To catch a long-lived particle: hit selection towards a regional hardware track trigger implementation

M. Mårtensson, M. Isacson, H. Hahne, R. Gonzalez Suarez and R. Brenner
Uppsala universitet,
Lägerhyddsvägen 1, 752 37 Uppsala, Sweden
E-mail: rebeca.gonzalez.suarez@physics.uu.se

ABSTRACT: Conventional searches for new phenomena at collider experiments tend to focus on prompt particles, produced at the interaction point and decaying rapidly. New physics models including long-lived particles that travel a substantial distance in the detectors before decaying provide an interesting alternative, especially in light of the lack of new phenomena at the current LHC experiments, and could solve unanswered questions of the Standard Model. Long-lived particles have characteristic experimental signatures that, while making them clearly distinct from other processes, also could make them potentially invisible to current data-acquisition methods. Specific trigger strategies need to be in place to target long-lived particles. In this paper, we investigate the use of tracker information at trigger level to identify displaced signatures. We propose two methods that can be implemented at hardware-level: one based on the Hough transform, and another based on pattern matching with patterns trained on displaced tracks.

KEYWORDS: Pattern recognition, cluster finding, calibration and fitting methods; Data reduction methods; Particle identification methods; Trigger algorithms

ArXiv ePrint: 1907.09846
1 Introduction

The different particles of the Standard Model (SM) display a wide range of lifetimes, from the very short, like the top quark ($0.5 \times 10^{-24}$ s), to the very long, like the proton ($> 2.1 \times 10^{29}$ years) [1]. In the same way, particles predicted by theories Beyond the SM (BSM) have different lifetimes. Particles with lifetimes long enough to give rise to distinct experimental signatures, such as detectable displaced vertices, feature in many of those. The unique signatures of such long-lived particles (LLPs) offer exciting opportunities for discovery of new physics at collider experiments, but at the same time they require specific detection strategies and dedicated searches [2] since they can be easily missed.

In this paper, we explore two methods, one based on the Hough transform, and another on pattern matching, to identify displaced tracks. These two methods can be implemented in hardware to be used to trigger on displaced signatures, targeting events containing LLPs for the High Luminosity upgrade of the LHC (HL-LHC) [3]. This study is performed using a subset of layers of the tracker, corresponding to what is referred to as “regional tracking” in the Hardware Tracking for the Trigger (HTT) for the ATLAS upgrade [4].

2 Motivation

Most direct searches for new physics at the LHC experiments focus on particles with short lifetimes. The LHC experiments were optimized to detect decays of such particles, like the Higgs boson, that decays almost immediately after being produced, with a lifetime on the order of $10^{-22}$ s. However, in the search of BSM effects at the LHC and the HL-LHC, LLPs provide a promising alternative [5].
There is a strong theoretical motivation for LLP searches. Models including LLPs could provide answers to central questions still unanswered by the SM, such as naturalness [6], dark matter [7, 8], baryogenesis [9], and neutrino masses [10], among others. This variety of LLP models cover a broad range of lifetimes, production mechanisms, and decay products, making the search for LLPs a very rich experimental area. Although LLPs are vastly unexplored they have been studied in previous colliders, and many theoretical models are under ongoing scrutiny or have been searched for at the LHC. Nevertheless, many others, such as dark showers [11] remain to be explored.

Unique signatures provide unique challenges, and there are different ways to improve our ability to record and analyze LLPs. Dedicated detectors, far from the interaction point, such as MATHUSLA [12], FASER [13], or CODEX-b [14], are one option. Another option is to optimize the trigger and reconstruction capabilities of the existing all-purpose detectors. Along those lines, ATLAS is currently investigating the reconstruction of LLPs in the trigger for Run 3 [15] and the potential of CMS to identify this kind of signatures at trigger-level at the HL-LHC has been highlighted in Reference [16].

The HL-LHC will provide challenging experimental conditions, with higher pile-up and occupancy, and much higher readout rates. In particular, the trigger and tracking systems of the HL-LHC experiments will be crucial for LLP searches. Dedicated LLP triggers are justified, since important signatures could be missed without them, such as neutral LLP decays within the tracker, or LLP with low-\(p_T\) objects in general. Ongoing LLP searches in ATLAS and CMS are already limited by the trigger systems.

