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Search for periodic low energy neutrino sources with the ANTARES telescope

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The ANTARES neutrino telescope operated in the Mediterranean sea from 2006 until its decommissioning in 2022. During its livetime, neutrino data was collected and analysed in the form of events. These were recorded by the data acquisition system upon the detection of sets of causally connected hits on the optical modules (OM). The event hits were then fitted to models describing neutrino interactions in order to obtain the energy and direction of the interacting neutrinos. Due to the distance between OMs this procedure was efficient for energies higher than 10 GeV, leaving the lower energy range inaccessible. Despite these limitations, a novel approach has been developed to search for periodic patterns in the optical module counting rates. This analysis could potentially reveal fluxes of low energy neutrinos from periodic sources such as pulsars.

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1. Introduction

Neutrino telescopes utilize arrays of Optical Modules (OM) immersed in transparent media to detect neutrino interactions. When charged particles generated by neutrino interactions produce Cherenkov radiation, it triggers signals, or hits, in the OMs. Causally connected hits detected by multiple OMs form events, which can be analyzed to determine the properties of incident neutrinos. The energy range accessible to a neutrino telescope depends on the instrumented volume and the spacing between photo-sensors.

ANTARES was a neutrino telescope that operated in the Mediterranean sea from 2006 until its decommissioning in 2022. Its design was optimised for the detection of neutrinos with energies higher than 10 GeV, leaving the lower energy range inaccessible. Despite these limitations it is, under certain circumstances, possible to detect fluxes of neutrinos below the energy threshold by using the photo-sensors as standalone detectors.

Previous studies [1] have investigated the detection of neutrinos with energies below the threshold of the standard triggering technique, particularly in the 10-100 MeV range from Core Collapse SuperNovae (CCSN). To detect neutrinos from a CCSN, OMs are used as standalone detectors, and their hit counting rates are monitored. An incoming flux of neutrinos from a CCSN would lead to a general increase in the counting rates above the optical background rates during the explosion. We will also use each OM as a standalone detector following a different approach which does not focus on transient phenomena such as CCSN, but instead allows to identify faint periodic signals that extend over long periods of time.

The method reported here involves analyzing the behavior of the PMT counting rates over time. A Fast Fourier Transform (FFT) is applied to the time stream of the PMT counting rates and a significant excess in the Fourier power spectrum is searched for. This requires the use of data different from the standard events that are recorded by neutrino telescopes. While the PMT counting rates are typically used for detector monitoring purposes and to simulate the optical background in detector simulations, they have never been considered for this type of analysis before. For the ANTARES neutrino telescope, over 14 years of data remain unanalysed to this day despite their scientific potential. This analysis can in constrain the emission of low energy neutrinos from pulsars, as predicted in previous studies [2].

This report is organised as follows: section 2 describes the available data. Section 3 describes the analysis strategy which includes a preprocessing of the data in order to address possible discontinuities in the time stream, non-uniformity of the background rates as well as variations on the data taking conditions. Section 4 shows the sensitivity to a neutrino flux emitted by a pulsar, and section 5 reports the conclusions of this work. For a more extensive and detailed version of this report, see [4]

2. Data description

The ANTARES neutrino telescope was installed in the Mediterranean Sea, and its primary data consists of hits generated when the signal in the PMT anode surpasses a predefined threshold. Hits can originate from neutrino interactions, atmospheric muons penetrating underwater, and optical background sources. The optical background is mainly caused by bioluminescent activity in the

