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Search for gamma-ray spectral lines from dark-matter annihilation with the DAMPE satellite

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Abstract. The annihilation of dark-matter particles may lead to the production of monochromatic gamma-ray emission. In this contribution, the search for spectral lines in the gamma-ray spectrum, using eight years of data collected with the space-borne Dark Matter Particle Explorer is presented. To improve the event selection, two machine-learning algorithms were developed and proved to outperform all the standard methods. No line signal was found between 5 GeV and 280 GeV in the considered region of interest. The constraints on the velocity-averaged cross section of the neutralino was estimated for the Einasto dark-matter density profile and compared to the one obtained with Fermi-LAT and H.E.S.S. data.

1 Introduction

Modern cosmological models include a nearly neutral, non-baryonic form of matter with extremely low speeds in the context of structure formation, commonly known as "cold dark matter" (CDM). In the ΛCDM framework, dark matter makes up 26.4% of the universe's critical density and 84.4% of its total matter content. Only a small portion, between 0.5% and 1.6%, is attributed to known particles, the standard-model neutrinos. The nature of the vast majority of dark matter, however, remains unknown today [1]. One of the most promising DM candidates is the neutralino χ, the lightest supersymmetric particle, formed as a mixture of four neutral supersymmetric states: the zino (superpartner of the Z boson), the photino (superpartner of the photon), and the two neutral Higgsinos (superpartners of the neutral components of the Higgs boson fields). This particle could annihilate via the process $\chi\bar{\chi} \rightarrow X\gamma$, with $X = \gamma$, Z or H. Approximating the neutralino speed as non-relativistic, this interaction would lead to a monoenergetic gamma-ray emission and therefore result into a smoking-gun signature in the gamma-ray spectrum [2].

In this work, a search for DM annihilation lines, performed using 8 years of the Dark Matter Particle Explorer (DAMPE) data, is presented. DAMPE is a satellite-based experiment for the detection of charged cosmic rays and gamma rays. After being launched on December 17, 2015 from the Jiuquan Satellite Launch Center in the Gobi Desert, DAMPE has been operating in a stable mode in a Sun-synchronous low Earth orbit. DAMPE consists of four subdetectors: the first from the top is the Plastic Scintillator Detector (PSD) that aims to measure the absolute value of the charge (|Z|), followed by the Silicon Tungsten tracKer-converter (STK) that allows to reconstruct the trajectory of the particle and enhance the photon conversion (~1 X_0), a Bismuth Germanium Oxide (BGO) calorimeter (~31 X_0)

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to measure the energy and separate electrons and photons from hadronic particles based on the shape of the shower they induce, and a NeUtron Detector (NUD) to enhance electromagnetic/hadronic particle separation. Thanks to its design, DAMPE is able to detect electrons, positrons and photons from a few GeV to 10 TeV, as well as protons and heavier nuclei from 10 GeV to several hundreds of TeV, with excellent energy and angular resolutions [3]. A scheme of the DAMPE experiment with its subdetectors is shown in the left plot of Fig. 1.

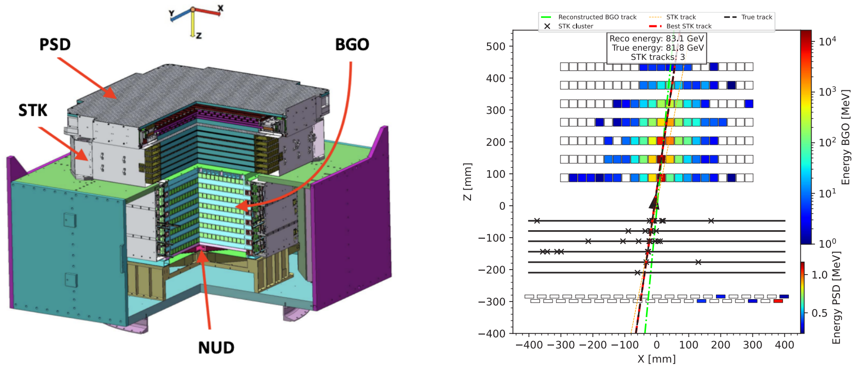

Figure 1. Left plot: Scheme of the DAMPE experiment with its subdetectors. Image taken from [3]. **Right plot:** Event display of a typical gamma-ray event entering from the PSD [4].