In this paper we focus on one of the most pressing needs in this area, the use of tracker information at trigger-level to identify LLPs. Track information was not available at trigger-level in Run-1 and Run-2 in ATLAS or CMS, but will start being used for Run-3 and beyond. Assuming a generic tracker composed of five pixel layers up to 300 mm and five strip layers up to 1000 mm, we can identify three kinds of signatures that we can target:

- **Detector-stable LLPs.** These are characterized by tracks that show anomalous ionization, i.e. a different energy loss pattern in the tracker than common SM particles. This includes the so-called heavy, stable charged particles (HSCPs), and magnetic monopoles. These kinds of LLPs have long decay lengths (\(c\tau > 1000\) mm).

- **Disappearing tracks.** Occur when a charged LLP decays inside the tracker (decay length \(c\tau \approx 100\) mm) into a neutral state and a soft SM charged particle, making it look like the original track has “disappeared”.

- **Displaced vertex/tracks.** This kind of signature occurs when a track displays a large transverse vertex displacement, incompatible with being produced at the interaction point. If more than one such track exists and they share a common point of origin, this conforms to a displaced secondary vertex. This kind of signatures have decay lengths of \(c\tau \approx 100–1000\) mm, and are the ones we are targeting in this paper. The exploration of the other two should be pursued also later on.

\(^{1}\)Pile-up is the mean number of simultaneous proton-proton interactions. A pile-up of approximately 200 is expected at High-Luminosity Large Hadron Collider (HL-LHC).
Another LLP signature which can profit from tracking information at trigger level are neutral LLPs decaying in the calorimeters, leaving trackless jets. Figure 1 shows a schematic sketch of these processes.

For the decay lengths of up to 350 mm (within the strip detector), which are targeted in this paper, there are a number of scenarios that could be explored: split-SUSY, R-Parity Violating (RPV) SUSY, Gauge Mediated Supersymmetry Breaking (GMSB), or Hidden Valley to name a few. However, we will not focus on a particular physics model at this point. Instead, we will focus on methods that could be used in hardware-based processing to trigger displaced signatures, no matter their underlying production mechanism. This could be used to define dedicated displaced triggers for specific signatures, but also, maybe more importantly, it could be used in combination with other triggers to reduce thresholds, something that can be critical for the detection of LLPs at the HL-LHC.

3 Simulation

A generic tracker similar to that used in ATLAS and CMS is modelled using the Geant4 [17] toolkit. The simulation uses a right-handed coordinate system with the z-axis pointing along the beam-line. The x- and y-axes make up transverse plane. The geometry is the same as that used in Reference [18] and depicted in figure 2. The barrel consists of five layers of pixel sensors, evenly spaced between 35 mm and 300 mm, and five double layers of strip sensors, evenly spaced between 400 mm and 1000 mm. The end-caps consist of seven layers of pixel and seven double layers of strip sensors. Both the pixel and silicon sensors are modelled as 320 µm thick silicon wafers. The active area of the pixel sensors is 40 mm × 40 mm, except in the innermost barrel and end-cap layers where the active width is 20 mm and the outermost end-cap layer where the active width is 80 mm. The active length of the strip sensors is 24 mm in the two innermost barrel double layers, and 48 mm in the three outermost barrel double layers. The active width of the barrel modules is 100 mm. In
Figure 2. Tracker geometry. The detector consists of 5 (7) pixel layers, shown in red, and 5 (7) strip double layers, shown in blue, in the barrel (end-cap) [18].

The continuous local hit coordinates \((x, y)\) are recorded modulo the readout granularity of the respective sensor [18]. The pixel granularity is \(25\,\mu m \times 250\,\mu m\) and the granularity of the strip sensors is \(80\,\mu m\) in the \(x\)-direction.

