

GFH-v2 pipeline for searches of long-transient gravitational waves from newborn magnetars

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(Received 2 December 2025; accepted 13 May 2026; published 15 June 2026)

This paper presents an enhanced methodology for searching long transient gravitational waves associated with a newborn magnetar, with particular focus on the regime in which the early spin down is dominated by gravitational-wave emission. The analysis is performed using a strongly improved version of the generalized Frequency Hough Transform algorithm, called GFH-v2. We describe the main developments introduced relative to the original implementation and outline the optimized parameter-space selection used in the search. We then compute the theoretical sensitivity of the method and compare it with an empirical sensitivity estimate obtained by injecting simulated signals into LIGO-Virgo-KAGRA O4a data. The updated framework achieves improved sensitivity and computational performance. These results provide a robust basis for future directed searches for long-transient gravitational-wave signals from core-collapse supernovae and other transient events in current and upcoming observing runs.

DOI: [10.1103/jqf5-hbzk](https://doi.org/10.1103/jqf5-hbzk)

I. INTRODUCTION

Continuous gravitational waves (CWs) are long-duration, nearly monochromatic signals typically emitted by non-axisymmetric rotating neutron stars [1–3]. Although still undetected, these signals will provide a powerful probe of neutron star properties, including their internal structure and spin evolution [4]. Searches for CWs have so far mainly focused on isolated or binary neutron stars, either known from electromagnetic observations or searched in all-sky surveys [2,3,5]. However, within the broad category of CWs lies a particularly intriguing subclass: long-transient gravitational waves (tCWs, a term first introduced by Prix *et al.* [6] to describe signals of intermediate duration) [1,2,7]. These are signals with durations ranging from thousands of seconds to days, characterized by nonlinear frequency evolution due to the intense rotational energy loss of the source.

tCWs represent a promising yet challenging frontier in gravitational wave (GW) observations. Among the

potential sources of such signals are newborn magnetars: rapidly rotating, highly magnetized neutron stars formed in the aftermath of catastrophic events such as core-collapse supernovae (CCSNe) or binary neutron star (BNS) mergers [8–12]. In newborn magnetars, gravitational wave emission may arise from nonaxisymmetric deformations induced by strong internal magnetic fields, residual asymmetries from the formation process, or other mechanisms such as bar-mode instabilities or fallback accretion.

Detecting tCWs offers a unique opportunity to probe extreme physics that is otherwise inaccessible: the equation of state of ultradense matter, the internal magnetic field configuration, and the dynamics of the newly formed remnant [13,14]. Additionally, this information could give us significant insight on the nature of the progenitor and the physical mechanisms during and after the merger or the core collapse [15].

However, these signals are difficult to detect due to their weak amplitude and broad parameter space. Hierarchical search strategies, particularly those employing semicoherent techniques, are essential to maintain sensitivity while keeping computational costs tractable. Semicoherent methods split the dataset into shorter segments, analyze each coherently, and then combine the results incoherently. This approach reduces computational cost while retaining most

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of the sensitivity of a fully coherent search. Several analysis methods have been developed to search for long-transient continuous gravitational waves, including transient extensions of the $\mathcal{F}$ -statistic and other approaches designed to account for signal durations ranging from hours to days [6,16–23]. One such approach is the Generalized Frequency Hough (GFH) pipeline [24], which was previously applied to the postmerger remnant of GW170817, though no signal was observed at the time, as the source distance was much larger than the potential reach of the search [15].

Building on that foundation, in this paper, we introduce an improved version of the method, which we call GFH-v2. It incorporates significant enhancements of the algorithm, resulting in higher sensitivity and better management of computational resources. As a consequence, it offers more promising detection prospects for the upcoming O5 science run of the LIGO-Virgo-KAGRA [25] detectors and future third-generation detectors, like the Einstein Telescope [26] and Cosmic Explorer [27].

The paper is structured as follows. In Sec. II, we briefly describe magnetars, the relevant equations describing their rotational evolution, and the main characteristics of the associated gravitational wave emission. Section III provides the basic concepts of the original GFH algorithm, while the new version, GFH-v2, and its methodological improvements are discussed in detail in Sec. IV. Within this section, we discuss in detail the astrophysically motivated search parameter space, including the choice of coherence time and observation-time window, as well as the technical enhancements to the analysis pipeline.

Section V deals with the semitheoretical estimation of the method's sensitivity, based on the assumption of Gaussian noise. In Sec. VI, we compare the theoretical results with an experimental computation, obtained by injecting simulated signals into data from the first part of the fourth LIGO-Virgo-KAGRA observing run. This section also includes detailed discussions on data characteristics, the injection setup, candidate selection, and efficiency analysis.

Finally, Sec. VII presents conclusions and future prospects of this work. Additional technical details, including a quantitative comparison of the GFH implementations, the derivation of the theoretical sensitivity formula, and the procedure adopted for the selection of the critical ratio threshold, are provided in Appendixes A–C, respectively.

II. NEWBORN MAGNETARS AND ASSOCIATED GW SIGNAL

Newborn magnetars, a type of highly magnetized neutron star, are thought to form in the aftermath of CCSNe explosions or in BNS mergers. These compact objects are characterized by extremely strong surface magnetic fields, typically of the order 10^{14} – 10^{15} G, and rapid initial spin periods of a few milliseconds ($P_0 \sim 1$ – 10 ms). Magnetars are typically born from progenitor stars with masses in the

range of 10 to $30M_\odot$ [12], and their formation rate in the galaxy is estimated to be 2.3 – 20 per kyr, corresponding to roughly 10% – 15% of all CCSNe [28].

