Sensitivity of the MicroBooNE experiment to dark trident interactions

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Abstract

This note describes an ongoing search for dark tridents in the MicroBooNE detector. The dark trident interaction is a proposed interaction of sub-GeV dark matter with ordinary matter that would allow an exploration of a hidden dark sector composed of a dark scalar or fermion χ and a dark photon $A^{'}$. This dark matter candidate can be produced at fixed-target neutrino beams such as the NuMI beam and travel uninterrupted to the MicroBooNE liquid argon detector. The interaction with the liquid argon occurs through the process $\chi + \mathrm{Ar} \rightarrow \chi + \mathrm{Ar} + A^{'}$ where the dark photon promptly decays inside the detector through: $A^{'} \rightarrow e^{+} + e^{-}$. Two event selection strategies are explored, one using boosted decision trees and the other one applying a convolutional neural network. For both analyses a projected sensitivity in MicroBooNE after 2×10^{21} protons on target is presented.

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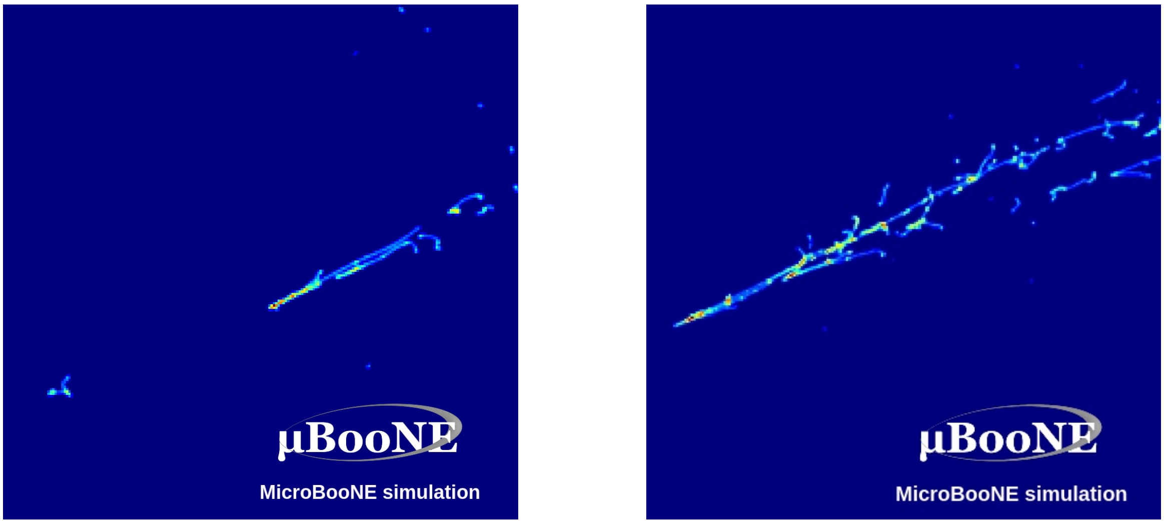


Figure 1: Event displays showing a simulated NCπ^0 interaction (left) and a dark trident interaction (right) inside the MicroBooNE detector.

1 Introduction

The dark trident [1] is a sub-GeV dark matter (DM) interaction with ordinary matter that allows the exploration of a hidden dark sector composed of a dark fermion χ and a massive dark photon A'. This interaction is based on an extension of the Standard Model given by the Lagrangian:

$$\mathcal{L} = \mathcal{L}_{\text{SM}} + \bar{\chi} i \gamma^{\mu} (\partial_{\mu} - i g_D A'_{\mu}) \chi - M_{\chi} \bar{\chi} \chi - \frac{1}{4} F'_{\mu\nu} F'^{\mu\nu} - \frac{\varepsilon}{2} F_{\mu\nu} F'^{\mu\nu} + \frac{1}{2} M^2_{A'} A'_{\mu} A'^{\mu} \,, \tag{1}$$

where ε is the kinetic mixing parameter and $M_{A'}$ is the dark photon mass. The range considered for each of these parameters in this study are: 10^{-6} - 10^{-3} for ε and 0.01 GeV/c^2 to 0.2 GeV/c^2 for $M_{A'}$. The term g_{D} is the dark photon gauge coupling and can be used to define a dark fine-structure constant as $\alpha_D = \frac{g_{\text{D}}^2}{4\pi}$. An analogous model assuming a scalar dark matter particle is also possible and will be used as a reference during the remainder of this note.