Tracks are described by helix parameters given by the position, momentum, and trajectory of the track at its closest approach to the \(z\)-axis: the transverse momentum \((p_T)\), the azimuthal angle \((\phi_0)\), the pseudorapidity\(^2\) \((\eta_0)\), the transverse impact parameter \((d_0)\), and the longitudinal impact parameter \((z_0)\) of the track. The coordinates of the production vertex of a track is given by \((x_V, y_V, z_V)\), or the radial coordinate \(d_V = \sqrt{x_V^2 + y_V^2}\) and the azimuthal coordinate \(\phi_V\). The directions of a track at the production vertex are denoted \(\phi\) and \(\eta\).

Muon tracks from displaced vertices are generated in a model-independent way using a particle gun implemented with Pythia 8.2 [19]. The position of the track vertex is determined by drawing the longitudinal, transverse, and azimuthal coordinates from flat distributions between \(-150–270\) mm, \(0–350\) mm, and \(\pm\pi\) rad respectively.

The tracks are generated such that they pass through all strip layers in the Region of Interest (RoI) defined by the geometric volume covered by prompt tracks with \(0.1 < \eta_0 < 0.3\), \(0.3 < \phi_0 < 0.5\), \(|z_0| < 150\) mm, and \(p_T > 4\) GeV. This is the reason for the asymmetric bounds on the \(z_V\) distribution. The upper bound needs to be extended to allow for full coverage for the strip modules in the RoI.

\(^{2}\)The pseudorapidity is defined as \(\eta = -\ln\tan(\theta/2)\), where \(\theta\) is the polar angle in the right-handed spherical coordinates.
Tracks are rejected if $|\phi - \phi_V| > \frac{\pi}{2}$ to bias against tracks going backwards toward the primary vertex. The transverse momentum $p_T$ is drawn between 4–400 GeV from a flat distribution in $1/p_T$. In total 60 M tracks are generated split equally between $\mu^+$ and $\mu^-$. Setting the bounds on the muon direction dynamically and rejecting tracks pointing toward the primary vertex skews the resulting distributions of the track direction and vertex position, shown in figure 3 (right), figure 4, and figure 5. However, the bias towards lower $d_V$ should not pose a serious problem. The distribution is reasonably flat up to $\sim 150$ mm, and the exponentially distributed decay length of an LLP will be similarly biased towards lower values.

This study uses hits in the outer layers of the tracker to get a maximum number of hits from displaced tracks. Eight layers of the strip detector are used: the six outer layers, i.e. the three outer double layers, and the outer layer of the two innermost double layers. The remaining tracker layers are not used but the material will affect the response in the outer layers. As previously stated, this corresponds to the regional tracking scenario of the HTT, used to perform fast initial trigger decisions after Level-0 [4].
Figure 5. Sample distributions of the vertex positions in the longitudinal plane (left) and transverse plane (right).

In the regional HTT the readout of the tracker is seeded by the calorimeters or muon detectors. Since at most 10% of the tracker volume will be read out at any time, the regional tracking can be run at a higher rate than the full readout of the tracker. This allows for lower thresholds on particles used in a regional trigger than for a trigger based on full readout.

4 Filtering of tracker hits

Here the two hardware based hit collection methods studied in this paper are described. Section 4.1 describes the Hough transform method, and section 4.2 describes the pattern matching method.

4.1 Hough transform method

The Hough transform was invented in 1959 to analyze photographic plates of bubble chambers [20]. Since then, the method has found use in various computer vision applications. With recent developments in GPU and FPGA technology, the interest in the Hough transform for tracking applications in high energy physics has been renewed. The Hough transform can be constructed for any curve that can be described with a few parameters. For each spatial point in image-like data, it calculates one of the unknown parameters from the parameterization and the point coordinates while sweeping the other parameters. It then casts votes in a histogram-like object called the accumulator. Points in the accumulator with a lot of votes are candidates realizations of the searched-for curve in the data.

