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Dark matter search towards the Sun using Machine Learning reconstructions of single-line events in ANTARES

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The ANTARES neutrino telescope stopped gathering data in February 2022, after nearly 16 years of operation. The detector consisted of 12 vertical lines forming a 3D array of photo-sensors, which instrumented about 10 megatons of Mediterranean seawater. We present a method using deep learning that improves the direction reconstruction of low-energy single-line events, for which the reconstruction of the azimuth angle of the incoming neutrino is particularly difficult. We also present a combination of machine learning techniques to reconstruct the energy of the same kind of events. Our results enhance the resolution of former reconstruction techniques, at least doubling our sensitivity in the range of energy of tens of GeV, which is highly relevant for dark matter searches and other physics studies. Here, we propose a binned Dark Matter (DM) search towards the Sun for ANTARES single-line events using the new reconstruction methods. We compute the neutrino flux sensitivity for different DM annihilation channels and particle candidate masses. In this first trial, the methodology is applied to a subset of ANTARES data: these results anticipate better sensitivities for low masses of DM candidates (below $\sim$ 150 GeV) and/or soft spectrum channels compared to those obtained based on standard reconstruction techniques once the method is applied to the whole ANTARES dataset.

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PoS(ICRC2023)1443

1. Introduction

ANTARES was the first deep-sea neutrino telescope [1]. It consisted of 12 vertical lines containing 25 storeys per line and 3 Optical Modules (OMs) per storey, forming a 3D array of photo-sensors with about 10 megatons of Mediterranean seawater instrumented. It detected Cherenkov light induced by secondary particles from neutrinos interactions. The detector stopped gathering data in February 2022, after nearly 16 years of operation. The information of a recorded event includes the run number, the position of OMs, their direction, the environmental conditions and the information of the PMTs in terms of so-called *hits*.

Current physics analyses in ANTARES are performed with reconstructed parameters from two methods. The most used one is based on classical maximum likelihood estimations [2] and it is particularly suited for the mid and high energy range (above $\sim$ 150 GeV). The other one is based on a standard χ^2 fit [3]: this second method is usually more efficient for the low energy range (below $\sim$ 150 GeV) in physics analysis. Using the criteria of this second approach, we can distinguish between single-line (SL) and multi-line neutrino events. For the first case, only the zenithal angle (θ) is reconstructed by the χ^2-like fit, while the azimuthal angle (ϕ) is missing. Thus, we propose a deep learning method to improve the reconstruction performance of θ for SL events and a first estimation of ϕ, to be applied to charged current muon-(anti)neutrino interactions. We also develop a machine learning technique to reconstruct the energy of these events, which is very challenging due to the physical processes involved. We combine neural networks (NNs) with a principal component analysis (PCA) [4] to this end.

Low energy studies in neutrino telescopes include dark matter searches. Weakly Interactive Massive Particles (WIMPs) are the most famous DM candidates nowadays. They appear naturally in several theories beyond the Standard Model (SM), such as Super Symmetry (SUSY) [5]. In these theories, WIMPs can decay or self-annihilate into SM particles. Indirect WIMP searches look for signals of these processes coming from massive celestial bodies where these particle are supposed to be gravitationally accumulated. The Sun is a promising source for DM signals, since WIMPs can scatter elastically with nuclei inside it, and lose enough momentum to become gravitationally trapped [6]. Thus, an indirect DM search towards the Sun is a well established analysis to prove the potential of our new reconstruction techniques in the low WIMP mass range. We develop a binned analysis, namely we consider only neutrinos inside a region of interest (RoI) around the Sun and ignore the rest. We study three possible self-annihilation channels ($b\bar{b}$, $\tau^+\tau^-$ and W^+W^-) for several possible WIMP masses.

Section 2 of this work addresses the development of the new reconstruction techniques, Section 3 describes the DM search methodology and Section 4 is dedicated to results and conclusions.