2 Gamma-ray selection algorithm

An efficient gamma-ray selection algorithm with high background rejection is required. A typical gamma-ray event is displayed on the right plot of Fig. 1, the photon passes through the PSD and the first STK layer without releasing energy, then converts in the second STK layer and induces an electromagnetic shower in the BGO calorimeter. After applying a standard preselection that: rejects events collected in the South Atlantic Anomaly (SAA), selects the track that best reconstructs the particle trajectory, and requires the track to be contained in the fiducial volume of the BGO calorimeter; additional criteria were added specifically for a gamma-ray selection, such as requiring narrow shower shapes in the BGO calorimeter and rejecting high-charge events. From this step, the dataset is assumed to contain mainly gamma-ray, electron and proton events. Given that protons are the most abundant component of cosmic rays and that electrons behave most like gamma rays in the detector, powerful tools were required to reject them. For this purpose, two dedicated machine-learning methods were developed.

2.1 Convolutional Neural Network (CNN) method for proton rejection

The main difference between a gamma-ray and a proton event is the shower topology in the BGO calorimeter, given that hadronic showers are considerably wider and longer than electromagnetic showers [5]. Using the footprint images of the calorimeter as input images, an appropriate method is to develop a Convolutional Neural Network (CNN), which is a class of neural networks that is particularly efficient for image processing, object classification and pattern recognition [6]. More details about the model and the training of this tool are described here [7]. A CNN score is attributed to each event such that the proton-like events get negative scores, while the gamma-ray-like events get positive scores. Requiring the CNN score to be positive leads to a gamma-ray efficiency of more than 99% over the entire energy range (from 1 GeV up to 1 TeV) and a background rejection power between 95% at low energies ($E_{\rm rec} \in [1, 30]$ GeV) and 99% at higher energies ($E_{\rm rec} > 30$ GeV). Hence, an outperforming separation method between hadronic and electromagnetic showers was successfully developed.

2.2 Boosted Decision Tree (BDT) method for electron rejection

The gamma-ray and the electron events can be differentiated before the gamma-ray conversion in an electron-positron pair, after which their behaviour is similar. Requiring no hit in the PSD would lead to a pure gamma-ray dataset, but on the other hand, would drastically reject many gamma-ray events. Given that the data are not linearly separable, an appropriate method is to use a multivariate technique called Boosted Decision Tree (BDT), which attributes a score based on the distributions of several variables [8]. A set of 22 variables was identified using attributes from the PSD, as well as from the first two STK layers. Given that the variables vary considerably with energy, due to the increased backscattering effect with increasing energy [9], three different BDTs were trained in three different reconstructed energy ranges: $E_{\text{rec}} \in [1, 100)$ GeV, $E_{\text{rec}} \in [0.1, 1)$ TeV and $E_{\text{rec}} \in [1, 10)$ TeV. On the left plot of Fig. 2, the training and test results of the BDT including energies from 1 GeV to 100 GeV are represented, whereas on the right plot the background rejection as a function of the signal efficiency curves for the three considered energy ranges are shown. Given that the backscattering effect strongly affects the BDT score and gets more important with higher energies [9], an energy-dependent criterion on the BDT score, leading to a gamma-ray efficiency of more than 90% in the entire energy range and an electron rejection power between 95% and 99%, was defined.

