



Search for long-lived particles using displaced vertices and missing transverse momentum

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04 Jul 2024 LLP2024

Published in PRD as DOI : <u>10.1103/PhysRevD.109.112005</u> arXiv: <u>2402.15804</u> <u>CMS-EXO-22-020</u>

Motivation

- Many physics models beyond standard model predict the existence of long-lived particles (LLPs)
- The long lifetimes of LLPs create unique signatures
 - Displaced vertex is one of them
- The ATLAS and CMS has conducted searches for displaced vertices before
 - <u>The previous CMS search</u> requires energetic final states
 - <u>The previous ATLAS search</u> requires large LLP lifetimes
- A gap is left by previous searches with relatively soft final states and small lifetimes



Motivation

- To fill the gap, this search targets at least 1 displaced vertex (within beampipe) + MET
 - Requiring only 1 displaced vertex enhances sensitivity to displaced vertices that are challenging to reconstruct
 - Single-produced LLP
 - Wider range of $c\tau$
 - MET helps exploring softer final states
- Search for signature and aim to be model independent
 - Different models can produce similar signatures in the detector
 - Used split SUSY and gluing GMSB samples as benchmark signal samples



Analysis Strategy

- Select events with **MET** (MET trigger + offline selection at 200GeV)
- Vertex reconstruction:
 - Select well-measured and displaced tracks
 - Apply the dedicated vertex reconstruction algorithm on selected tracks
 - Select events with at least 1 vertex
- Machine learning:
 - Apply the interaction network to further discriminate signal from background
- Background estimation:
 - Define signal region by requiring vertex and ML output
 - Estimate background using events in control regions based on ABCD method
- Calculate **limits** based on the number of events in search regions

Vertex Reconstruction

Track selection

- This analysis uses the same vertex reconstruction algorithms as <u>arXiv:2104.13474</u>
- Tracks used to reconstruct displaced vertices are required to be well-measured and displaced:
 - Track $p_T > 1 GeV$
 - Have a measured hit in the innermost barrel pixel layer
 - Have measured hits in at least two pixel layers
 - Have measured hits in at least six strip tracker layers
 - Have transverse impact parameter (d_{xy}) significance of at least 4



Vertex Reconstruction

- Fit selected tracks into vertices with Kalman filter \bullet
- Iteratively **merge or reallocate track** for vertices • that share tracks
- **Remove tracks** that significantly changes a vertex's • z position to mitigate the effect of **pileup tracks**
- Select vertices with quality criteria:
 - Be composed of at least 3 tracks ($n_{\text{track}} \ge 3$)
 - $n_{\text{track}} \ge 5$ are signal-like, $n_{\text{track}} = 3$ or 4 are control regions
 - Be within the beam pipe radius to suppress background from material interactions
 - $\sigma_{dBV} < 25 um$
 - To get rid of b hadron decays





Beam Spot

Background Source

- Vertex selections remove almost all SM LLP decays
- The remaining dominating background displaced vertices result from unrelated tracks randomly crossing each other



Machine Learning

- Introduced Interaction Network as an event discriminator to
 - Increase the efficiency of selecting signal from background events
 - Perform background estimation
- Interaction Networks are a kind of Graph Neural Network
 - Designed to predict final states of multi-body interactions
 - Tracks are treated as single objects in the network and the "interactions" between each pair of tracks are calculated
 - Interaction Network can exploit more subtle relationships between tracks from LLPs than displaced vertex reconstruction alone
- Track information used in ML are: p_T , η , ϕ , dxy_{BS} , $sig(dxy_{BS})$, dz_{BS} , $sig(dz_{BS})$
- <u>DisCo</u> is applied to make ML output (S_{ML}) **uncorrelated** with n_{track} for background estimation



Machine Learning

- The trained Interaction Network is very powerful discriminating signal from background
 - Outstanding performance is observed for signal models with different mass splittings and ct values
- Events with $S_{\rm ML}$ >0.2 are selected as signal-like





Background Estimation

- Search Regions:
 - Signal region: $n_{\text{track}} >= 5$ and $S_{\text{ML}} > 0.2$
 - Validation region: $n_{\text{track}} = 4$ and $S_{\text{ML}} > 0.2$
 - Control regions: $n_{\text{track}} = 3 \text{ or } S_{\text{ML}} < 0.2$
- A data-driven ABCD method is used to estimate the background
 - *n*_{track} and *S*_{ML} are the two variables that define the search regions
 - The ABCD method requires n_{track} and S_{ML} to be decorrelated, which is achieved by applying <u>DisCo</u> technique when training the ML model



Systematic Uncertainties

- Reconstruct **two-track displaced vertex** of $K_s^0 \rightarrow \pi^+\pi^-$ decay
- Artificially displace tracks in background events to mimic LLP decays
 - Vertex reconstruction efficiency
 - ML tagging efficiency

| Systematic uncertainty | Magnitude (%) |
|--|---------------|
| Track reconstruction | 6–21 |
| Vertex reconstruction | 3–20 |
| ML tagging | <24 |
| $\vec{p}_{\rm T}^{\rm miss}$ selection | ≤ 8 |
| PDF uncertainty | 1–85 |
| Trigger efficiency | 1–6 |
| Pileup | 2–15 |
| Integrated luminosity | 1–3 |
| L1 trigger inefficiency | ≤ 1 |
| Total | 8–91 |