2. Neutrino reconstruction for single-line events

Since the detector measures Cherenkov light induced by secondary charged particles, neutrino properties must somehow be inferred. Traditional methods are usually based os statistical reconstructions. Here, we develop machine learning techniques to accomplish this goal for ANTARES SL events selected through the usual χ^2 fit used in the collaboration [3]. We focus on the reconstruction of direction, the closest point to the detector and the energy of track-like events, considering only

PoS(ICRC2023)1443

muon-(anti)neutrino charged current interactions (ν_μ^{CC}). This kind of events are more suitable for track reconstructions since the muon produced can travel very long distances in water.

The machine learning algorithms are trained with Monte Carlo (MC) simulation that takes into account all the physics that occur in the telescope for the neutrino events [7]. A random set of data is chosen from 2008 to 2017, representing less than the 10% of the available data.

The reconstruction of the closest point of the track to the detector is done as an intermediate step for the energy reconstruction, as will be explained later, so its results are not going to be discussed in detail. Similar algorithms are separately trained for shower-like events, from electron neutrinos and neutral current muon neutrino interactions. However, these events are not used in the DM search and their reconstruction performance will not be discussed here.

2.1 Direction reconstruction

The direction is reconstructed in terms of the zenithal (θ) and azimuthal (ϕ) angles that fully determine the track direction: $\bar{u} = (\cos\phi\sin\theta, \sin\phi\sin\theta, \cos\theta)$. To this end, we combine the architecture of a Deep Convolutional Network (DCN) [8] with the predictions of a Mixture Density Network (MDN) [9]. Many architectures and hyper parameters were explored and optimized. The result of this exploration determined that the angles are best predicted by two separately trained networks, one for each angle. Also, due to the cyclical property of the ϕ angle, it had to be determined from the inferred Cartesian coordinates X and Y: $\phi = \arctan(Y/X)$. The use of a MDN output layer allows to predict not only the variables (μ) but also an error estimation (σ) for each angle. This is achieved by using as loss function ($\mathcal{L}$) the opposite of the log-likelihood of the Gaussian distribution.

$$\mathcal{L} = \ln(\sqrt{2\pi}\sigma) + \frac{1}{2}\left(\frac{y_t - \mu}{\sigma}\right)^2, \tag{1}$$

where y_t is the true value of the parameter we try to reconstruct. In order to feed the network, we transform the events hit data into images, since they carry the information received by the detector PMTs. For further details about the method, see [10].

Evaluation of the technique shows an improvement for the zenithal angle compared to the traditional method, as the mean angular error is reduced from 15.5° to 7.5°. Furthermore, the estimation of the azimuthal angle, with a mean error of ~40°, can be considered as a success due to the physical limitation inherent to the problem addressed. Some results can be seen in Figure 1, where the functionality of the error estimation is showed. Extra checks were performed, such a 5-fold cross-validation and a comparison between real data and MC simulation with positive results.

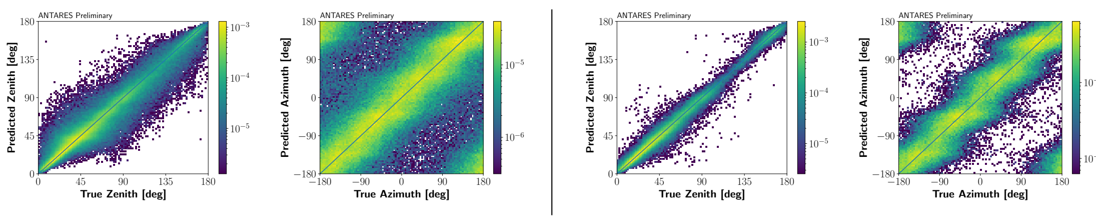

Figure 1: Comparison between reconstructed and simulated values of the zenith and azimuth angles. **Left:** full test set. **Right:** 50% of the test set according to the lowest σ values for each angle.

2.2 Energy reconstruction

For the energy reconstruction, we tried, in analogy with the case of the angles, to train a NN for its inference. After many tries, we tested the combination of NNs with a PCA [4]. The idea behind this new approach is that the layers of networks previously trained to predict neutrino properties may extract information related to all the physical parameters of the event. Thus, the activations of all the layers of these networks for a given event may be used to infer the energy of that event.