Charged particles trace out helices as they propagate through a uniform magnetic field. Viewing the track along the magnetic field lines, in what is called the transverse plane of the detector, they appear as circular arcs. The radius of curvature is proportional to the transverse momentum $p_T$ and the azimuthal angle $\phi_0$ according to

$$A \frac{qB}{p_T} = \frac{\sin(\phi_0 - \phi)}{r},$$  \hspace{1cm} (4.1)

where $q$ is the elementary charge, $B$ is the electromagnetic field strength, and $A$ is a unit conversion constant with value $A \approx 1.5 \times 10^{-4}$ GeV cm$^{-1}$ mm$^{-1}$ T$^{-1}$. This equation is used as the basis of the Hough transform studied in this paper. It is straightforward to loosen the vertex constraint imposed
by equation (4.1). The downside to doing so is that the Hough transform needs to be applied to pairs of hits, which increases the number of computations needed dramatically. This paper aims to investigate the performance of the Hough transform when keeping it as simple and computationally inexpensive as possible. Therefore, the vertex constrained variant is the one studied.

The accumulator is constructed similarly to a 2-dimensional histogram with $\phi_0$ on one axis and $AqB/p_T$ on the other. The bins in the accumulator keep track of which layers have hits that are consistent with a track parameterized by the $\phi_0$ and $AqB/p_T$ of that bin. Each bin also keep track of which hits have been used to fill it. The goal here is not to use the track parameters $p_T$ and $\phi_0$ from the Hough transform as is, but rather to select hits to send to a subsequent, dedicated track fitter, for instance, a linearized track-fit using precomputed constants, such as the one planned for the ATLAS Phase-II upgrade [4]. Hits are selected from a single bin in the accumulator by applying a threshold on the number of hits. The requirement is that the bin should have at least six hits and, in addition, that the two nearest neighbouring bins along constant $AqB/p_T$ should have at least five hits, and that the next-to-nearest neighboring bins along constant $AqB/p_T$ should have more than four hits.

The Hough transform is applied in small RoIs of $0.2 \times 0.2$ in $\Delta \eta \times \Delta \phi_0$. However, the regions are 300 mm wide in the longitudinal impact parameter $z_0$. To improve the rejection of unwanted soft-QCD background, the RoIs are split into several slices in $z_0$. This and more details of the Hough transform implemented here are described in Reference [18]. Here, we apply the Hough transform to tracks with displaced vertices.

The results are presented in terms of the efficiency to detect tracks from signal and the power of rejecting the unwanted soft QCD background. The efficiency is studied using muon tracks generated in the way described in section 3. A track is considered found if at least six hits originating from the track pass the Hough transform selection. The hits are required to be in unique detector layers and to belong to the same bin in the accumulator. The rejection is studied in terms of the number of possible combinations of hits that survive the Hough transform. It is calculated as

$$\sum_b \left( \prod_l n_{b,l} \right),$$

(4.2)

where $n_{b,l}$ is the number of hits in layer $l$ in accumulator bin number $b$.

The Hough transform is tuned to provide at least 99% efficiency of finding tracks from prompt muons ($d_0 < 2$ mm) while minimising the number of hit combinations in minimum bias with pile-up 200. This is done by varying the number of bins in $AqB/p_T$, the number of bins in $\phi_0$, and the number of $z_0$-slices. The muon and minimum bias simulation used for this are the same ones described in Reference [18]. Figure 6 shows the efficiency versus number of hit combinations for muon tracks embedded in minimum bias with pile-up 200 in the $0.1 < |\eta| < 0.3$ RoI. Each point is a separate configuration of the Hough transform. Point 1 has just above 99% efficiency and is selected as the nominal configuration; it has 95 bins in $AqB/p_T$, 63 bins in $\phi_0$, and 6 splits in $z_0$. Another configuration, point 2 in figure 6, is selected as an alternative configuration with higher efficiency. For point 2, the number of bins in $AqB/p_T$ is 63, otherwise the configuration is the same as point 1.
4.2 Pattern matching method

Hit filtering using pattern matching is a method that can be easily implemented in hardware-based processing using content addressable memory (CAM) [21]. The method was successfully demonstrated in the fast online tracker for the CDF silicon vertex trigger [22] at Fermilab. The method is currently being implemented in the Fast TracKer (FTK) [23] system for the ATLAS experiment at CERN and is the baseline method to be used for the high luminosity upgrade of the ATLAS tracker [4].