The dark fermion or scalar which could serve as a dark matter candidate can be produced through the decay of neutral mesons such as π^0s or ηs produced in the NuMI beam through the following processes:

$$\pi^0 \to \gamma \chi \bar{\chi} \qquad \eta \to \gamma \chi \bar{\chi} \,. \tag{2}$$

The resulting dark matter beam travels uninterrupted to the MicroBooNE detector [2] where it can scatter off an argon nucleus radiating a dark photon through the process:

$$\chi + \text{Ar} \to \chi + \text{Ar} + A' \,. \tag{3}$$

The emitted dark photon promptly decays inside the detector into an electron-positron pair, producing a distinctive final state that can be registered by the MicroBooNE detector. In most cases, dark trident events are reconstructed as one shower due to the small opening angle of the electron-positron pair and in a few cases as two showers arising from a common vertex without any gap between them. The backgrounds for this search are neutrino interactions that can mimic the topology previously described. For instance, one background is neutrino neutral current (NC) interactions resulting in the emission of a neutral meson such as π^0s and ηs that subsequently decay in to a pair of photons. Additionally, neutrino NC single photon emission can also be mistaken for dark trident signal if the photon is reconstructed as a very collimated positron-electron pair. Event displays of a simulated NCπ^0 event and a simulated dark trident event are shown in Figure 1.

There have been estimates that MicroBooNE has an important opportunity to set competitive limits on this interaction by analyzing the data that have been collected with the NuMI beam [1], but this estimate is not based on a realistic MicroBooNE simulation. Thus, the aims of this note are to evaluate the efficiency of MicroBooNE for this interaction channel, perform an accurate estimate of the neutrino background rate using the MicroBooNE simulation and to present a projected sensitivity of MicroBooNE for the full NuMI dataset ($\sim 2 \times 10^{21}$ protons on target).

2 Signal and background simulation

The background events considered in this analysis are simulated using the generator `GENIE` [3] which is interfaced with `LArSoft`. A full simulation of the neutrino beam is performed and a filter is applied in order to select samples of neutrino NCπ^0, NCη and NCγ interactions. After the generation step, events are passed through the standard MicroBooNE detector simulation and reconstruction. Other sources of background are being studied such as charged current interactions and photon emission from cosmic rays and will be included in future iterations of this analysis.

The simulation of the dark trident signal is performed in four stages:

1. Generate the flux of neutral mesons in the NuMI beam.
2. Decay the mesons into dark matter particles.
3. Simulate the interaction of the dark matter particles with the liquid argon.
4. Propagate the secondary particles in the detector.

2.1 Neutral meson flux

As mentioned in the introduction, the dark matter particles can be genenerated by the decay of neutral mesons (π^0s and ηs) produced in the NuMI beam. An official simulation of the neutral meson flux is obtained using the `g4numi` simulation package [4] and for each simulated meson, position, energy and momentum are saved.

2.2 Dark matter production: BdNMC

The dark matter production from the neutral meson decay is handled by the `BdNMC` simulation package [5]. By taking the list of mesons from `g4numi` as input, `BdNMC` simulates the radiative decay of π^0s and ηs to a photon and a pair of dark matter particles via an off-shell dark photon. The position and momentum of the dark matter particle is generated randomly taking into account kinematic constraints. The particles whose trajectories intersect the MicroBooNE detector are saved along with the initial meson.

2.3 Dark matter scattering

The list of intersecting DM particles is fed to a custom DM-Ar scattering generator. The position of the interaction vertex is chosen randomly along the interaction path of the dark matter particle while the timing is calculated from the time of creation of the dark matter particle and the time of flight to the vertex position. An offset is added to account for the difference between the beam t_0 and the zero of the detector clock. Vertex positions and momenta of the outgoing e^+e^- are simulated according to the kinematics of the scattering. The activity of the recoiling nucleus is not considered since for light mediators ($M_{A'} \leq 100$ MeV), the energy transferred to the argon nucleus is below its binding energy and the expected hadronic activity should be small [1].