The application of this new approach results in a considerable improvement with respect to pure NN approaches. The layer activations of the networks used to reconstruct the zenithal angle and the closest point to the detector are chosen as independent dimensions for a PCA. In turn, the activations of the network used to infer the azimuthal angle are not used because using them do not result into any improvement, and we neither expect any correlation between this parameter and the energy deposited in the detector.

PCA belongs to the family of dimension reduction methods [4], aiming at identifying a reduced set of features that represent the original data in a lower-dimensional subspace with a minimal loss of information. The original possibly correlated variables are transformed into a set of new linearly uncorrelated ones, called principal components. To each new component is assigned an explained variance, representing the amount of variance of the original dataset that it can explain. The normalized value of this parameter is called explained variance ratio. This variable tends to decrease very rapidly until it reaches a plateau, once the components are arranged from higher to lower explained variance. The most informative and usually selected new components are those found before reaching fully the plateau, according to the so-called elbow rule.

To make the elbow rule more precise, we compute the following ratio for each i-th component: $(V_{i-1} - V_i)/(V_i - V_{i+1})$. We then select the first clear maximum after the plateau is reached to keep that number of components. The new components are then used as an array input to a feed-forward NN in order to reconstruct the energy. The last layer and the loss function are modified to include the MDN architecture. After several optimizations and many approaches were tried, we finally came to define the final procedure for this task.

A pre-selection on the dataset is required with some properties predicted by the networks explained above. Since the secondary muons can have very long paths, only part of their energy is deposited in the detector. However, by choosing events that with paths very close to the detector, it is possible to work with more suitable cases for the energy reconstruction. The reconstructed distance of the closest point of the track (R_c) is set to be less than 50 m and the vertical distance of that point to the center of the detector ($|Z_c|$) must be less than 150 m, since the detector height is around 350 m. We also apply quality criteria to minimize noisy events, applying: $\sigma_\theta < 8.6°$, $\sigma_{R_c} < 4.3\ m$ and $\sigma_{Z_c} < 6.2\ m$, which are error estimations from previous networks. The values are the medians of the full data set used to test the previous networks. This pre-selection is performed before the training of the PCA.

Due to the large range of energies that the events present (from 5 GeV up to 10 TeV), the network can predict more easily the decimal logarithm of the energy instead of the actual value. Also, a weighting factor must be introduced in the loss function to take into account the uneven distribution in the energy range. It also appeared that it was better to reconstruct the energy of the muon rather than that of the neutrino.

PoS(ICRC2023)1443

Results for the pre-selected test set can be seen in Figure 2, showing the utility of the $\sigma_{\log_{10}(E_\mu/[\mathrm{GeV}])}$ in selecting the best predictions. Even if the reconstruction is not ideal, due to the physical difficulties in predicting track energies with SL events, we consider these results good.

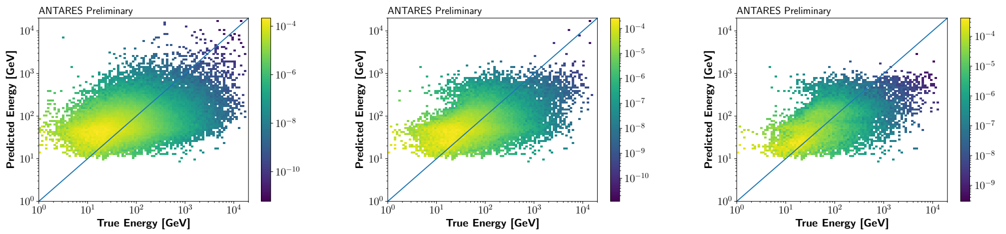

Figure 2: Comparison between reconstructed and simulated values of the muon energy. **Left:** full test set. **Mid and right:** 50% and 25%, respectively, of the test set according to the lowest $\sigma_{\log_{10}(E_\mu/[\mathrm{GeV}])}$.