Results and Interpretation

- Performed a maximum likelihood fit on all search regions under the background-only hypothesis
- No significant excess over the backgroundonly prediction is observed



$$\begin{array}{cccc} n_{\rm track} = 3 & n_{\rm track} = 4 & n_{\rm track} \geq 5 \\ \hline \text{Predicted } S_{\rm ML} > 0.2 & -(\text{E}) & 38.0 \pm 6.0 \ (\text{C}) & 5.2 \pm 0.5 \ (\text{A}) \\ \hline \text{Observed } S_{\rm ML} > 0.2 & 203 \ (\text{E}) & 38 \ (\text{C}) & 9 \ (\text{A}) \\ \hline \text{Observed } S_{\rm ML} < 0.2 & 6327 \ (\text{F}) & 1276 \ (\text{D}) & 152 \ (\text{B}) \end{array}$$

Results and Interpretation



- The sensitivity extends to c au from 0.1 to 1000mm and Δm as low as 20GeV
 - Best limit achieved at $c\tau$ of 10mm
- For Δm of 100GeV, gluinos with mass below 1800GeV are excluded for $c \tau$ in 1-100mm
- For Δm above 50GeV, gluinos with mass below 1600GeV are excluded for c au in 1-30mm
- · Most stringent limit to date

Results and Interpretation



- Achieves the upper limit of O(1fb) for gluinos with c au from 0.1 to 1000mm
- Excludes gluinos with $c\tau$ in the range 0.3–100mm and masses below 2240GeV
- Most stringent limit for gluinos with $c\tau$ <6mm

Summary

- A search for long-lived particles using displaced vertex and missing transverse energy is presented
 - The first CMS search that targets one displaced vertex and missing traverse energy
 - Customized vertex reconstruction is used to reconstruct the displaced vertex
 - Machine learning algorithm is applied to discriminate signal from background
 - A data-driven background estimation based on vertex reconstruction and machine learning is developed
 - World leading sensitivity is achieved for the split SUSY and gluing GMSB benchmark models

Thanks!

Backup

Machine Learning

- Interaction Network is very computationally expensive so only the leading 50 tracks in the event without displacement requirement are fed into ML
- Data and background simulation are mixed together as **background** for training
- Different mass points and lifetimes of signal samples are mixed as signal for training
- Training and testing events are selected to be orthogonal to avoid bias
 - Training and testing selections are shown in the table below
- $\underline{\rm DisCo}$ is applied to make $S_{\rm ML}$ uncorrelated with $n_{\rm track}$ for background estimation

| Training | Testing |
|--|--|
| Pass event preselection with modified range E^{miss}_{T NoMu} [80,200) GeV Have at least one reconstructed vertex | Pass event preselection (including <i>E</i>^{miss}_{T NoMu} > 200 GeV) Have at least one reconstructed vertex |

Machine Learning

- The decorrelation effect for background is studied
- Categorize background MC events based on $S_{\rm ML}$:
 - $0 < S_{\rm ML} < 0.2$
 - $0.2 < S_{\rm ML} < 0.6$
 - $0.6 < S_{\rm ML} < 1.0$
- *n*_{track} distributions are consistent for different categories
- $n_{\rm track}$ and $S_{\rm ML}$ are not correlated



Analysis Selection

- Analysis Selection:
 - MET trigger and filters
 - $E_T^{miss} > 200 \ GeV$
 - Has at least 1 displaced vertex that satisfies:
 - Be composed of at least 3 tracks
 - $\circ \sigma_{dBV} < 25 um$
 - Within beam pipe
- Search Regions:
 - Signal region: $n_{\text{track}} >= 5$ and $S_{\text{ML}} > 0.2$
 - Validation region: $n_{\text{track}} = 4$ and $S_{\text{ML}} > 0.2$
 - Control regions: $n_{\text{track}} = 3 \text{ or } S_{\text{ML}} < 0.2$



Signal Efficiency Track reconstruction efficiency

- Reconstruct **two-track displaced vertex** of $K_s^0 \rightarrow \pi^+\pi^-$ decay
- Compare the d_{BV} of K_s^0 vertices between data and simulation
- Each K_s^0 vertex include 2 tracks
 - Failing to reconstruct one track \rightarrow failure of reconstructing the K_s^0 vertex
 - K_s^0 reconstruction efficiency \rightarrow track reconstruction efficiency
- Data and simulation agree within 2% in all $d_{\rm BV}$ bins
- Track reconstruction efficiency → systematic uncertainty



Signal Efficiency Artificially Displaced Vertices

- Make artificially displaced vertices to study:
 - Vertex reconstruction efficiency
 - ML tagging efficiency
- Artificially displace tracks in background events to mimic LLP decays
- Procedure:
 - Move jets away from their original positions
 - Move direction is determined by the vector sum of the momentum of moved jets with a smearing on the angle
 - Certain jet variables and transverse LLP travel distance are reweighted to better mimic the signal signature



Signal Efficiency

• Vertex reconstruction efficiency is

calculated as: $eff = \frac{N_{reconstructed vertices}}{N_{all artificial vertices}}$

- The efficiency increases with $c\tau$ and reaches a plateau after 10mm
- Data/simulation ratio stays around 85% for different $c\tau$
- The data/simulation ratio is used to
 - Calibrate the vertex reconstruction efficiency
 - Calculate systematic uncertainty



Signal Efficiency

• ML tagging efficiency is calculated as

$$eff = \frac{N_{S_{\rm ML}} > 0.2}{N_{all \ events}}$$

- ML recognizes most of the events as signal → model independence
- The data/simulation ratios are close to one for different $c\tau$
- The data/simulation ratio are used to calculate systematic uncertainty