A pattern is a set of hits. In order to efficiently use memory resources, the hits in a pattern have lower resolution than the tracker clusters of hits. This is done by grouping a number of tracker strips or pixels into super strips. A group of 16 tracker strips has a Super Strip Width (SSW) of 16. A typical signal from a high-$p_T$ particle generates single hits in different detector layers. By simulating a large number of single particles in a $p_T$ range of interest, a bank of signal patterns can be generated. The maximum number of patterns that can be stored depend on the size of the pattern bank. The number of patterns required to reach high track efficiency depends on the granularity and $p_T$ range of the patterns. With a higher granularity (lower SSW) or larger $p_T$ range, more patterns are required to reach high efficiency. If the patterns are too coarse however, the method looses its power to reduce background. The optimal is hence to have a pattern granularity which gives high efficiency and few fakes with given resources to store patterns.

Detailed description of the method used in this study is described in Reference [18]. In the study presented in this paper we investigate the effect of extending a pattern bank originally trained for prompt muons produced in the central interaction region with 10% and 20% extra patterns that have been trained with muons originating from displaced vertices inside the tracker. We restrict the study to a single region of the tracker and use only its outermost layers. In the same way as for the previous method, this scenario corresponds to regional tracking in the HTT [4].

![Figure 6](image.png) Efficiency of finding hits from simulated tracks of muons embedded in minimum bias with pile-up 200 plotted against the number of hit combinations. Each point is a separate configuration of the Hough transform. The working points annotated 1 and 2 are used in this paper.
5 Results

Figure 7 shows the efficiency as function of $p_T$ and $d_V$ of the truth track for the displaced-vertex sample with the Hough transform configured for working point 1 (this is the mode optimized for finding prompt muons from the beam spot). The efficiency is 19% at 4 GeV, peaks at 10–20 GeV with 27%, and decreases to 22% above 67 GeV. The efficiency as a function of $d_V$ starts at 80% for $d_V = 0$ mm and decreases to 25% at $d_V = 50$ mm; it also has a peculiar shape with a minimum at 150 mm. Figure 8 shows the same plots when the Hough transform is configured for working point 2. The efficiency increased with respect to working point 1, especially for $d_V < 50$ mm. It also plateaus at approximately 40% for $p_T > 10$ GeV, rather than decreasing at higher $p_T$. The efficiencies for the other track parameters are found in appendix A.

Figure 9 shows two-dimensional efficiency distributions as a function of the impact parameter ($d_0$) and $p_T$ of the track. As expected, the Hough transform has trouble finding tracks with low $p_T$ and high $d_0$. 
Figure 9. Efficiency of finding at least 6 hits in unique layers out of 8 as a function of $p_T$ and $d_0$ for the Hough transform method. The left figure shows configuration 1 while the right figure shows configuration 2.

Figure 10. Number of hits passing the Hough transform for minimum bias events with a pile-up of 200.

Track from soft QCD events generally have $p_T$ lower than the minimum of 4 GeV that the Hough transform is configured for. This is the reason the Hough transform can suppress such backgrounds. Figure 10 shows the distributions of the number of hits from minimum bias with pile-up 200 that pass the Hough transform selection for working point 1; the mean number of hits passing the Hough transform is 56.

The left panel of figure 11 shows the number of hit combinations in minimum bias, calculated according to equation (4.2), for the Hough transform using working point 1. The mean is 84, but the distributions has a long tail with the 99th percentile at 2017 combinations. The right panel of figure 11 shows the results for working point 2 that has 63 bins in $A_{qB}^{p_T}$ compared to working point 1 that has 95 $A_{qB}^{p_T}$ bins. The number of hit combinations increases to a mean of 300 with 99th percentile at 6530 combinations.
Figure 11. Distribution of the number of possible hits combinations in a minimum bias sample with pile-up 200, requiring at least 6, 7, or 8 hits in unique layers out of 8, for configurations 1 (left) and 2 (right), Hough transform method.

Figure 12. Efficiency for tracks from displaced vertex with pattern banks trained on prompt muons from beam spot for SSW of 16 and 32 as a function of $p_T$ (left) and transverse vertex displacement (right).