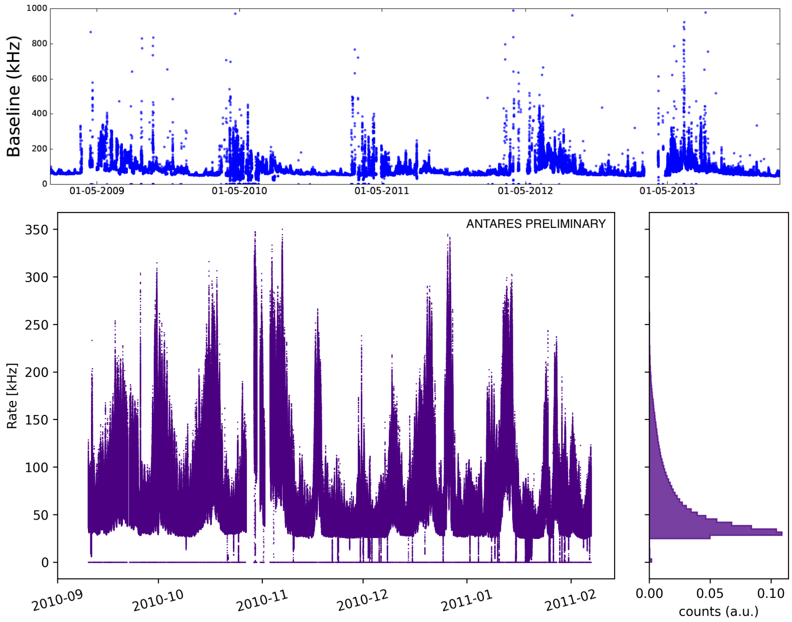

Figure 1: Time evolution of the counting rates in ANTARES. Top: time evolution of the rates of an ANTARES OM during 4 years of time. Bottom: Average rate for all the detector OMs for the period between September 2010 and February 2011

environment and the decay of ^{40}K in the sea water and OM glass. Due to the high rate of optical background, long-term storage of raw data is impractical. ANTARES implemented selective data storage, where the raw hit stream was processed by trigger algorithms to reduce data volume and organize it into different data types.

The data processing involved dividing the incoming stream into time slices of 104 ms. The data filter stored the total hit counts recorded by each PMT during each triggered time slice, allowing for the extraction of the PMT counting rates with a sampling frequency of approximately 9.5 Hz. Although there may be occasional data gaps due to trigger requirements, the ANTARES data filter configuration ensured a trigger rate above 10 Hz since 2009.

Figure 1 top, presents the counting rates of an ANTARES OM over time. It can be observed that during the spring period, the rates increase, which correlates with elevated bioluminescent activity at the detector site [3]. For this study, a data sample was selected from a period of low bioluminescent activity, specifically from 10-09-2010 to 06-02-2011. Figure 1 bottom illustrates the average counting rate for all OMs during the chosen period, with the rate distribution shown in the right panel, having a mean value of 62.46 kHz.

3. Analysis design

To detect periodic signals in counting rate time series, we apply an FFT (Fast Fourier Transform) on the selected period and use the Fourier power spectrum as a test statistic. However, certain complexities associated with the input data need to be taken care of. These include data gaps within the time series, the potential length of the dataset surpassing computational limits for FFT calculations, and the absence of an accurate model to describe background rates, which makes the derivation of the test statistic distribution unachievable. This section outlines the methodologies employed to overcome these challenges.

Removing gaps from the time series data The data aqcuisition for ANTARES was performed through data taking runs with irregular recording times. Within each run, the counting rates were evenly sampled, enabling accurate calculation of the Fourier spectrum for each run. To enhance the sensitivity of the FFT for a fixed signal-to-noise ratio, it is desirable to combine multiple runs into a single extended time series. However, due to dead time during run changes, the runs of ANTARES do not seamlessly connect to each other, resulting in gaps in the time series and an unevenly spaced dataset. To address this, data padding is applied by introducing replacement values, which are computed as the mean of the surrounding time series, to fill these gaps and create an evenly spaced time series [5]. However, the implementation of ANTARES data collection presents an additional challenge. Since the time difference between consecutive runs may not be an integer multiple of the sampling interval (dt), data padding alone cannot generate a perfectly uniformly spaced input series. Therefore, additional resampling is required to obtain an evenly spaced time series.