3. DM search towards the Sun

SUSY theories predict the self-annihilation or decay of WIMPs into SM model particles [5]. The annihilation is most likely to happen in massive celestial objects in which DM may be gravitationally accumulated, like the Sun [6], due to the very small WIMP cross-section. The signal of this process from the Sun could be indirectly detected by neutrino telescopes, as secondary particle flux from the annihilation might interact in its core producing an expected neutrino flux at the Earth.

Here, we develop the methodology for a binned DM search towards the Sun using the reconstruction techniques explained above, by adapting previous analysis methodologies [11] to our new reconstructed parameters based on the Model Rejection potential technique [12]. The average upper limit neutrino flux at a 90% confidence level is computed as:

$$\bar{\Phi}^{90\%}_{\nu+\bar{\nu}} = \frac{\bar{\mu}^{90\%}}{Acc \cdot T_{eff}}, \tag{2}$$

where $\bar{\mu}^{90\%}$ is the average upper limit for an expected poissonian background under the Feldman-Cousins approach [13], Acc is the acceptance of the detector to a given neutrino flux and T_{eff} is the livetime that the detector has been taking data. The acceptance is computed as the averaged effective area of the detector over the neutrino spectra from different DM annihilation channels which resulted from WimpSim [14] for the $b\bar{b}$, $\tau^+\tau^-$ and W^+W^- channels.

According to the Model Rejection potential technique, the optimization procedure consists of selecting the set of parameters for the DM search that gives the lowest value of $\bar{\Phi}^{90\%}_{\nu+\bar{\nu}}$ sensitivity for each WIMP mass and annihilation channel.

Thus, we compute the expected background in the detector and its effective area, which defines the perpendicular area to a given detected flux that the telescope would have if its efficiency in detecting that flux were 100%. These computations are performed blindly for several sets of parameters that are optimized, which define the RoI and the reconstruction quality. To blind the data, we randomly shuffle the dates of each event, changing their celestial coordinates during the optimization process. This procedure is repeated 500 times in order to reduce statistical fluctuations, giving stability to the computations.

The parameters optimized are three. The first is the angular error estimation (σ_Ω), used as quality parameter and derived from the estimation error in the predicted angles: $\sigma_\Omega^2 = \sin^2\theta \cdot \sigma_\phi^2 + \sigma_\theta^2$. The other two parameters define the RoI of the study, that is implemented asymmetrically since the reconstruction for SL events are very asymmetric. It is defined by the semi-length of the angular aperture in the zenithal angle (R_θ) and in the azimuthal angle (R_ϕ). For the optimization, the quality parameter σ_Ω spans from 5° to 35° in steps of 2°. R_θ spans from 3° to 15° in steps of 1° and R_ϕ spans from 20° to 50° in steps of 10°.

3.1 Effective area and acceptance

The effective area is dependent on the configuration of the detector and it is computed using the same MC simulations used for training the reconstruction algorithms. These simulations reproduce the time-dependent behaviour of the detector, including its loss of efficiency with time [7]. Only simulations of muon neutrinos are used due to the fact that they are most suitable for point sources searches.

To compute the effective area, we take the SL events from the MC simulations and apply them several cuts based on the optimization parameters, as well as others to ensure the quality of the events. First, we select only events reconstructed as up-going, since most of the background in a neutrino telescope comes from the atmospheric muons produced by the cosmic rays. We also apply the quality cuts used in the pre-selection of events to train the energy reconstruction algorithm. After that, the quality cut is applied, meaning that only events with σ_Ω less than the value being tested are kept. Then, we only keep the events in the Sun zenith band, since the study is blind in the azimuth coordinate: $|\theta_{Sun} - \theta_{true}| < R_\theta$. A further direction cut is applied: $|\theta_{rec} - \theta_{true}| < R_\theta$ and $|\phi_{rec} - \phi_{true}| < R_\phi$, ensuring that the event would be detected inside the RoI around the Sun. For these direction cuts, we take into account the transformation between the direction to where the neutrino is going and the direction from where it comes. Finally, an energy cut is applied: $E_{\mu,rec} < M_{WIMP}$ and $E_{\mu,rec} > 10\ GeV$, to remove bad energy predictions. In this way, the effective area is now dependent of the WIMP mass we are testing.