At the time of their birth, magnetars are expected to possess asymmetries resulting in a highly variable mass quadrupole moment, leading to the emission of gravitational waves [29–33]. Mechanisms driving these asymmetries include strong interior magnetic fields, a secular bar-mode instability [34], formation of accretion-induced mountains on the surface [35,36], etc., which generate long-lived nonaxisymmetric deformations, which are necessary for GW emission. GW emission, with power $\dot{E}_{\text{GW}}$, happens at the expense of the star's rotation frequency according to [37]

$$\dot{E}_{\text{GW}} = \frac{32}{5} \frac{G\epsilon^2 I^2 \Omega^6}{c^5}, \quad (1)$$

where $\epsilon = (I_{xx} - I_{yy})/I_{zz}$ is the ellipticity, defined in terms of principal moment of inertia, $I \equiv I_{zz}$ is the moment of inertia with respect to the rotation axis, and Ω is the angular frequency. Throughout this work, we assume that the ellipticity remains constant over the signal duration. A time-dependent ellipticity would modify both the GW amplitude and the spindown evolution of the signal and is beyond the scope of this study. From Eq. (1), the angular frequency decreases as

$$\dot{\Omega} = -\frac{32}{5} \frac{G\epsilon^2 I \Omega^5}{c^5}. \quad (2)$$

These equations highlight how magnetars can efficiently lose rotational energy via GW emission, especially in the early stages of their evolution. In this work, we focus on the simplified case in which the early spindown of the source is dominated by GW emission. This represents a limiting scenario where GW emission is assumed to be stronger than magnetic dipole radiation. In reality, newborn magnetars may experience a combination of spindown mechanisms. However, adopting the GW-dominated case allows us to work with a well-defined signal model that is suitable for developing and testing the analysis pipeline. More general scenarios including additional spindown contributions will be explored in future work.

The GW signal emitted by a rotating rigid neutron star has an amplitude proportional to the square of the GW frequency [38]. For systems where the spin frequency evolves with time, such as a newly born magnetar, the amplitude becomes time dependent through the instantaneous GW frequency $f_{\text{gw}}(t)$:

$$h_0(t) = \frac{4\pi^2 G I \epsilon}{c^4} \frac{f_{\text{gw}}^2(t)}{d}. \quad (3)$$

For a rigid nonprecessing neutron star rotating about a principal axis, the GW emission occurs at twice the

rotational frequency¹ [37]:

$$f_{\text{gw}} = 2f_{\text{rot}} = \Omega/\pi. \quad (4)$$

The rotational frequency evolution of the magnetar can be described, in general, by a power law spindown model,

$$\dot{f}_{\text{rot}} \propto -f_{\text{rot}}^n, \quad (5)$$

where n is the braking index which depends on the physical mechanism responsible for the spindown (e.g., magnetic dipole radiation, GW emission, or particle winds) [39].

The corresponding evolution for the GW frequency can then be written as

$$\dot{f}_{\text{gw}} = -kf_{\text{gw}}^n. \quad (6)$$

Integrating Eq. (6) yields the frequency evolution

$$f_{\text{gw}}(t) = \frac{f_0}{\left(1 + \frac{t-t_0}{\tau}\right)^{1/(n-1)}}, \quad (7)$$

where f_0 is the initial frequency at reference time t_0 and the characteristic timescale τ is

$$\tau = \frac{1}{(n-1)kf_0^{n-1}}. \quad (8)$$

The proportionality constant k depends on the underlying emission process. In this work, we focus on the GW-driven spindown case with $n = 5$ [40,41], assuming rotation about a principal axis of inertia for which the proportionality constant is

$$k = \frac{32\pi^4 G}{5c^5} \epsilon^2 I. \quad (9)$$

Substituting Eq. (7) into Eq. (3), the amplitude becomes

$$h_0(t) = \frac{4\pi^2 G I \epsilon}{c^4 d} f_0^2 \left(1 + \frac{t-t_0}{\tau}\right)^{-1/2}. \quad (10)$$

Figure 1 illustrates the dependence of signal amplitude on initial spin frequency and ellipticity for a range of plausible values.

The moment of inertia I can be approximated as a function of the compactness β using the empirical formula [42],

$$I \approx MR^2(0.247 + 0.642\beta + 0.466\beta^2), \quad (11)$$

¹This relation holds for nonprecessing neutron stars rotating about a principal axis. Other mechanisms, such as r -modes or precession, may produce GW signals at different frequencies and with more complex evolution.

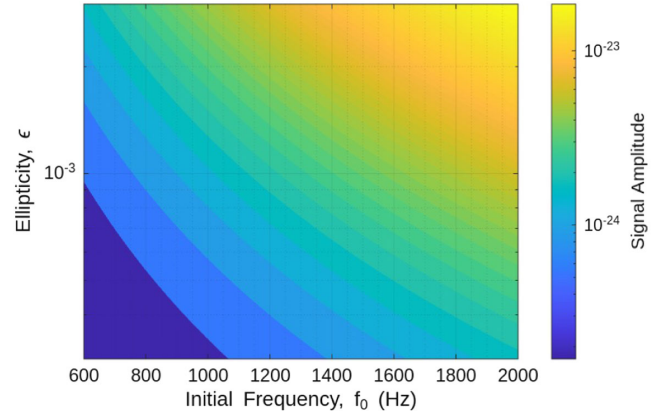


FIG. 1. Gravitational-wave strain amplitude $h_0(t=t_0)$ as a function of initial spin frequency $f_{\text{gw}}(t_0) \equiv f_0$ and ellipticity ϵ . The source distance is fixed to 1 Mpc for illustration purposes. The moment of inertia is computed using Eq. (11) for $M = 1.4M_\odot$ and $R = 12$ km.

where

$$\beta = \frac{GM}{c^2 R}. \quad (12)$$

This relation holds for $\beta > 0.1$ and assumes a neutron star with a maximum mass M_{max} (the maximum mass allowed by the equation of state) satisfying $M_{\text{max}} \geq 1.97M_\odot$.