Using the tools described in this section, Monte Carlo datasets for a scalar dark matter model are created following one of the benchmarks presented in [1] with parameters $\varepsilon = 0.001$, $\alpha_{\mathrm{D}} = 0.1$. All the distribution plots shown later in this document follow the same parameters with a dark photon mass value of 0.05 GeV/c^2.

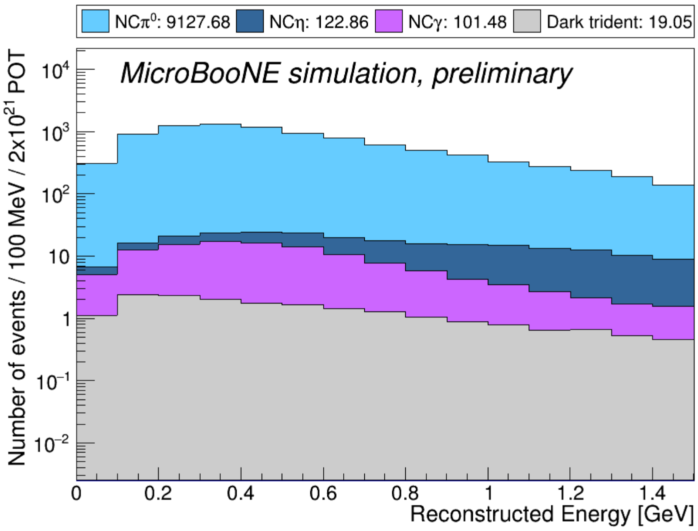


Figure 2: Total reconstructed energy of dark trident events and neutrino backgrounds. The signal sample corresponds to the benchmark described in section 2.

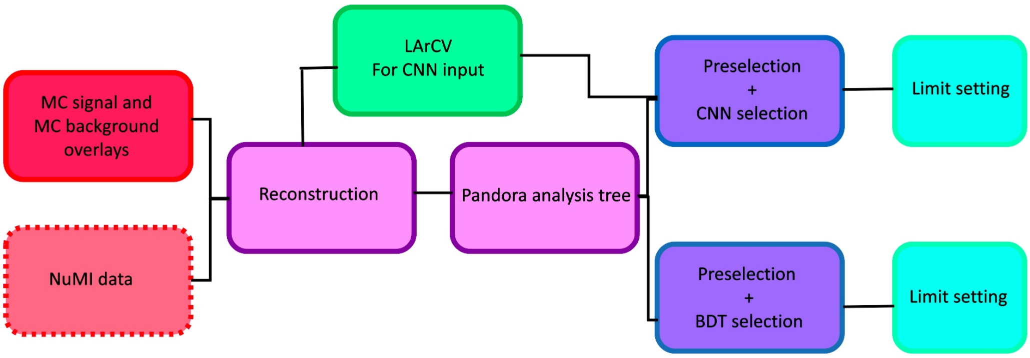


Figure 3: Overview of the two analysis chains presented in this note. Analysis of the NuMI data is planned for the near future.