After all the cuts are apply, the remaining events are used to compute the effective area for each neutrino energy bin following the same approach as in [11]. Simulations are scrambled 500 times, so the final result is the mean value for each set of cuts.

Once the effective are is computed, we average it with the neutrino energy spectra ($\mathrm{d}N_\nu/\mathrm{d}E_\nu$) expected from the three different WIMP annihilation channels. The spectra are computed by WimpSim [14]: this program takes into account the annihilation process inside the Sun, the decay of secondary particles to neutrinos and their propagation from the Sun to the Earth with oscillations. Thus, the acceptance of the detector to that specific neutrino fluxes is a function of the channel and WIMP mass:

$$Acc(M_{WIMP}) = \frac{\sum_{j=\nu,\bar{\nu}} \int_0^{M_{WIMP}} A_{eff}(E_j) \cdot \frac{\mathrm{d}N_j}{\mathrm{d}E_j} \cdot \mathrm{d}E_j}{\sum_{j=\nu,\bar{\nu}} \int_0^{M_{WIMP}} \frac{\mathrm{d}N_j}{\mathrm{d}E_j} \cdot \mathrm{d}E_j} \quad (3)$$

3.2 Background

The background is computed by counting the number of real data events that pass almost the same cuts made for the effective area, except for the cut in the Sun zenith band that is done with the reconstructed values of the events and the cut on the RoI that is not performed, since the true directions are unknown. Then, since this computation is blind in azimuth, the background is re-normalized to the solid angle of the RoI, multiplying by R_ϕ and dividing by 180°.

Data is scrambled 500 times, so the result is the average value of all the computations. We multiply by a factor 20 the background in order to simulate a similar effective time to that of [11]. From the background we then compute the average background upper limit ($\bar{\mu}^{90\%}$) [12].

4. Results and conclusions

The methodology is applied to a small ANTARES dataset due to computational limitations at the moment. For this subset we have, after the statistical boosting of the background, $T_{eff} = 10.95$ years. Previous methodology developed for SL events is also applied to the same dataset in order to compare the performances. The ratio between the flux sensitivity with this new methodology and the previous one is presented in Figure 3. We see an improvement for all channels tested and all WIMP masses. Thus, we may expect to improve by a factor larger than 2 the flux sensitivities in the WIMP mass range where the SL events are already dominant (below ~ 150 GeV) when the method is applied to the full ANTARES dataset.

The new reconstruction methods developed in this work are ready for application and will be included in the final analyses of ANTARES with its full dataset. Further applications of the methods here presented are DM searches in the Galactic Plane and neutrino oscillation studies, among others.

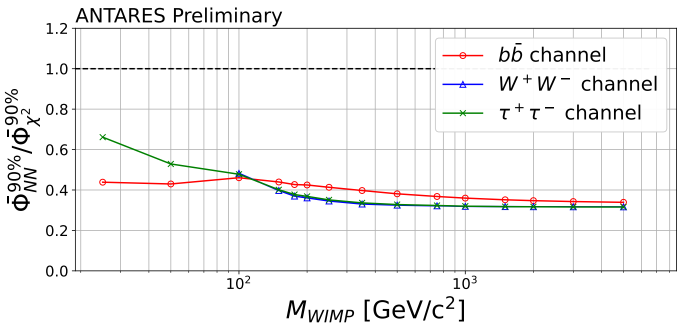

Figure 3: Average upper limit neutrino flux sensitivity ratio between our new method ($\bar{\Phi}^{90\%}_{NN}$) and previous methodology ($\bar{\Phi}^{90\%}_{\chi^2}$) for the same ANTARES subset of SL event data.

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