Figure 12 shows the efficiency as function of $p_T$ and $d_V$ of the truth track for the displaced-vertex sample with the pattern matching method when using a pattern bank trained on muons originating from the beam spot, that is: not trained for tracks from displaced vertex, which is the default system. The pattern banks are trained to give an efficiency above 99 % with a minimum of 6 matched hits in an 8 hit pattern. The study shows about 4 % efficiency for SSW of 16 for finding tracks from muons with displaced vertex above 150 mm, with efficiency increasing for low $d_V$. The corresponding number for SSW of 32 is around 10 %. The efficiency is expected to approach 99 % for $d_V$ approaching 0 mm, however, figure 12 shows an efficiency of $\sim 30$ % for tracks using a SSW of 32. The prompt muon tracks used to train the pattern banks used in figure 12 are generated from flat distributions in $0.1 < \eta < 0.3$ and $0.3 < \phi < 0.5$. This is in contrast with how the displaced tracks are generated, where the direction depends on the vertex position as discussed in section 3. Restricting the displaced tracks to the same region as the prompt tracks recovers the efficiency as further demonstrated in appendix B.
Figure 13. Efficiency for displaced tracks as a function of $p_T$ (left) and transverse vertex displacement (right), using a dedicated pattern bank trained for displaced tracks with 100k patterns, and a SSW of 16, pattern matching method.

Figure 14. Efficiency for displaced tracks as a function of $p_T$ (left) and transverse vertex displacement (right), using a dedicated pattern bank trained for displaced tracks with 200k patterns, and a SSW of 16, pattern matching method.

Figure 13 shows the efficiency as function of $p_T$ and $d_V$ of the truth track for the displaced-vertex sample with the pattern matching method when using a dedicated pattern bank trained for displaced tracks with 100 k patterns, and a SSW of 16. The efficiency is around 10% at $d_V = 20$ mm and stays flat at about 4% from $d_V = 50$ mm. By doubling the size of the pattern bank this efficiency becomes higher: above 8% for the whole $p_T$ spectrum, peaking at 10 GeV, and reaching 20% for low values of $d_V$, as shown in figure 14. Figure 15 shows the efficiency when using a pattern bank of 200 k patterns and a SSW width of 32. In this configuration, the efficiency stays well above 20% overall, reaching more than 50% of efficiency for low values of $d_V = 50$ mm.

In a realistic scenario, the budget of patterns to be stored will have to be shared between prompt and displaced patterns. Figure 16 shows the efficiency for displaced tracks using a mixed pattern bank with 1 M patterns where 100 k correspond to displaced signatures and 900 k correspond to prompt tracks. The efficiency stays well above 20% for all values of $d_V$ and peaks at 30% for
relatively low $p_T$ tracks of 10–20 GeV. A mixed pattern bank with a higher number of patterns trained on displaced tracks, for example 20%, as shown in figure 17 would perform even better, with almost flat efficiencies around 30% for high values of $d_V$ and small values of $p_T$. To dedicate more than 10% of the pattern banks to displaced tracks is something that could be considered in practice since it does not seem to affect, in a significant way, the efficiency for prompt tracks. This is evident from the results presented in figure 18, where the efficiency as a function of $p_T$ for prompt tracks stays above 99% for the full range.

Finally, we can also check the number of hit combinations in minimum bias for the pattern matching method, calculated in the same way as for the Hough transform. Figure 19 shows the distribution of the number of possible hits combinations in a minimum bias sample with pile-up 200, using a pattern bank of 1M patterns trained with 10% and 20% displaced tracks and only prompt tracks. In figure 20 we can see the number of hit combinations when using 16 SSW compared with
Figure 17. Efficiency for displaced tracks as a function of $p_T$ (left) and transverse vertex displacement (right), using a mixed pattern bank with 1M patterns from which 200k correspond to displaced patterns, using a SSW of 32, pattern matching method.

Figure 18. Efficiency for prompt tracks using a mixed pattern bank with 1M patterns from which 100k (left) or 200k (right) correspond to displaced patterns, using a SSW of 32, pattern matching method.

