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Poissonian analysis of glitches observed in the LIGO gravitational wave interferometers

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Abstract. Glitches are non-Gaussian transient noises that impact the ability to identify true gravitational wave signals. This study aims to analyze the statistical behavior of the main types of glitches during an observational run using computational methods, investigating whether their temporal distributions follow a Poisson pattern. This analysis may provide insights into their physical origins, facilitating their mitigation and contributing to the improvement in the quality of gravitational wave detections.

Resumo. Os "glitches" são ruidos transitórios não gaussianos que afetam a capacidade de identificar sinai reais de ondas gravitacionais. Busca-se então, por meio de métodos computacionais, analisar o comportamento estatístico dos principais tipos de glitches ao longo de uma corrida observacional, investigando se suas distribuições temporais seguem um padrão de Poisson. Essa análise pode oferecer pistas sobre suas origens físicas, facilitando sua mitigação e contribuindo para a melhoria na qualidade das detecções de ondas gravitacionais.

Keywords. Gravitational waves – Interferometers – Data analysis

1. Introduction

Gravitational waves arise as a direct consequence of the General Theory of Relativity Einstein (1916, 1918), which describes gravity as a deformation of space-time caused by concentrations of energy and matter. When a mass distribution is accelerated, perturbations are triggered in the fabric of space-time that propagate throughout the Universe at the speed of light — being more intense in the case of compact objects, such as neutron stars or black holes, due to their concentration of large amounts of mass in a small volume. These perturbations allow us to study the most energetic and extreme phenomena in the cosmos. The detection of gravitational waves represents one of the most significant advances in modern astrophysics, ushering in a new era of observing the universe. This offers unique opportunities to explore high-energy phenomena and to test the limits of the General Theory of Relativity Abbott et al. (2019) under extreme conditions (strong-field and relativistic velocities).

However, the statistical significance of these signals is often challenged by non-Gaussian transient noise events known as glitches Ashton (2023). These aperiodic events, captured by the interferometers, can mask or even mimic real gravitational wave signals, reducing the statistical confidence of detections and increasing the false alarm rate Buikema et al. (2020). As a result, it becomes essential to investigate the origin, nature, and distribution of these glitches in order to minimize their impact on observational data.

The Poisson distribution describes the probability of occurrence of discrete and statistically independent events within a fixed interval, assuming a constant average rate. Many environmental and instrumental noise processes deviate from this Poissonian behavior. In this work, we perform a Poissonian analysis of glitches recorded during the third observing run of the LIGO interferometers Davis et al. (2021), with the goal of characterizing their temporal distribution and identifying patterns that may provide clues about their physical causes. In this context, the use of computational methods and detailed statistical analyses enables a quantitative approach to assess whether certain types of glitches follow a Poisson distribution, offering insights into their origin and potentially assisting in the mitigation of such noise.

1.1. Data

The characterization of the LIGO interferometers and the monitoring of their glitch activity are essential for understanding the nature of transient noise events. The classification of glitches provides important clues about their potential sources, particularly when events share similar morphological features. In this context, the Gravity Spy Glanzer et al. (2023) Zevin et al. (2024) framework employs a machine learning model trained on time–frequency spectrograms to classify glitches into predefined morphological classes, using triggers generated by the Omicron pipeline Robinet et al. (2020). Omicron identifies transient excess power relative to the background noise through Q-transform spectrograms, while Gravity Spy restricts its analysis to events within the 10–2048 Hz frequency range. In this study, only glitches classified by Gravity Spy with a confidence level of at least 90% were considered.

2. Methodology

The analysis focuses on glitches from the O3a and O3b observational runs, corresponding to the first and second halves of the third observing run of the LIGO interferometers, using publicly available data Abbott et al. (2023). These runs were analyzed separately to avoid mixing different experimental conditions that could affect the statistical consistency of the results. The temporal behavior of glitches was modeled using the Poisson distribution, which describes the occurrence of statistically independent events under the assumption of a constant average rate. If a given glitch morphology exhibits significant deviations from Poissonian behavior, this suggests that its underlying physical origin is likely non-Poissonian.