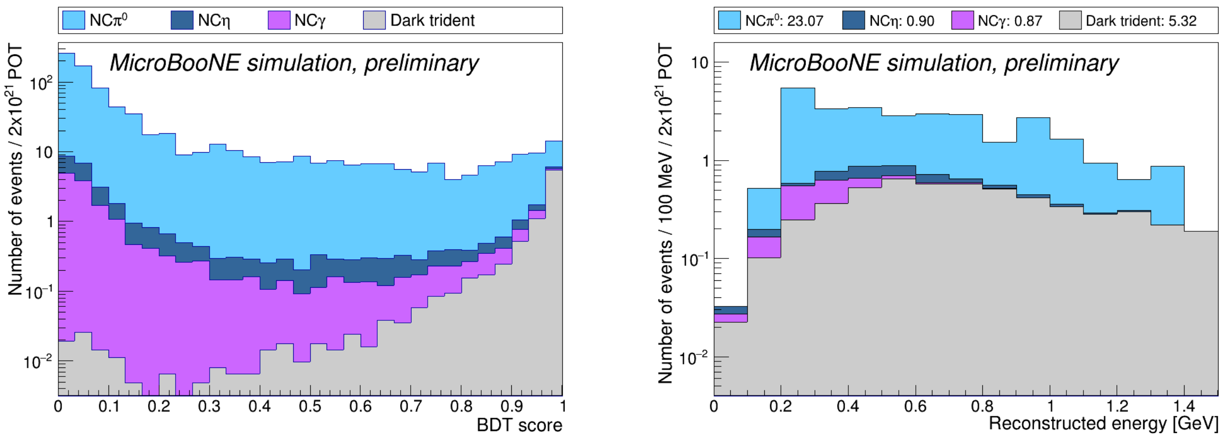
3 Analysis overview

All the simulated datasets are reconstructed using the Pandora framework [6]. Pandora outputs several high-level reconstructed features, such as spatial points clustered as showers/tracks, energy of each reconstructed object and interaction vertex. Energy distributions of the reconstructed signal and background datasets are shown in Figure 2.

Two different workflows have been designed to reduce the number of background events: one using boosted decision trees and a second one applying a state of the art deep learning (DL) classification algorithm. Each event selection chain is run in parallel and sensitivities to the dark trident interaction are calculated using the events that passed each selection. A diagram showing an overview of both analyses is presented in Figure 3.

3.1 Boosted decision tree selection

This analysis strategy focuses on events that are reconstructed as one shower and no tracks, which is the most common signal topology. A preselection on the number of reconstructed showers and tracks is performed in order to obtain a sample that contains events with this particular signature. Even though the preselection reduces the number of background events, the number of NCπ^0 interactions after this step is still considerable (~ 765 events for 2×10^{21} POT). To discriminate the dark trident signal events from the remaining background events, a BDT is implemented using the `XGBoost` library [7]. The BDT uses Pandora reconstructed variables associated to the shower of each event and is trained to distinguish dark tridents from $NC\pi^0$ events. The output of the BDT is a score for each event which ranges from 0 (background like) to 1 (signal like). An event selection using the BDT score distribution is performed by keeping the events with a score greater than 0.9. For the benchmark parameters described in section 2, a signal efficiency of 22.3% and a background rejection efficiency of 99.8% are obtained. Additionally, we have found that the rejection efficiency of the BDT selection is similar on $NC\eta$ and $NC\gamma$ backgrounds and that the selection efficiency at other dark photon mass points does not vary significantly. Nevertheless, a training of the BDT including different dark photon masses in the training set is planned for a future iteration of this analysis. Distributions of the BDT score and shower energy after event selection for both signal and the three classes of backgrounds are shown in Figure 4.



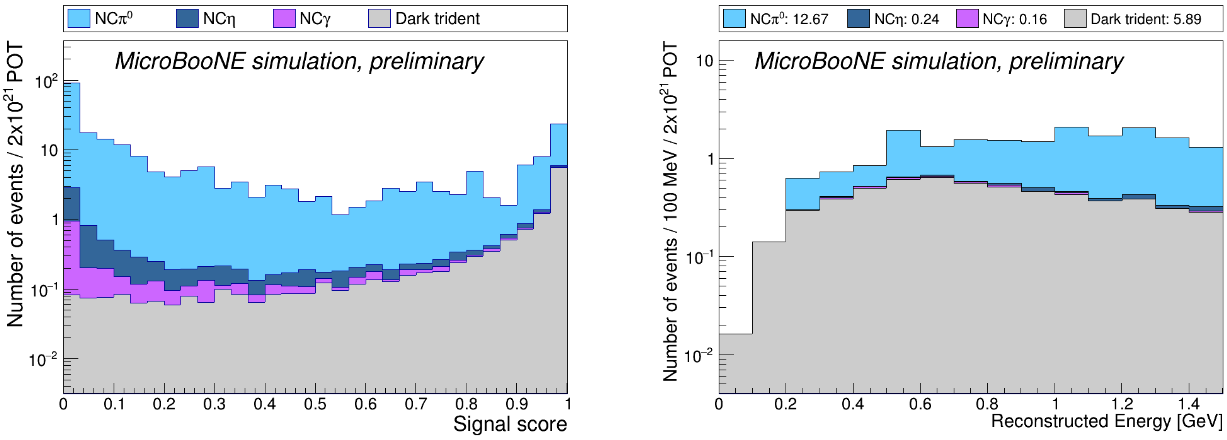
(a) BDT score of signal and backgrounds.