32 SSW (left), as well as the number of hit combinations when requiring at least 6, 7, or 8 hits in unique layers out of 8 (right), on a pattern bank trained with only prompt tracks.

6 Summary and discussion

We have studied with full detector simulation two methods that can be implemented in hardware-based processing, such as the proposed hardware track trigger for the Phase-II upgrade of the ATLAS detector for the HL-LHC [4], to identify displaced tracks. The first method, based on the Hough transform, shows promising efficiencies: above 20% for displaced tracks with very high transverse vertex displacement, maintaining a flat efficiency around 40% for $p_T > 10$ GeV. The second method, based on pattern recognition, tests the possibility of modifying the regular pattern banks trained for prompt muons produced in the central interaction region by including 10% and 20% extra patterns trained with muons originating from displaced vertices inside the tracker. The
Figure 19. Distribution of the number of possible hits combinations in a minimum bias sample with pile-up 200, using a pattern bank of 1M patterns trained, using a SSW of 32, with: 10% displaced tracks (red), 20% displaced tracks (yellow), and only prompt tracks (blue). Pattern matching method.

Figure 20. Distribution of the number of possible hits combinations in a minimum bias sample with pile-up 200, for 16 SSW and 32 SSW (left); and requiring at least 6, 7, or 8 hits in unique layers out of 8, with a SSW of 32 (right). Pattern matching method using a pattern bank trained only with prompt tracks.

Efficiency of the pattern matching is above 30% for displaced tracks while maintaining above 99% efficiency for prompt tracks.

Both methods will increase the load on the data acquisition system because of additional hits from minimum bias. However, this effect can be kept small if only events of interest are sent to the hardware-based processing for long-lived particles, how this can be done for the two methods here discussed is left for a future study.

This is a preliminary study that anticipates a promising performance of dedicated trigger strategies for the search for long-lived particles at the HL-LHC. With small additional resources, the sensitivity for long-lived particles can be improved. We propose that such resources are reserved in the design of the future tracker triggers for the HL-LHC.
Acknowledgments

The Swedish Research Council supports Rebeca Gonzalez Suarez (VR 2017-05092) and Richard Brenner (VR 2015-04955).

A Additional efficiency distributions for the Hough transform

In the main body of the paper, the efficiency distributions are only presented as a function of $p_T$ and transverse vertex displacement. Here, the distributions for $\eta_0$, $\phi_0$ and $z_0$ are presented in figures 21, 22, and 23 respectively.

![Figure 21](image1.png)

**Figure 21.** Efficiency of finding at least 6, 7, or 8 hits in unique layers out of eight, as a function of $\eta$, for configuration 1 (left) and 2 (right), Hough transform method.

![Figure 22](image2.png)

**Figure 22.** Efficiency of finding at least 6, 7, or 8 hits in unique layers out of eight, as a function of $\phi_0$, for configuration 1 (left) and 2 (right), Hough transform method.
Figure 23. Efficiency of finding at least 6, 7, or 8 hits in unique layers out of eight, as a function of $\phi_0$, for configuration 1 (left) and 2 (right), Hough transform method.

B Additional efficiency distributions for the pattern matching method

Figure 24. Efficiency of matching at least 6 hits in unique layers out of 8, as a function of $d_V$ and $\eta$ (left), and $d_V$ and $\phi$ (right), using 1M patterns trained on prompt tracks and a SSW of 32, pattern matching method.

Figure 25. Efficiency of matching at least 6 hits in unique layers out of 8, as a function of $\eta$ and $\phi$, requiring $d_V < 10$ mm (left), and $d_V < 2$ mm (right), using 1M patterns trained on prompt tracks and a SSW of 32, pattern matching method.
Figure 26. Efficiency of matching at least 6 hits in unique layers out of 8, as a function of $d_V$ and $z_V$, requiring $0.1 < \eta < 0.3$ and $0.3 < \phi < 0.5$, using 1M patterns trained on prompt tracks and a SSW of 32, pattern matching method.