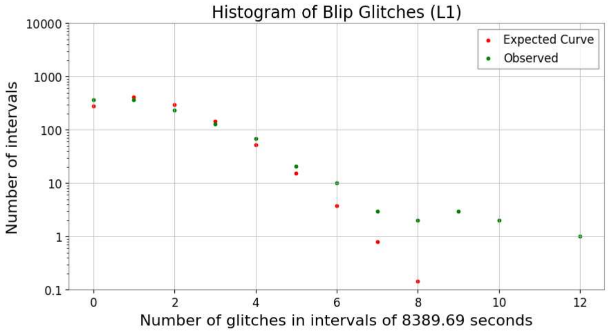

Figure 1: Blip glitches in intervals of 8,389.69 seconds during O3a in the L1 detector.

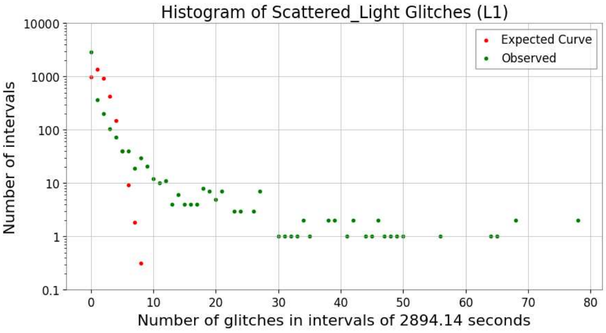

Figure 2: Scattered Light glitches in intervals of 2,894.14 seconds during O3a (L1).

To perform the analysis, the data were segmented into time intervals of fixed duration t_0, and the number of glitches within each interval was counted. Only periods during which the interferometer was actively collecting data were considered, ensuring that the segmentation respected the detector duty cycle and preserved statistical integrity. The average glitch rate was computed and used to model the expected distribution of events, allowing a direct comparison between observed and theoretical values. This approach enables the identification of statistical deviations from the Poisson model and provides insight into the temporal structure and physical origin of different glitch classes.

It is worth noting that some glitch morphologies do not have sufficient data for the statistical distribution analyzed to exhibit a well-defined behavior. In such cases, the estimation of the coefficient of determination R^2 may be compromised due to the small sample size, impacting the validity of the modeling through Poisson fitting. Therefore, it is ensured that the relative uncertainty of the analyzed classes is less than or equal to 5%.

3. Results

The analysis yields histograms of the temporal distribution of glitches compared to the frequency of observed events, with the expectation based on the Poisson statistical model. The observed curves are shown in blue, and the expected Poisson distributions for each glitch are indicated in red. The agreements or discrepancies between the observed data and the proposed statistical model are quantitatively assessed using the correlation coefficient, R^2.

To illustrate the results of the statistical classification, we present representative cases of both Poisson-like and non-Poisson-like behaviors. Among the morphologies studied, some classes follow the expected Poissonian distribution. The Blip glitches (Figure 1) yield coefficients of determination above 0.9 across multiple detectors and observing runs, values that are consistent with a simulated ideal poisson behaviour curve.

In contrast, Scattered Light glitches (2) provide a clear example of a class with strong deviations from Poisson statistics, with R^2 values well around 0.3, although the simulated R^2 values are close to 1, as expected.

4. Conclusion

The statistical analysis of different types of glitches indicates that only a fraction of them are compatible with a Poisson distribution. A Poisson behaviour follows a stochastic distribution consistent with random physical sources such as thermal noise, quantum background fluctuations and shot noise. Glitches of the types Blip, Koi Fish, and Extremely Loud exhibited temporal patterns consistent with a constant occurrence rate, thus agreeing with the Poisson distribution. This statistical adherence suggests that their causes are directly related to processes that are also Poissonian in nature.

On the other hand, glitches with non-Poissonian signatures, such as Scattered Light and Whistle, exhibit inconsistent temporal patterns, indicating the influence of non-Poissonian external sources as their origin.

In particular, scattered light arises from small surface imperfections on the test mass mirrors that cause a fraction of the laser beam to scatter, reflect off moving surfaces such as chamber walls, and recombine with the main beam, thereby introducing phase noise in the interferometer signal Soni et al. (2020). Therefore, the cause of this noise might be related to seismic noise actuating on the movement of the chamber walls. While Whistle glitches, in turn, are associated with radio-frequency signals that couple to the detector electronics through beating with the Voltage Controlled Oscillators of LIGO Gravity Spy Team (2025).

These results suggest that the statistical classification of glitches may serve as an auxiliary tool for identifying their physical causes and, consequently, for their mitigation. In future work, we aim to extend this analysis to further investigate the physical origin of these glitches.

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