Data splitting The sensitivity of an FFT increases with the length of the input dataset. However, combining the full ANTARES livetime data into a single dataset is not feasible due to computational limitations and due to the requirement for certain properties, such as background stability and PMT efficiencies, to remain approximately constant for accurate sensitivity calculations. To address this, the proposed approach involves dividing the full time series into smaller, equally sized sub-datasets representing periods with consistent data taking conditions. Power spectra are then calculated for each sub-dataset and averaged to obtain a final spectrum. This process of splitting and averaging results in a loss of sensitivity, determined by the signal-to-noise ratio (SNR) and the length of the sub-datasets. The SNR is determined as the ratio of the signal and background intensities, A_s and σ_N as described in section 4. The analysis of a large dataset with known distribution of the Fourier power spectrum demonstrates this sensitivity loss, as is shown in figure 2. For SNRs larger than a certain threshold, approximately 10^{-5}, a significant loss of sensitivity occurs. However, this loss typically affects regions where the p-value is already very low, and therefore, it does not significantly impact claims of discovery. For lower SNRs, the loss of sensitivity is negligible as both the single FFT and averaging FFT approaches are unable to differentiate between signal and noise.

Data filtering To identify signals in a dataset dominated by background, a common approach is to compare the observed data with the expected behavior assuming the dataset consisting of only background. This comparison involves deriving a test statistic from observable quantities, such as the Fourier power spectrum, and comparing its value with the corresponding distribution for the background-only case. However, representing experimental data with a simple mathematical model is often challenging, and simulations are typically used to derive these distributions. In this analysis, simulating the background is not possible due to the lack of an accurate model for the behavior of bioluminescent activity, which is a significant contribution to the background in ANTARES rates.

To address this challenge, the "Red Noise Filter" (RNF) is applied. The RNF is a crucial step in the analysis as it transforms the background spectrum of ANTARES into a frequency-independent spectrum, also known as white noise, for which the Fourier powers follow an analytical distribution

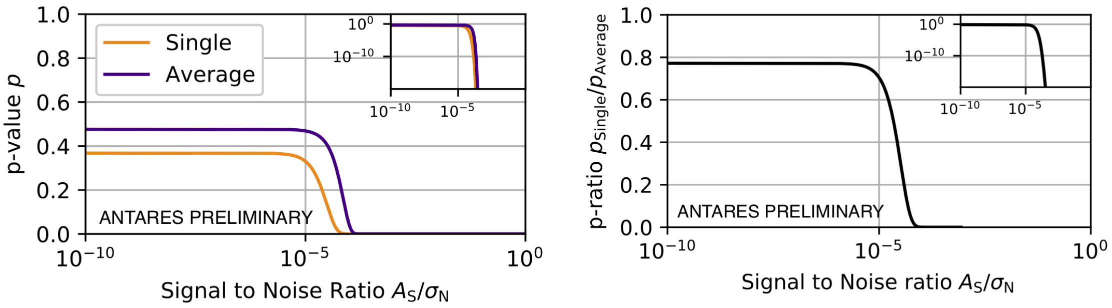

Figure 2: Effect of dividing the dataset into subsamples and averaging the resulting FFT spectra as a function of the signal to noise ratio. The parameters A_S and σ_N define the intensity of the signal and noise respectively for the model described in section 4. Left: p-value of the expected Fourier response in dependence of the signal to noise ratio for the single and averaged FFT. Right: Ratio of the p-values of the expected Fourier response in dependence of the signal to noise ratio.