(b) Energy distribution of selected events

Figure 4: BDT score and energy distribution of selected events with a BDT score greater than or equal to 0.9. The signal sample was produced by following the benchmark described in section 2.

3.2 Deep learning selection

The second strategy uses a DL classifier instead of a BDT. A preselection on the number of showers and their direction is implemented to assist in background reduction and to produce a dataset suitable to be processed by the DL algorithm. The DL classifier used in this workflow is a convolutional neural network (CNN) which is an algorithm specialized in tasks that involve image processing such as object detection, face recognition and autonomous driving. The chosen CNN model is similar to the one used by the Multiple Particle Identification Network (MPID) [8], but with a final layer composed of two neurons to perform a binary classification. For training, high resolution 2D images obtained from the Monte Carlo simulation of the dark trident signal and $NC\pi^0$ background are fed to the CNN. The set of 2D images is produced by feeding the information obtained after the reconstruction chain into the `LArCV` package [9]. Furthermore, the images are cropped around the interaction vertex to reduce the size of the files, training time and memory resources. Similar to the BDT case, the output of the CNN is a probability score that goes from 0 (background like) to 1 (signal like). During this work we have found that even though the CNN was trained against one background class and for one dark photon mass value, it also performs well on other background classes such as $NC\eta$ or $NC\gamma$ and signal events simulated from other mass points. The CNN score is used to make an event selection by keeping only those events with a score value greater than or equal to 0.9. As a reference, for a dataset simulated with a dark photon mass value of 0.05 GeV/c^2, the final selection after the CNN step reaches a signal efficiency of 23.7 % and a background rejection efficiency of 99.7%. The CNN score and energy distributions of signal and background datasets are shown in Figure 5.



(a) CNN score distribution of signal and backgrounds.

(b) Energy distribution of selected events.

Figure 5: CNN score and energy distribution of selected events with a CNN score greater than or equal to 0.9. The signal sample was produced by following the benchmark described in section 2.

4 Estimated sensitivity

Using the generator described in section 2, the expected number of interactions in the MicroBooNE detector for different combinations of ε^2 and $M_{A'}$ after 2×10^{21} protons on target (POT) can be calculated. The number of background events for the same amount of data is assumed to be Gaussian distributed considering the high number of background events expected ($\sim 10^4$). This information can be used to obtain a 95% confidence level exclusion region on the dark trident parameter space. To quantify an excess in the number of signal events over the number of background events, a one-sided Gaussian distribution is used. The statistical uncertainty in the number of events is approximated as $\sigma \sim \sqrt{\mathrm{N}}$, where N is the expected number of background events after the selection. The event excess Δ for one-sided confidence level CL is given by:

$$\mathrm{CL} - 0.5 \approx \int_{N}^{N_{obs}} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(N_{obs}-N)^2}{2\sigma^2}} dN_{obs} \tag{4}$$

$$= \int_{0}^{\Delta} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\Delta^2}{2\sigma^2}} d\Delta = \frac{1}{2}\mathrm{erf}\left(\frac{\Delta}{\sqrt{2\sigma^2}}\right) \tag{5}$$

$$\Delta \approx \sqrt{2\sigma^2}\,\mathrm{erf}^{-1}(2(\mathrm{CL}-0.5)) \, . \tag{6}$$

For a 95% confidence level, and an uncertainty on the expected background number given by $\sqrt{\mathrm{N}}$, the excess can be further approximated to:

$$\Delta \approx 1.645\sqrt{\mathrm{N}} \, . \tag{7}$$

For both event selection workflows, the region that can be excluded at 95% confidence level is the area of the parameter space constrained by the equation:

$$N_S(M_{A'}, \varepsilon)\epsilon_S(M_{A'}) = 1.645\sqrt{N_B \epsilon_B} \, , \tag{8}$$

where $N_S(M_{A'}, \varepsilon)$ is the expected number of dark trident interactions as a function of the parameter space and N_B is the expected number of backgrounds. The signal selection efficiency $\epsilon_S(M_{A'})$ and the background rejection efficiency ϵ_B depend on the classifier used. The estimated MicroBooNE exclusion contour for the BDT and CNN analyses using two values of α_{D} are presented in Figure 6.

