_i}}{N_{OM}} \tag{4}$$

where N_{OM} denotes only those OMs that received a hit. R can therefore be seen as a measure of the average time residual of the photons and is largely independent from the detector acceptance for a given track. The muon energy can directly be obtained from a polynomial fit to the distribution of R in the simulated data. This energy approximation is well established within ANTARES and has successfully been used to calculate a limit on the cosmic ray flux [2]. Its distribution for upgoing tracks can be seen in Fig. 3.

3.3. Maximum likelihood method

Instead of using only single parameters for energy estimates, methods spanning a larger parameter space are likely to improve energy resolution. This calls for a mathematical approach to model the complex dependence between the chosen parameters and the energy, which has to include photon propagation, detector response and background. In the Maximum Likelihood approach, these effects are described by an analytical PDF, which is used to derive the probability of photon detection $P_{OM}(E)$ at a certain OM. The likelihood for an event is then given by

$$\mathcal{L} = \prod_{i}^{N_{OM}} P_i(E) \tag{5}$$

where N_{OM} is the number of OMs. The probability is described by different expressions, depending on whether or not photons producing charge A were detected at the OM:

$$P(A; \langle n \rangle) = \sum_{n=1}^{n_{max}} P_P(n; \langle n \rangle) \cdot P_G(A; n) \tag{6}$$

$$P(0; \langle n \rangle) = e^{\langle n \rangle} + P_{threshold}(\langle n \rangle). \tag{7}$$

In the case of photon detection, Eq. (6) describes the probability to measure amplitude A if the mean number of expected photons $\langle n \rangle$ is assumed, which itself is dependent on the energy of the track, $\langle n \rangle(E)$. In this formula, $P_P(n; \langle n \rangle)$ is the Poissonian probability of n photons arriving at the OM if $\langle n \rangle$ are expected, weighted by the Gaussian probability of $P_G(A; n)$ that these photons produce amplitude A in the OM. In the case of no photon detection, Eq. (7) represents the two probable causes by either having no photon present at the OM, although $\langle n \rangle$ are expected, or having a photon that produces a charge which is below the PMT threshold of the OM. In order to maximize the likelihood, $-\log(\mathcal{L})$ is minimized and the resulting energy estimate $\hat{E}$ shifted to represent the true muon energy through a linear correction, which is shown in Fig. 4. This method has already been used for an unfolding of the neutrino spectrum [4].

3.4. Neural network approach

Apart from the parametric approach using an analytic PDF, machine-learning algorithms are an established method to derive the dependence between sets of variables in a semi-parametric way. In the case of feed-forward Artificial Neural Networks (ANN), the functional dependence between an input vector of observables $\hat{x}$ and the output $\hat{E}$ is modelled by the nodes and connections between the nodes of the ANN. In each node, all input values to the node are added up and analysed by the so-called activation function g. If the output of a node is connected to the input of another node, this connection is given a weight w. Therefore, the dependence between inputs $\hat{x}_i$ and output y in each node can be

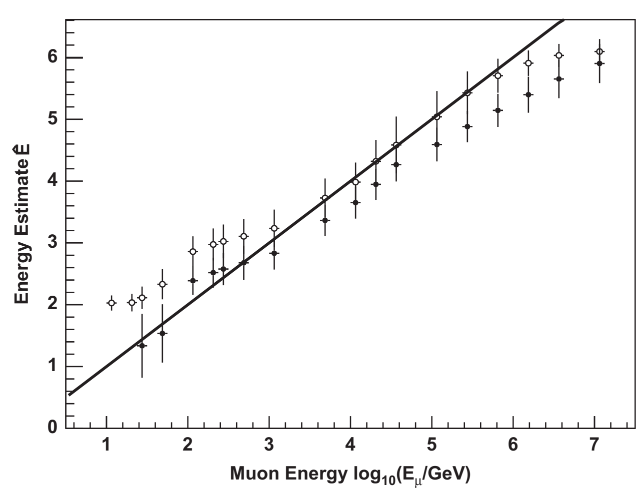

Fig. 4. Energy estimates from Maximum Likelihood (black markers) and ANN (white markers) for repeated simulations of upgoing muon tracks at discrete energies.

given as

$$y = g\left(\sum_i w_i \hat{x}_i\right) \quad (8)$$

such that an ANN can be seen as multidimensional array of functions to represent the dependence between input and output. In order to adapt an ANN to a given set of simulated data ($\hat{x}_{MC}$, E_{MC}) during learning, an error function $\mathcal{E}(\hat{E}(\hat{w}_{MC},\hat{x}),E_{MC})$ describing the overall error on a set of data between desired ANN output E_{MC} and achieved output E, depending on the individual connection weights of the ANN, is used. During learning, the connection weights $\hat{w}$ are adapted such that $\mathcal{E}(\hat{E}(\hat{w},\hat{x}),E_{MC})$ is minimized. The resulting ANN can therefore be seen as a representation of the PDF describing the relation between input parameters $\hat{x}$ and output $\hat{E}$ and the learning process as analogous to the minimization step in the Maximum Likelihood method, with the main difference that the latter uses an analytical PDF while the ANN derives the PDF from a set of simulated data.

In ANTARES, the input vector consists of 56 different features including the number of hits, total charge and average time residual of the hits of the event, which are in a preprocessing step decoupled through application of a Principal Component Analysis (PCA) to reduce the dimensionality of the problem. The PCA transforms the input vector into feature-space, in which all components are orthogonal to each other, which leads to a more efficient training of the ANN [5]. The output of this 'ANNergy-Estimator' can be seen in Fig. 4. In the low energy region, adaption of the ANN to specific observables describing the length of the muon track is under investigation and might offer access to energy reconstruction for muon energies below 100 GeV.

4. Conclusion

For many analyses, energy reconstruction of the neutrino-induced muon is of essence and various muon energy estimators have been developed. Energy reconstruction in ANTARES is relying on the characteristics of muon energy loss and uses both the increased number and the delayed arrival times of photons emerging from radiative processes along the muon track. These parameters are either used separately as energy estimate, like the R-value and in the dE/dx-Estimator, or an energy estimate is derived from multiple parameters by usage of a PDF. This is implemented both with an analytical PDF through a Maximum Likelihood method or by machine learning from Monte Carlo simulation through an Artificial Neural Network. All estimates presented here focus on muon energies above 1 TeV, although reconstruction for energies below 100 GeV, using the total track length of the muon, are also under investigation.

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