References

[1] Particle Data Group collaboration, Review of Particle Physics, Phys. Rev. D 98 (2018) 030001.
[2] J. Alimena et al., Searching for Long-Lived Particles beyond the Standard Model at the Large Hadron Collider, arXiv:1703.04497.
[3] G. Apollinari, O. Brüning, T. Nakamoto and L. Rossi, High Luminosity Large Hadron Collider HL-LHC, CERN Yellow Rep. (2015) 1 [arXiv:1705.08830].
[4] ATLAS collaboration, Technical Design Report for the Phase-II Upgrade of the ATLAS TDAQ System, CERN-LHCC-2017-020, ATLAS-TDR-029.
[5] L. Lee, C. Ohm, A. Soffer and T.-T. Yu, Collider Searches for Long-Lived Particles Beyond the Standard Model, Prog. Part. Nucl. Phys. 106 (2019) 210 [arXiv:1810.12602].
[6] H. Cai, H.-C. Cheng and J. Terning, A Quirky Little Higgs Model, JHEP 05 (2009) 045 [arXiv:0812.0843].
[7] N. Arkani-Hamed, D.P. Finkbeiner, T.R. Slatyer and N. Weiner, A Theory of Dark Matter, Phys. Rev. D 79 (2009) 015014 [arXiv:0810.0713].
[8] M. Pospelov and A. Ritz, Astrophysical Signatures of Secluded Dark Matter, Phys. Lett. B 671 (2009) 391 [arXiv:0810.1502].
[9] S. Ipek and J. March-Russell, Baryogenesis via Particle-Antiparticle Oscillations, Phys. Rev. D 93 (2016) 123528 [arXiv:1604.00009].
[10] S. Antusch, E. Cazzato and O. Fischer, Displaced vertex searches for sterile neutrinos at future lepton colliders, JHEP 12 (2016) 007 [arXiv:1604.02420].
[11] T. Cohen, M. Lisanti, H.K. Lou and S. Mishra-Sharma, LHC Searches for Dark Sector Showers, JHEP 11 (2017) 196 [arXiv:1707.05326].
[12] MATHUSLA collaboration, MATHUSLA: A Detector Proposal to Explore the Lifetime Frontier at the HL-LHC, arXiv:1901.04040.
[13] FASER collaboration, *FASER’s physics reach for long-lived particles*, Phys. Rev. D **99** (2019) 095011 [arXiv:1811.12522].

[14] V.V. Gligorov, S. Knapen, M. Papucci and D.J. Robinson, *Searching for Long-lived Particles: A Compact Detector for Exotics at LHCb*, Phys. Rev. D **97** (2018) 015023 [arXiv:1708.09395].

[15] ATLAS collaboration, *First tracking performance results from the ATLAS Fast TracKer*, ATL-DAQ-PROC-2019-010.

[16] Y. Gershtein, *CMS Hardware Track Trigger: New Opportunities for Long-Lived Particle Searches at the HL-LHC*, Phys. Rev. D **96** (2017) 035027 [arXiv:1705.04321].

[17] GEANT4 collaboration, *GEANT4: A Simulation toolkit*, Nucl. Instrum. Meth. A **506** (2003) 250.

[18] J. Gradin, M. Mårtensson and R. Brenner, *Comparison of two hardware-based hit filtering methods for trackers in high-pileup environments*, 2018 JINST **13** P04019 [arXiv:1709.01034].

[19] T. Sjöstrand et al., *An Introduction to PYTHIA 8.2*, Comput. Phys. Commun. **191** (2015) 159 [arXiv:1410.3012].

[20] P.V.C. Hough, *Machine Analysis of Bubble Chamber Pictures*, Conf. Proc. C **590914** (1959) 554.

[21] M. Dell’Orso and L. Ristori, *VLSI structures for track finding*, Nucl. Instrum. Meth. A **278** (1989) 436.

[22] A. Bardi et al., *SVT: An Online silicon vertex tracker for the CDF upgrade*, Nucl. Instrum. Meth. A **409** (1998) 658.

[23] M. Shochet, L. Tompkins, V. Cavaliere, P. Giannetti, A. Annovi and G. Volpi, *Fast TracKer (FTK) Technical Design Report*, CERN-LHCC-2013-007, ATLAS-TDR-021.