III. GENERALIZED FREQUENCY HOUGH

The GFH transform is a semicoherent, hierarchical search algorithm designed to detect long-transient gravitational wave signals whose frequency evolves nonlinearly over time [24]. It extends the original Frequency Hough (FH) method [43,44], which was primarily developed for detecting continuous wave signals with linearly evolving frequency.

The method starts from the *Short Fourier Transform Databases* (SFDB) [45,46], which contain sequences of short Fourier transforms generated from calibrated strain data [47,48]. The data are initially divided into overlapping segments of equal length, with a 50% overlap. Each segment has duration T_{FFT} and is transformed using the Fast Fourier Transform (FFT) algorithm. The SFDB spans the full frequency band (0–2000 Hz), with FFTs typically covering timescales of the order of thousands of seconds. We first read the SFDB and extract the desired frequency band. The FFTs are then inverse transformed back to a time series and subdivided into shorter segments with the desired FFT length for the analysis.

The construction of the *Peakmap* proceeds by computing, for each of the N FFTs, the ratio between the periodogram (i.e., the squared modulus of the FFT) and the corresponding average spectral estimate computed in the frequency domain [44]. The most significant peaks in this ratio, that is, local maxima whose normalized power

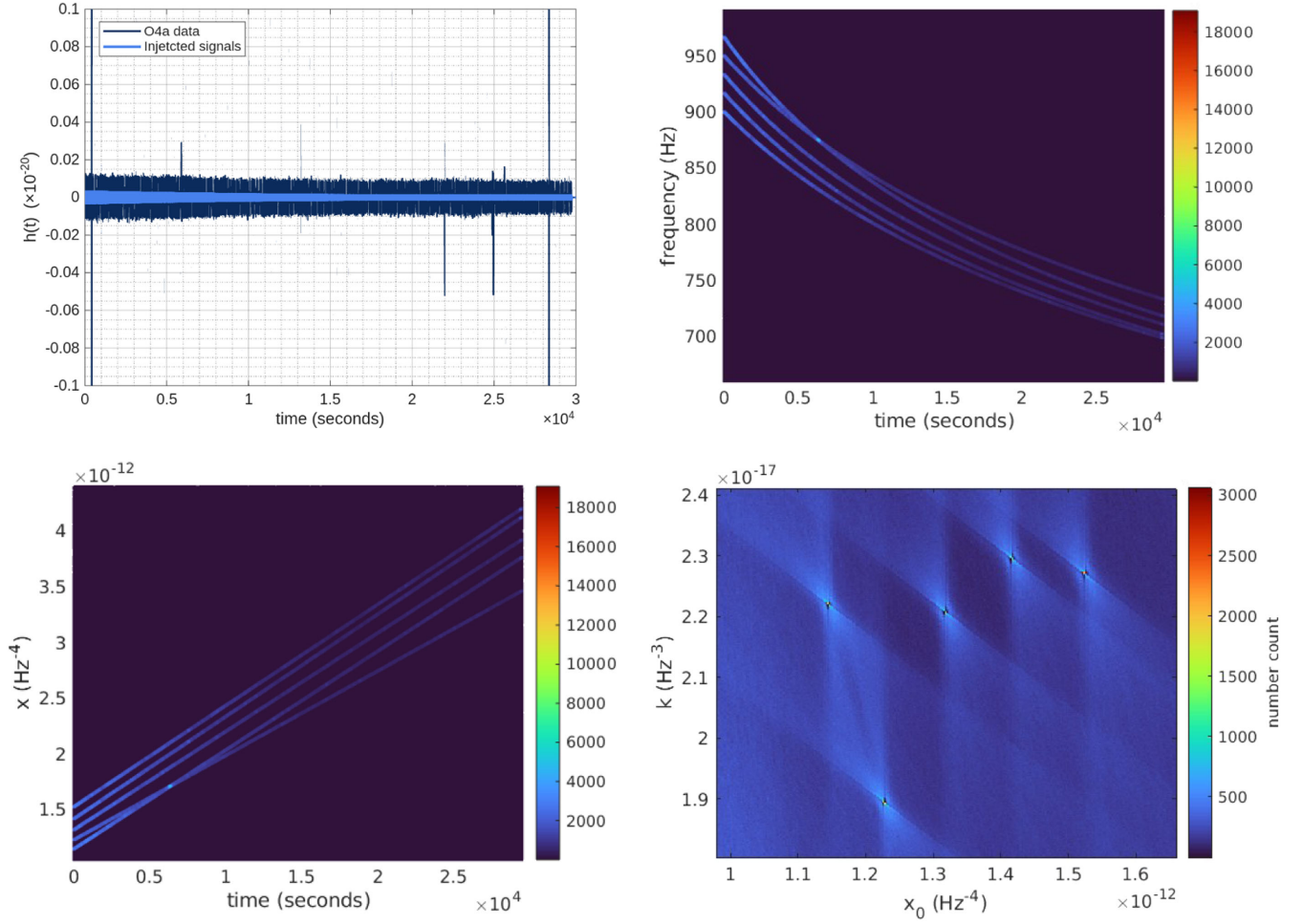


FIG. 2. Workflow of the GFH transform. Top left: raw strain data with injected signals. Top right: original time-frequency peakmap. Bottom left: coordinate-transformed peakmap, where signal trajectories become linear; color indicates normalized power of the peaks (applies also to the original peakmap above). Bottom right: resulting Hough map, corresponding to five simulated signals injected in O4a LIGO Livingston data [49,50] with $f_0 = 900\text{--}1000$ Hz, $\epsilon = (2.5\text{--}3) \times 10^{-3}$, at a distance of 0.1 Mpc and sky location of SN2023ixf.

