

Unveiling the Rich and Diverse Universe of Subsecond Astrophysics through LSST Star Trails

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Abstract

We present a unique method that allows the LSST to scan the sky for subsecond stellar variability. The method has operational and image processing components. The operational component is to take star trail images, which facilitate sub-exposure photometry. The image processing component is to use deep learning to sift for transient events on timescales down to 10 ms. We advocate for coupling this capability with the LSST's unrivaled $319.5 \text{ m}^2\text{deg}^2$ etendue to produce the first optical survey of the universe on these timescales. We explain how this data will advance both planned lines of investigation and enable new research in the areas of stellar flares, cataclysmic variables, active galactic nuclei, Kuiper Belt objects, gamma-ray bursts, and fast radio bursts.

1 White Paper Information

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1. **Science Category:** We introduce a mechanism that enables the LSST to provide new data with much higher time resolution that not only enhances existing investigations, but allows LSST to contribute to new science use cases that generally lie within the *Exploring the Changing Sky* and *Milky Way Structure and Formation* categories.
2. **Survey Type Category:** We propose inserting occasional star trail images into the main *Wide-Fast-Deep* survey.
3. **Observing Strategy Category:** While different fields are conducive to different aspects of our method - for example, searching open clusters for flare stars - it is largely agnostic of where the telescope is pointed. Furthermore, our proposal can be trivially interleaved with the main LSST survey.

2 Scientific Motivation

Describe the scientific justification for this white paper in the context of your field, as well as the importance to the general program of astronomy, including the relevance over the next decade. Describe other relevant data, and justify why LSST is the best facility for these observations. (Limit: 2 pages + 1 page for figures.)

A wide range of astrophysical phenomena ranging from local Kuiper Belt object occultations to cosmic gamma-ray bursts manifest on subsecond time scales. Conventional optical telescopes rely on charge-coupled devices (CCDs) which typically take around ten seconds to read out. This readout time limits the time resolution they can achieve and precludes them from participating in high time resolution investigations. Furthermore, the special instruments that can image optical bands at high speeds have fields of view that are typically a few arcminutes, or less than 1/1000th of the LSST field of view. We present a mechanism that allows the LSST to explore the subsecond universe and describe how this unique data will (i) enhance planned LSST investigations of active galactic nuclei (AGN), stellar flares, and exoplanets and (ii) enable new LSST science with Kuiper Belt objects, fast radio bursts (FRBs), gamma-ray bursts (GRBs), and cataclysmic variables.

This proposal relies on a key insight originally from [Howell & Jacoby \(1986\)](#) and further developed in [Thomas & Kahn \(2018\)](#): star trail images are a conduit to achieving subsecond photometry of stellar sources. In star trail images, the tracking is turned off so the telescope rotates with the Earth during the exposure. Stellar sources are stretched into coherent linear trails, which show how the flux of the sources changes throughout the exposure. [Figure 1](#) shows a simulated LSST star trail image with a one second exposure time. This choice of exposure time is elaborated on in [Section ??](#). We then train a deep neural network to scan these large, unorthodox images and detect variability.

The input to the network is a 80x80 pixel crop of an LSST star trail image, the output is a binary classification which determines whether the sample is worth following up. As in many deep learning applications, high quality data and training feedback are essential. We use a suite of LSST simulation tools to produce realistic images. We sample visits from the *minion_1016* OpSim observing run, then we use CatSim to procure catalogs for each visit, then we use PhoSim to produce high fidelity simulated images of the catalogs ([Delgado et al., 2014](#); [Connolly et al., 2014](#); [Peterson et al., 2015](#)). We add a new interface into the PhoSim code to simulate *bursts* - a tophat change in flux added to an otherwise flat and static light curve of a source - parameterized by the magnitude change and duration. We train the network over 5 epochs of 80,000 sample 80x80 pixel crops, half of which contain a burst. We train the network to both predict whether the burst exists and to predict the exact photons resulting from the change in flux. [Figure 2](#) highlights this process.

We assess the performance of our technique on visits and corresponding images that the network was not trained on. [Figure 3](#) shows the results. These results are competitive with the state of the art ([Dhillon et al., 2016](#)).

AGN/Blazars

Stellar Flares
Exoplanets
Gamma-Ray Bursts
Kuiper Belt Objects
Fast Radio Bursts
Cataclysmic Variables

Conclusion.