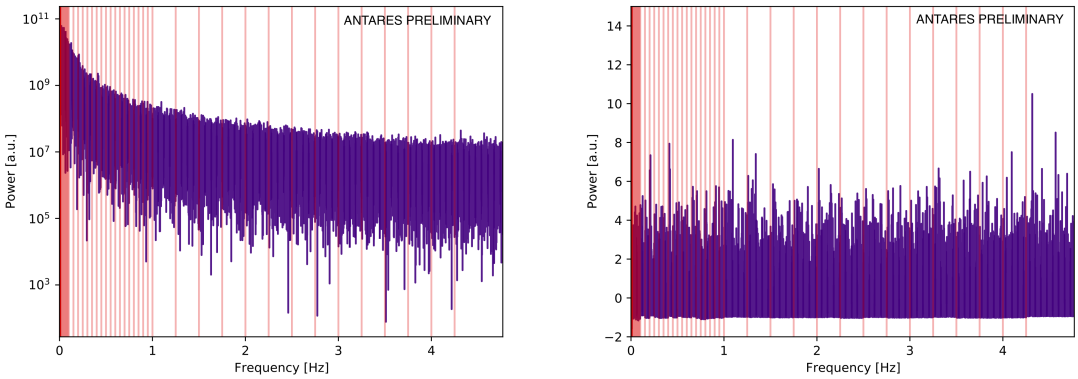

Figure 3: Effect of the red noise filter applied to a 8 hour run of the ANTARES data. Left: The unfiltered FFT power spectrum showing a frequency dependence. Due to its increase at low frequencies, this is often referred to as red noise. The vertical red lines show the segments into which the spectrum is divided to apply the red noise filter. Right: The filtered FFT spectrum. After the filtering, the power spectrum is independent from frequency.

(see section 4). Experimental spectra do not follow a white noise distribution but instead exhibit a frequency-dependent noise pattern, as shown in Figure 3 left. This frequency dependence is often referred to as "red noise," characterized by a steep decline at frequencies below approximately 1 Hz. Consequently, the background cannot be described analitically as for white noise.

The RNF works by dividing the frequency spectrum into smaller segments. For each segment, the mean (μ) and standard deviation (σ) are calculated, and the segment is then normalized using the formula $X_k' = (X_k - \mu)/\sigma$, where X_k and X_k' represent the value of the kth frequency bin before and after normalization, respectively. The normalized segments have a zero mean and a unit standard deviation. After applying this to all segments, the resulting spectrum becomes approximately frequency-independent and can be treated as a white spectrum. Figure 3 right demonstrates the outcome of applying the RNF, where the spectrum exhibits no frequency dependence.

4. Sensitivity to a periodic neutrino flux from a pulsar

The analysis strategy described in Section 3 enables the calculation of the FFT's discovery power for identifying potential periodic signals in the ANTARES Optical Module (OM) rates, which could originate from periodic astrophysical sources like pulsars. To perform this calculation, it is essential to model both the signal and background, taking into account the known properties of the background and employing signal models. In this study, a gaussian white noise model is utilized for the background, while a pure sine wave represents the signal.

Moreover, to mitigate the effects resulting from the relative motion between the Earth and the source, a source-dependent correction is applied to the time of arrival data. This correction is necessary to eliminate any distortions introduced by this motion.

Furthermore, the analysis sensitivity can be enhanced for time profiles of any complexity by implementing techniques such as harmonic summing. This technique enables the aggregation of multiple harmonics of a periodic signal, thereby increasing the probability of signal detection.

Modelling signal and background Predictions have been made in scientific literature regarding the emission of neutrinos from pulsars at energies below the typical trigger thresholds of neutrino telescopes [2]. Nevertheless, these predictions do not provide precise models regarding neutrino spectra or energy ranges. Consequently, in this study the signal is modelled as a monochromatic neutrino beam which arrives at the detector with a frequency equal to the observed pulsar frequency in the electromagnetic spectrum. The time profile of the signal is modelled as a sine wave whose amplitude represents the neutrino flux. The relation between an incoming neutrino flux F_ν, and the number of expected neutrinos n_ν detected by an OM is given by: $n_\nu(E) = F_\nu(E) \cdot \sigma(E) \cdot N_\mathrm{A} \cdot \rho \cdot V_\mathrm{eff}(E) \cdot \epsilon$, where $\sigma(E)$ is the neutrino cross section at energy E, and $N_\mathrm{A} \cdot \rho$ represents the number of targets, given by the product of the Avogadro's constant and the water density. The term $V_\mathrm{eff}(E) \cdot \epsilon$ represents the product of an ideal OM effective volume $V_\mathrm{eff}(E)$, and it's efficiency ϵ. Background is modelled by a gaussian white noise.