exceeds a predefined threshold, are identified and collected to form a time-frequency map of selected peaks.

The original FH transform maps these peaks from the time-frequency plane of the detector into the frequency-spindown parameter space of the source, assuming a linear frequency evolution. In this case, the gravitational-wave frequency can be written as a Taylor expansion around the reference time t_0 ,

$$f(t) = f_0 + \dot{f}(t - t_0), \quad (13)$$

where f_0 is the source frequency at t_0 and $\dot{f}$ is the first-order spindown parameter. In the FH framework, each peak (t, f) in the detector's peakmap is mapped into a line in the $(f_0, \dot{f})$ source plane:

$$\dot{f} = -\frac{f_0}{t - t_0} + \frac{f}{t - t_0}. \quad (14)$$

Clusters of intersecting lines in this parameter space correspond to candidate CW signals.

However, this linear approximation breaks down for newborn magnetars or other transient sources with rapid frequency decay, where the frequency evolution instead follows a power law [see Eq. (7)].

The GFH transform overcomes this limitation by introducing a change of variables,

$$x = \frac{1}{f^{n-1}}, \quad x_0 = \frac{1}{f_0^{n-1}}, \quad (15)$$

which linearizes the trajectory. In this (t, x) space, the frequency evolution becomes a straight line,

$$x(t) = x_0 + (n - 1)k(t - t_0). \quad (16)$$

Each peak (t, x) in the transformed peakmap is then mapped into a line in the (x_0, k) space:

$$k = -\frac{x_0}{(n-1)(t-t_0)} + \frac{x}{(n-1)(t-t_0)}. \quad (17)$$

As in the FH, true signals appear as clusters of intersecting lines in this parameter space, but now the method remains efficient even for rapidly evolving sources with power-law frequency decay.

An example of the GFH workflow is shown in Fig. 2. The upper panels display the input strain and its corresponding original peakmap, while the lower panels show the coordinate-transformed peakmap and the resulting Hough map where the clusters indicate potential signal candidates. The clusters appear slanted because the reference time t_0 is set at the start of the dataset.

The Hough maps are built to cover a range of (x_0, k) bins according to two discrete grids. The grid spacings δx_0 and δk are chosen following the procedure described in Ref. [24]. Specifically, δk is set such that the spindown remains constant when moving one frequency bin $\delta f = 1/T_{\text{FFT}}$. The spacing δx_0 is chosen as the smallest step corresponding to the maximum frequency analyzed. With these choices, the grids uniformly cover the (x_0, k) parameter space, ensuring that all signal trajectories are properly sampled in the Hough map.

To uniformly explore the parameter space, they are then partitioned into rectangles, where significant candidates are selected as excesses of counts and are then classified using a critical ratio statistic,

$$\text{CR} = \frac{y - \mu}{\sigma}, \quad (18)$$

where y is the number count in the outlier bin of the map and μ and σ are the mean value and standard deviation computed in the map, to estimate the noise floor. Candidates from different detectors are compared to identify coincident events, further reducing false alarms. Following Ref. [44], candidates are considered coincident if they are close within a defined distance in the (x_0, k) parameter space, computed as

$$d_{\text{coin}} = \sqrt{\left(\frac{x_{0,2} - x_{0,1}}{\delta x_0}\right)^2 + \left(\frac{k_2 - k_1}{\delta k}\right)^2}, \quad (19)$$

where δx_0 and δk are the grid spacings in x_0 and k , respectively.

After GFH identifies candidates, we refine their parameters through a follow-up by making a heterodyne correction which is explained in detail in Ref. [24]. Using the estimated parameters (initial frequency f_0 , spindown $\dot{f}_0$, braking index n , and start time t_0), we heterodyne the original strain to correct the phase evolution, making the signal nearly monochromatic. This allows longer T_{FFT} for better frequency resolution. A refined Hough transform then checks signal consistency and updates the CR. Only

candidates with improved CR are kept for further analysis, enhancing sensitivity and reducing false alarms.

The GFH algorithm was applied to the postmerger analysis of GW170817 [15], demonstrating its capability to search for signals with significant spindown, although no detection was made in that search.

IV. GFH-V2 METHODOLOGY

Building upon the original GFH framework, the updated GFH-v2 pipeline introduces a set of methodological and computational improvements in order to enhance both sensitivity and efficiency. The new implementation uses astrophysical motivated parameter constraints together with significant enhancements to the analysis workflow, resulting in a more sensitive, and computationally optimized search framework.

The following subsections summarize the main developments introduced in GFH-v2.

A. Search parameter space

The choice of the search parameter space is guided by both astrophysical considerations and computational feasibility. The properties of a newborn or rapidly rotating neutron star determine the frequency evolution and amplitude of the emitted gravitational waves, while the relative geometry between the source and the detector, such as the sky position of the source and its orientation with respect to the detector, affects the observability at Earth.