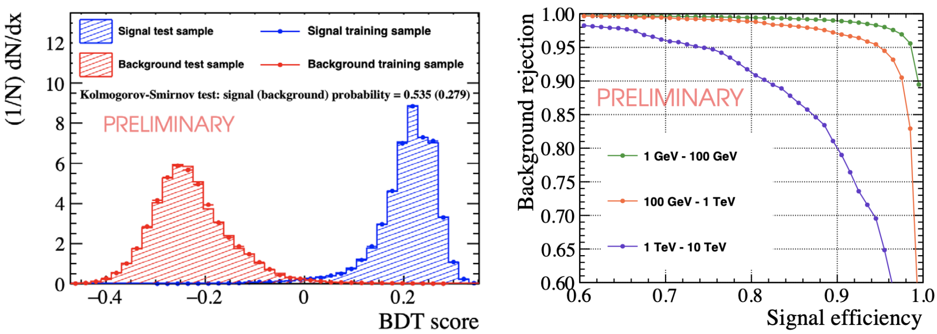

Figure 2. **Left plot:** BDT score distributions of the training (points) and the test (filled histogram) datasets, in red for background (MC electrons) and in blue for the signal (MC gamma rays). **Right plot:** Background rejection as a function of the signal efficiency for the three considered energy ranges.

3 Search for dark matter annihilation lines

To enhance the sensitivity in the search for possible line-like features in the gamma-ray flux, the R16 Region Of Interest (ROI) has been considered to optimize the signal-to-noise ratio for the Einasto DM density profile. This ROI is defined as a circular region around the Galactic center with 16° radius, excluding a rectangular region where the absolute values of the Galactic longitude and latitude are $\geq 5°$ and $\leq 5°$, respectively [10]. With the selected gamma-ray events within the R16, a maximum likelihood fit procedure in sliding energy windows was performed to evaluate the significance of a hypothetical signal line. This signal was modelled as a Gaussian distribution including the DAMPE Instrument Response Functions (IRFs), the commonly produced gamma-ray flux is modelled as a single power-law function. The Test Statistics (TS) values are evaluated for each energy window as $\text{TS} = -2\ln(\hat{\mathcal{L}}_{\text{null}}/\hat{\mathcal{L}}_{\text{sig}})$, where $\hat{\mathcal{L}}_{\text{null}}$ and $\hat{\mathcal{L}}_{\text{sig}}$ are the maximum likelihood values of the null and signal model respectively [11]. No significant line was found and a 95% confidence level (CL) upper limit (UL) was set on the DM induced gamma-ray flux, displayed on the left plot of Fig. 3 together with the result of Fermi-LAT [11]. From the flux UL, the UL on the velocity-averaged cross section of the DM annihilation into $\gamma\gamma$, $\langle\sigma v\rangle_{\gamma\gamma}$, was derived. It is shown on the right plot of

Fig. 3 together with the ULs from Fermi-LAT [11], H.E.S.S. [12] and a previous DAMPE analysis [10]. Thanks to the excellent energy resolution of DAMPE and to improved background rejection techniques, the ULs obtained from this analysis are stronger compared to previous works.

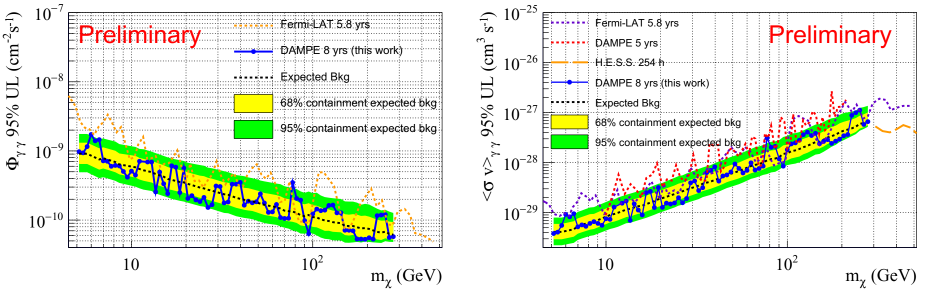

Figure 3. Left plot: The 95% CL UL on the DM annihilation-induced gamma-ray flux in the R16 ROI as a function of the DM particle mass, m_χ, together with the result of Fermi-LAT [11] results for comparison. **Right plot:** The UL set on the $\langle \sigma v \rangle_{\gamma\gamma}$, in comparison with results from a previous DAMPE analysis [10], Fermi-LAT [11] and H.E.S.S. [12].

Acknowledgments

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