The relevant parameters of the model are the amplitude and frequency of the signal A_S, f_S, as well as the standard deviation of the gaussian noise σ_N. The mean of the gaussian white noise, as well as a possible offset of the signal can be chosen to have the same value, though these parameters cancel out in the calculation of the p-value.

Data Barycentrisation Barycentrisation of the incoming data is a standard in pulsar astronomy and accounts for the relative motion between the Earth and the source. The observed arrival times of the pulsar signal can be affected by several factors including the relative motion between the Earth and the Sun, as well as the relative motion between the pulsar and its companion object in case that it exists. Not correcting for these effects would introduce a time variation on the observed pulsar frequency. The corresponding peak in the Fourier power spectrum would appear broadnened, its absolute power would decrease, and the sensitivity would be lowered. Barycentrisation, transforms the arrival time of the signal to the observatory into the reference frame centred on the Solar System barycenter, which to a good approximation can be considered inertial [5]. It is worth noting that since this procedure depends on the coordinates of the source, applying it enhances the signal of the analysed source, while it is expected to wash out the signal from sources in other

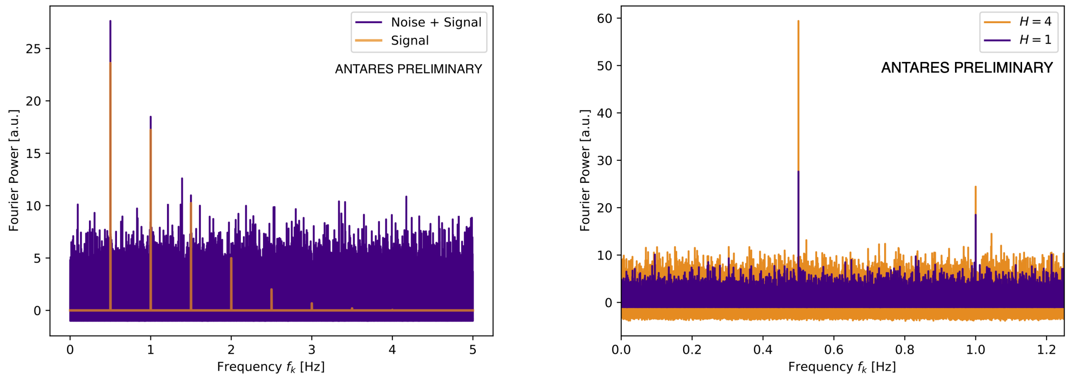

Figure 4: Harmonic summing procedure. Left: power spectrum of white noise and MVMD signal. Right: power spectrum after applying harmonic summation. The power spectrum gets reduced, and the signal is enhanced.

directions. Barycentrisation can therefore help to search for signal from a particular direction, which is otherwise not possible du to the lack of directionality information in the rate data.

Harmonic summation The results shown so far, assume a sinusoidal time profile for the signal. However, the expected time profiles are more complex than a pure sine function. For instance, a standard time profile used to model pulsar emission is the Modified Von Mises Distribution (MVMD). When the power spectra for both such time profiles are compared, both show a peak at the fundamental frequency of the signal. Additionally, peaks with smaller power will show up at integer multiples of the fundamental frequency for the non sinusoidal signal. This is a consequence of Fourier's theorem, which says that any periodic function can be expanded as an infinite sum of trigonometric terms, where each term corresponds to a higher harmonic. The harmonic summation procedure allows to account for non pure sinusoidal time profiles. This procedure requires the frequency of the expected signal, and transforms the power spectrum as $X'_{\mathrm{HS}}(k) = \sum_{h=1}^{H} X(hk)$, where $X(k)$ and $X'(hk)$ respectively represent the value of the kth frequency bin before and after applying the harmonic sum up to order H. As a result, the power spectrum is shortened and higher harmonics get stacked to lower ones, thereby increasing their power. The maximum value of H is determined by the frequency of the expected signal and by the sampling frequency, which defines the maximum available frequency in the power spectrum. This procedure is illustrated in figure 4.