Table I summarizes the key physical parameters relevant to a newborn, rapidly rotating magnetar. The initial frequency f_0 , ellipticity ϵ , and inclination angle ι primarily determine the evolution of the signal, including the FFT coherence time T_{FFT} , the observation time T_{obs} , and the frequency band spanned by the signal.

The parameter ranges are chosen based on astrophysical expectations. The ellipticity $\epsilon \in [3 \times 10^{-4}, 3 \times 10^{-3}]$ spans plausible values for newly born, rapidly rotating magnetars, motivated by magnetic deformation, residual formation asymmetries, and bar-mode instabilities [11,32,51]. The initial frequency $f_0 \in [600, 2000]$ Hz covers the early spindown phase where gravitational-wave emission

TABLE I. Parameter ranges and fixed values used for the injection study.

Parameter	Range/value
Initial frequency, f_0 (Hz)	600–2000
Ellipticity, ϵ	3×10^{-4} – 3×10^{-3}
Inclination angle, ι (deg)	0–180
Braking index, n	5
Neutron star mass, M ($M_\odot$)	1.4
Neutron star radius, R (km)	12
Sky longitude (RA) (deg)	210.91 (equatorial)
Sky latitude (Dec) (deg)	54.31 (equatorial)

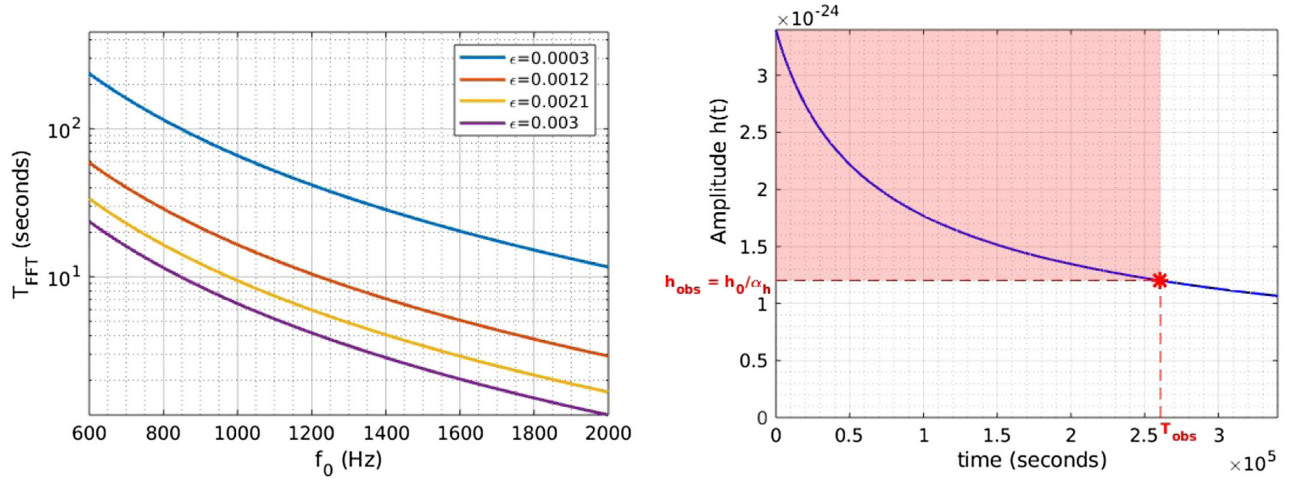


FIG. 3. Left: FFT duration T_{FFT} versus f_0 for different ellipticities [see Eqs. (22) and (23)]. Right: definition of the observation time T_{obs} from the decay of the signal amplitude for a fixed reduction factor α_h shown for $\epsilon = 0.002$ and $f_0 = 900$ Hz.

is strongest [11,33,52,53]. Inclination $\iota \in [0, 180^\circ]$ is sampled uniformly in $\cos \iota$, covering all orientations.

The sky location corresponds to the nearby core-collapse supernova SN 2023ixf, discovered in May 2023 in the Pinwheel Galaxy (M101) at a distance of approximately 6.4 Mpc [54–56]. SN 2023ixf is among the closest Type II supernovae in the past decade, with multiwavelength observations suggesting the possible formation of a magnetar remnant. Its proximity and well-determined position make it a convenient and astrophysically motivated reference target. The O4a data segment used for the injection study does not overlap with the epoch of the supernova event, ensuring that no real signal from this source is present in the analyzed dataset.

Each parameter combination uniquely determines the expected signal evolution. In particular, the coherence time T_{FFT} is set to ensure the signal remains within a single frequency bin (Sec. IV A 1), while the observation time T_{obs} is defined based on the signal amplitude decay (Sec. IV A 2). The neutron star moment of inertia is computed using Eq. (11), assuming $M = 1.4M_\odot$ and $R = 12$ km.

While Table I defines the representative parameter space for this study, the GFH-v2 methodology is general and can be applied to other astrophysically motivated parameter sets. Details of the signal injection procedure used to validate the pipeline are given in Sec. VI B.