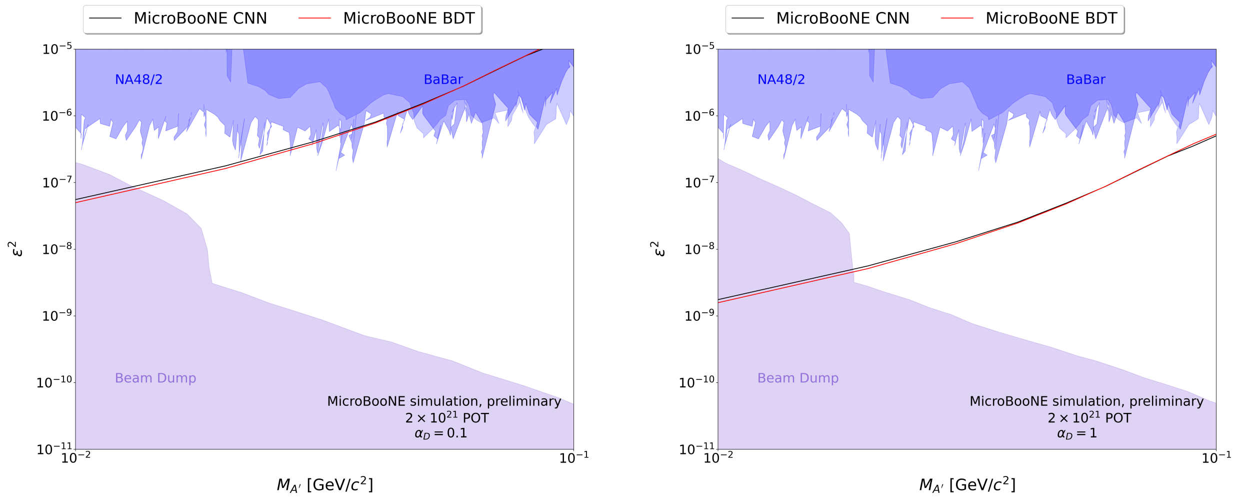


Figure 6: MicroBooNE expected sensitivity at 95% confidence level for the CNN selection (solid black line) and the BDT selection (solid red line). The plot on the left considers a Standard Model coupling value of $\alpha_\mathrm{D} = 0.1$ meanwhile the right plot is for $\alpha_\mathrm{D} = 1$. Existing limits on dark photon decay searches from BaBar [10], NA48/2 [11] and beam dump experiments [12, 13, 14] are also shown.

5 Conclusions and outlook

Through this note, we have introduced an in-development dark matter search in the MicroBooNE detector, that could potentially be the first search for dark matter using a LArTPC operating primarily as a neutrino experiment. In the presented analysis, we have used two different strategies to search for the dark trident signal, one using a BDT and an alternative method using state-of-the-art deep learning techniques. Both workflows reach similar signal efficiencies between $18\% - 25\%$ depending on the mass point and a background rejection of $\sim 99.7\%$. We have estimated that for an accumulated data of 2×10^{21} POT from the NuMI beam, MicroBooNE could set competitive limits on the dark trident interaction. Although this preliminary analysis has shown the potential of MicroBooNE for this search, there are some improvements that need to be implemented before performing the full analysis on the NuMI dataset. For both analysis chains, improvements to enhance the background rejection and signal efficiency are under active study, including the possibility of combining BDTs and the CNN to present a fully-combined analysis. Also, the evaluation of the following systematic uncertainties is ongoing:

1. Neutral meson rate uncertainty
2. Dark trident cross section uncertainty
3. Detector associated uncertainties

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