Discovery power After modelling signal and background as described above, applying the RNF described in section 3, and considering harmonic summation, the p-value of the combined signal and background model follows a non-central χ^2 distribution with $2 \cdot H$ degrees of freedom and non-centrality parameter $\lambda = 2 + N/2 \cdot (A_S/\sigma_N)^2$, where N is the total number of points in the time series. One can therefore calculate the p-value in the (F_ν, E_ν) plane. For the current example, the pulsar Vela X-1 has been selected [6]. It is located at a distance of 1.4 kpc and its observed spin frequency is 3.5 mHz. Figure 5 left shows the 5σ contour as a function of the neutrino flux at the detector, and neutrino energy. The color scale indicates the number of detected neutrinos for the full ANTARES detector per unit time. The results can be expressed as a function of the neutrino

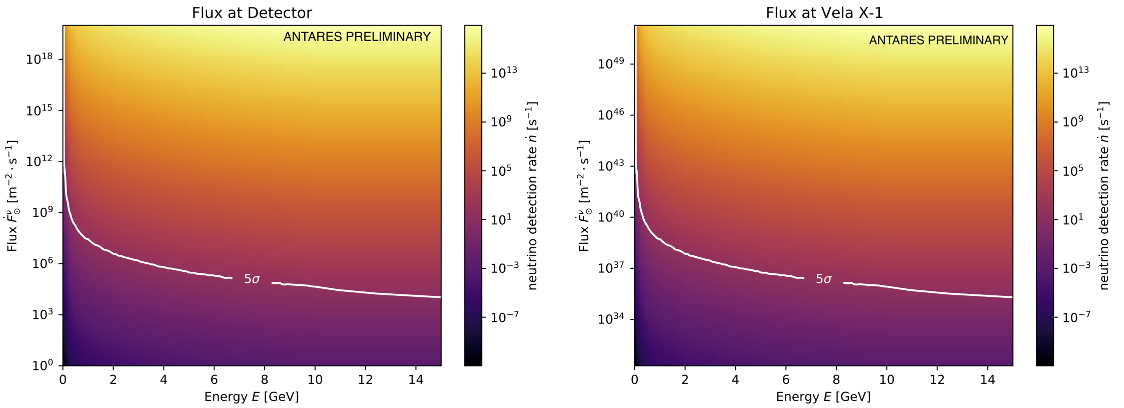

Figure 5: Discovery power as a function of the neutrino energy and flux. The color map indicates the number of detected neutrinos per unit time for the full detector. Left: flux at the detector. Right: Flux at the source.

flux at the source by using the inverse square law. These results correspond to a data taking period 98 days between 01-11-2010 and 07-02-2011, during which the data taking conditions remained constant.

5. Conclusions

A study has been presented that allows to use OM counting rates to detect periodic fluxes of neutrinos below the trigger threshold with neutrino telescopes. By applying this method to the full ANTARES livetime, about 14 years of data can be used to set limits to neutrino emission from pulsars.

References

[1] Mushtukhov et al. *Implementation and first results of the KM3NeT real-time core-collapse supernova neutrino search*. Eur. Phys. J. C 2022 82, 317. 2018;

[2] Mushtukhov et al. *Ultraluminous X-ray sources as neutrino pulsars*. MNRAS. 2018; 476(3): 2867-2873.

[3] Tamburini et al. *Deep-Sea Bioluminescence Blooms after Dense Water Formation at the Ocean Surface*. PLOS ONE. 2013; 8(7): e67523.

[4] M.Eff *Search for low-energy periodic neutrino sources with ANTARES* https://ecap.nat.fau.de/wp-content/uploads/2023/03/KM3NeT_THES_2023_001_MSc_Periodic_low_energy_neutrino_sources.pdf

[5] D.R. Lorimer and M. Kramer. *Handbook of Pulsar Astronomy*. Cambridge University Press

[6] Q. Z. Liu et al. *Catalogue of high-mass X-ray binaries in the Galaxy (4th edition)* A&A 455, 1165–1168 (2006)