1. Coherence time

The coherence time T_{FFT} defines the duration of data segments over which we compute Fourier transforms. The choice of T_{FFT} depends on the expected signal evolution. It must be short enough that the signal's frequency drift, due to $\dot{f}_{\text{gw}}$, remains within a single frequency bin during that time interval, but long enough to limit sensitivity loss. Assuming the frequency drift is approximately linear over

a FFT segment, a condition largely verified for the typical segment durations we employ,² the frequency change during T_{FFT} is

$$\Delta f \simeq |\dot{f}_{\text{gw}}| T_{\text{FFT}}. \quad (20)$$

To keep the signal power within a single frequency bin of width $1/T_{\text{FFT}}$, we require

$$\Delta f \lesssim \frac{1}{T_{\text{FFT}}}. \quad (21)$$

Combining the two expressions gives

$$|\dot{f}_{\text{gw}}| T_{\text{FFT}} \lesssim \frac{1}{T_{\text{FFT}}} \Rightarrow T_{\text{FFT}} \simeq \frac{1}{\sqrt{|\dot{f}_{\text{gw}}|}}. \quad (22)$$

In practice, to ensure that the signal remains confined within one frequency bin throughout the FFT duration, we evaluate $|\dot{f}_{\text{gw}}|$ at the start of the signal ($t = t_0$), where the spindown is largest. This provides a conservative estimate of T_{FFT} .

The spindown rate $\dot{f}_{\text{gw}}$ is related to the ellipticity ϵ through Eq. (2),

$$\dot{f}_{\text{gw}} = -\frac{32\pi^4 G c^2 I f_{\text{gw}}^5}{5c^5}, \quad (23)$$

showing that higher ellipticity or frequency results in a faster spin evolution and hence a shorter coherence time. Figure 3's left panel illustrates the resulting dependence of T_{FFT} on both f_0 and ϵ .

²In practice, the GFH transform follows the full power-law frequency evolution. The linear approximation using only the first-order spindown is employed only to set the maximum T_{FFT} for each segment. Higher-order terms are negligible over the short segment duration, making this approximation safe.

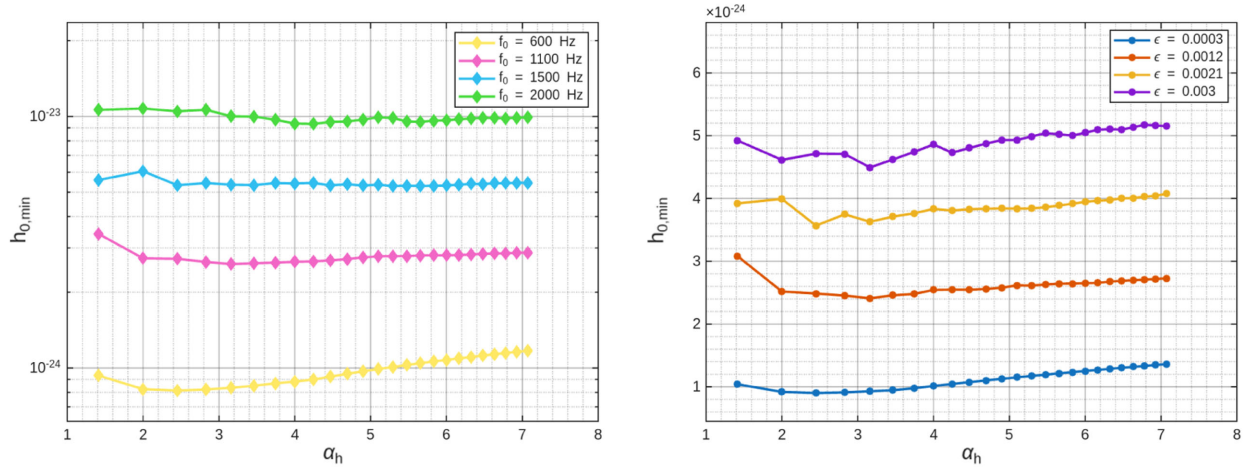


FIG. 4. Left: sensitivity $h_{0,\min}$ as a function of α_h for different initial frequencies f_0 and fixed ellipticity $\epsilon = 0.001$. Right: dependence of $h_{0,\min}$ on α_h for different ellipticities ϵ at a representative $f_0 = 1000$ Hz.

2. Observation time window

In contrast to previous searches where the observation time T_{obs} is often fixed (see, e.g., Ref. [15]), we adopt a strategy that optimizes T_{obs} based on the signal amplitude decay. Specifically, we define T_{obs} as the time it takes for the signal amplitude $h(t)$ to reduce to a chosen fraction of its initial value h_0 , controlled by the amplitude reduction factor α_h :

$$T_{\text{obs}} = t \quad \text{s.t.} \quad h(t) = \frac{h_0}{\alpha_h}.$$

Figure 3's right panel illustrates this definition for a representative case with $f_0 = 900$ Hz, $\epsilon = 0.002$, and a fixed α_h .

To select an optimal value of α_h , we evaluate the sensitivity $h_{0,\min}$ as a function of α_h across several representative frequencies and ellipticities, using the formulation described in Sec. V [Eq. (24)]. As shown in the left panel of Fig. 4, the sensitivity initially improves with increasing α_h as more data are integrated but eventually saturates or worsens as the signal amplitude becomes too weak to contribute effectively. Similarly, the right panel of Fig. 4 further illustrates the dependence of $h_{0,\min}$ on α_h for different ellipticities ϵ . The optimal α_h is therefore chosen as the value that minimizes $h_{0,\min}$, corresponding to the best achievable sensitivity for a given f_0 and ϵ . The variation in $h_{0,\min}$ is moderate and in some cases shows a weakly defined minimum that determines the optimal value of α_h . In cases where the dependence is relatively weak, this result indicates that shorter observation times can be safely used without significantly affecting the sensitivity, thereby reducing computational cost. In other cases, the minimum is more pronounced, and selecting the optimal α_h leads to a non-negligible improvement in sensitivity.