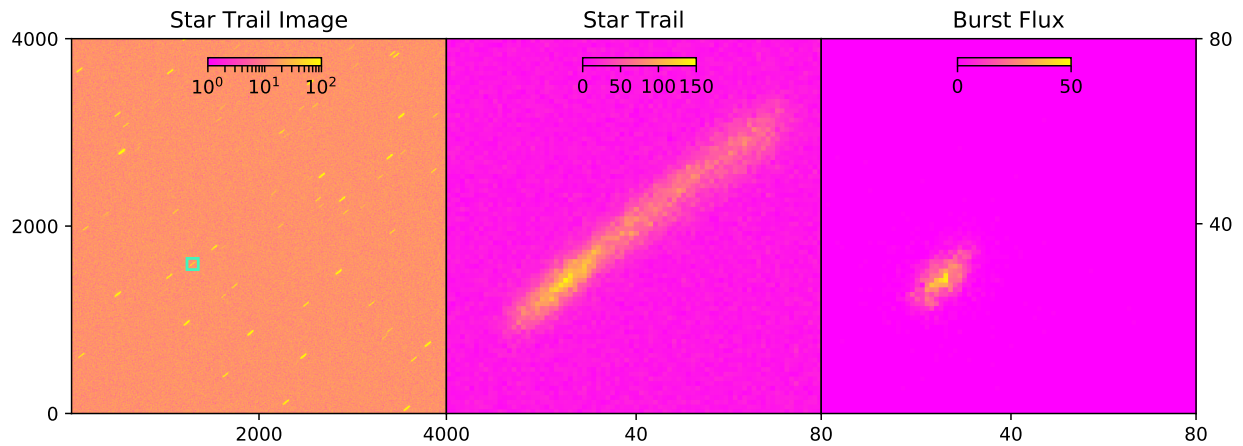


Figure 1: *Left:* a star trail image corresponding to a 1 second exposure on a single LSST CCD in the ‘r’ filter. *Middle:* zoom-in of a single star trail that is in the green box region in the full image. *Right:* zoom-in of the extra flux due to the burst.

References

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- Delgado, F., Saha, A., Chandrasekharan, S., et al. 2014, in Proc. SPIE, Vol. 9150, Systems Engineering, and Project Management for Astronomy VI, 915015
- Dhillon, V. S., Marsh, T. R., Bezawada, N., et al. 2016, in Proc. SPIE, Vol. 9908, Ground-based and Airborne Instrumentation for Astronomy VI, 9908
- Howell, S. B., & Jacoby, G. H. 1986, 98, 802, doi: [10.1086/131828](https://doi.org/10.1086/131828)

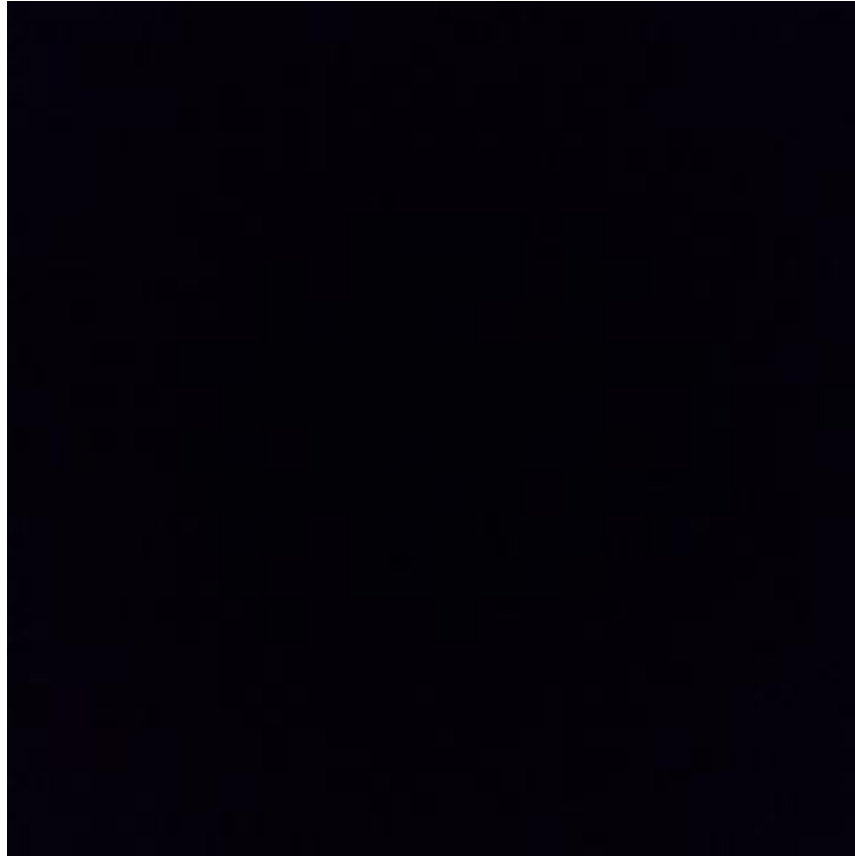


Figure 2: Image processing pipeline.

Peterson, J. R., Jernigan, J. G., Kahn, S. M., et al. 2015, *Astrophysical Journal, Supplement*, 218, 14, doi: [10.1088/0067-0049/218/1/14](https://doi.org/10.1088/0067-0049/218/1/14)

Thomas, D., & Kahn, S. 2018, *The Astrophysical Journal*, 868, doi: [10.3847/0004-637X/830/1/27](https://doi.org/10.3847/0004-637X/830/1/27)



Figure 3: Detection accuracy and performance limits.