The observation times T_{obs} derived from this optimization are shown in Fig. 5, where each point corresponds to the duration associated with the optimal α_h . This approach

refines the search strategy by excluding data with negligible signal amplitude, thereby maintaining sensitivity while reducing computational cost.

The frequency band for the analysis is then chosen according to this duration: starting from the initial frequency f_0 , we include frequencies down to the value reached at T_{obs} due to the spindown corresponding to the chosen f_0 and ϵ . This ensures that only the portion of the data contributing meaningfully to the detection is analyzed.

B. Implementation of the GFH-v2 algorithm

The GFH-v2 algorithm significantly differentiates from the old GFH [24] and, actually, is completely new for several aspects. One big difference concerns the preprocessing of the detectors' data. Originally, the blocks of FFTs from the SFDB files, which are typically thousands of seconds long, were reprocessed and divided in shorter

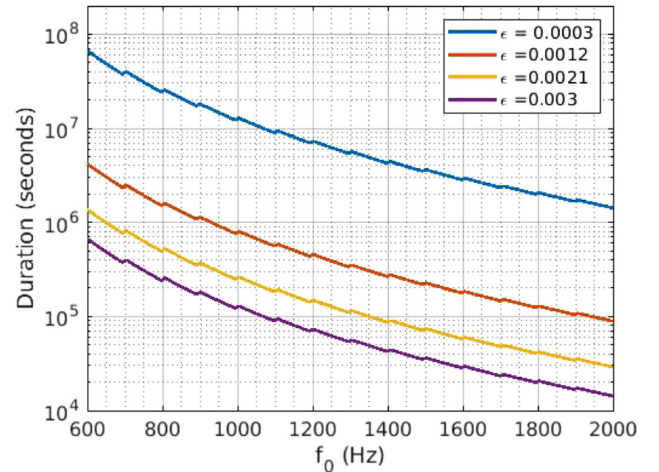


FIG. 5. Observation time T_{obs} as a function of f_0 for different ellipticities, corresponding to the optimal α_h derived from Fig. 4.

Fourier-transformed segments with typical length of tens of seconds [see Eq. (22) for the determination of T_{FFT}] and cut to the desired frequency range. Possible injections of simulated signals for validation purposes were done on that set of reduced FFTs, and the corresponding peakmap was created by identifying significant local maxima in the normalized power spectrum of each FFT segment (see Sec. III). In the GFH-v2, the blocks from the SFDB are directly combined together and inverse Fourier transformed to create a subsampled, complex reduced-analytic time series that covers the frequency range spanned by the signal during T_{obs} (from f_0 down to the value reached due to spindown; see Sec. IV A 2). This format is analogous to the Band-sampled data (BSD) [57], widely used in CW searches. However, the additional cleaning steps applied in standard BSD, which are designed to remove persistent narrowband artifacts in quasimonochromatic CW searches, are not applied here, since the signal evolves over a broader frequency range. This approach allows all the manipulations, like injection of signals or generation of the peakmap, to be done easily exploiting the existing libraries and making the code easily accessible to the gravitational-wave community [58].

The other big change concerns the implementation of the core of the GFH-v2 transform itself. In the original GFH, each peak from the peakmap was transformed into a line in the Hough space through an algorithm based on a double nested loop. The first loop spans between the different times in the peakmap, selecting the peaks happening at those times, while the second loop writes on the Hough map spanning through all the values of the k parameter according to a discrete grid. The main limitations of this algorithm are its computational efficiency and the fact the loops for different peaks could access the same memory locations for writing, limiting the possibility to parallelize the operation and to exploit modern computing architectures. In the GFH-v2 implementation, the loop over time is removed. The loop now runs over the grid in k : each value corresponds to a different slope of the signal in the linearized peakmap, according to Eq. (16). For each k value, the whole peakmap is integrated along the corresponding slope by combining one linear transformation and the computation of an histogram along the grid of transformed frequencies x_0 . In this study, the histogram counts are unweighted (each peak contributes a value of one); the use of weights is planned for future improvements.

The result of the histogram fills one column in the Hough map at the location corresponding to the selected k value. This new implementation of the transform is made by means of highly optimized functions, which compute the 1D histograms using buffer arrays to speed up memory access. Compared to the original implementation, where the Hough map was computed through a double nested loop over time indexes and k values with direct memory access, the GFH-v2 avoids the outer time loop and

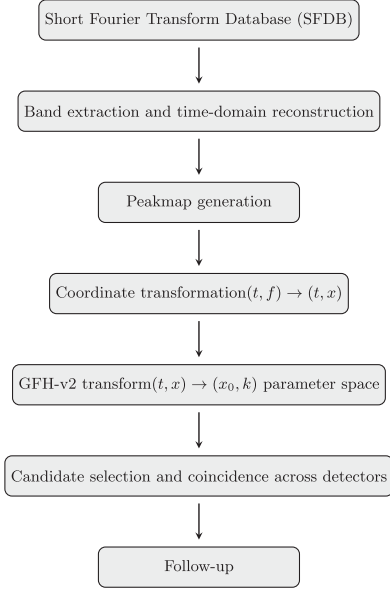


FIG. 6. Schematic view of the GFH-v2 pipeline workflow.

efficiently integrates the entire peakmap along each k value. Quantitative tests show that the computing time is reduced by approximately 1 order of magnitude. A detailed comparison of the old and new implementations, including computing times as a function of the number of cores, is provided in Appendix A. The implementation details and the actual code for the new GFH-v2 are documented in Ref. [58]. Moreover, each different k value of the grid is mapped in a different column in the Hough map, so the loop can be performed in parallel exploiting hyperthreading or multicore CPUs. While the pipeline can also be executed on graphical processing units (GPUs) [59], the current search is efficiently performed on standard CPU resources; GPU execution is available if needed for future searches with higher computational demands.

A schematic representation of the complete GFH-v2 workflow is shown in Fig. 6, summarizing the main processing steps from the input SFDB to the follow-up [58] (see Sec. III and Ref. [24] for details on the heterodyne-based candidate refinement).

V. THEORETICAL SENSITIVITY

Theoretical sensitivity provides a baseline to evaluate the performance of the GFH-v2 pipeline and to quantify the impact of detector noise and analysis parameters. For tCW searches from newborn magnetars, the standard CW sensitivity expression can be generalized to account for the rapidly evolving frequency. The resulting minimum detectable strain is derived in Ref. [60],

$$h_{0,\min} = \mathcal{A}_{\min} f_0^2, \quad (24)$$

where

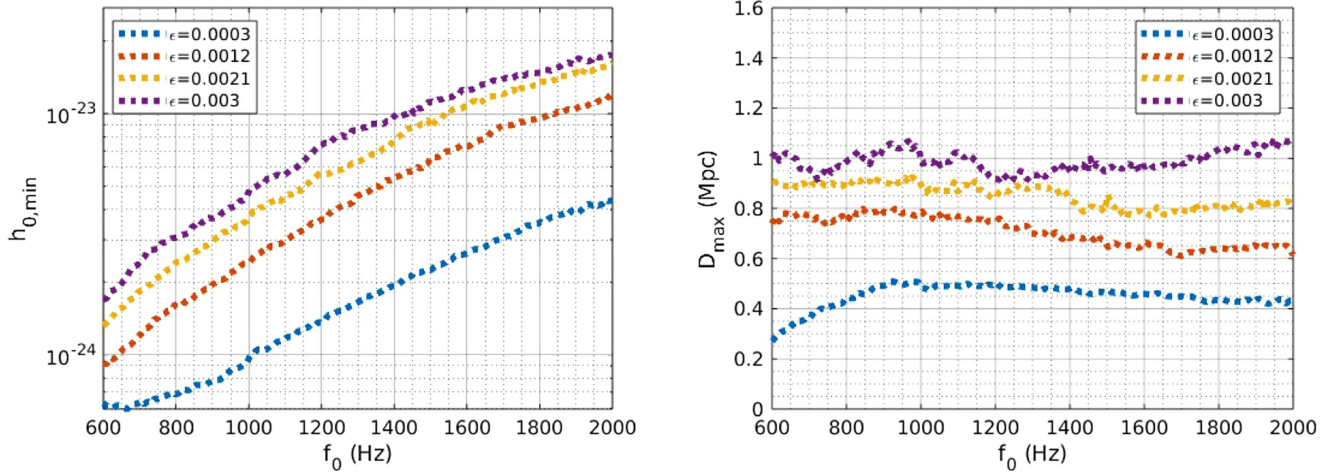


FIG. 7. Theoretical sensitivity obtained using full O4a LIGO data for the Livingston and Hanford detectors [49,50], taking the maximum PSD value between the two detectors at each frequency to ensure a conservative estimate [see also Fig. 8 (left panel) for the PSD overview]. Left: minimum detectable strain amplitude $h_{0,\min}$ as a function of the signal initial frequency f_0 . Right: corresponding maximum detectable distance $D_{\max}$ as a function of f_0 . Both panels refer to $\Gamma = 90$ and a critical ratio threshold of $CR_{\text{thr}} = 7$.

$$\begin{aligned} \mathcal{A}_{\min} = & \sqrt{\frac{2\pi}{2.4308}} \frac{N_{\text{eff}}^{1/4}}{\sqrt{T_{\text{FFT}}}} \left(\frac{p_0(1-p_0)}{p_1^2} \right)^{1/4} \\ & \times \left(\sum_{i=1}^{N_{\text{seg}}} \frac{f_i^4 (F_+ A_+ + F_{\times} A_{\times})^2}{S_n(f_i)} \right)^{-1/2} \\ & \times \sqrt{CR_{\text{thr}} - \sqrt{2} \text{erfc}^{-1}(2\Gamma)}. \end{aligned} \quad (25)$$

Note that $\mathcal{A}_{\min}$ carries units of Hz^{-2} , which compensate the explicit f_0^2 factor in Eq. (24), ensuring that the strain amplitude $h_{0,\min}$ remains dimensionless. Here, $N_{\text{eff}} = T_{\text{obs,eff}}/T_{\text{FFT}}$ is the number of effective segments, where $T_{\text{obs,eff}}$ is the total duration of science data within the selected observation time T_{obs} [50]. With interlaced FFTs, the total number of FFTs is $N_{\text{seg}} = 2N_{\text{eff}}$. The quantity p_0 represents the probabilities of selecting a noise peak above a peak-selection threshold θ (typically $\theta = 2.5$ [61]) applied to the normalized periodogram in each FFT, whereas p_1 represents the linear change in the peak-selection probability when a weak signal of amplitude λ is present ($p_\lambda = p_0 + p_1\lambda$). They are given by

$$p_0 = e^{-\theta} - e^{-2\theta} + \frac{1}{3}e^{-3\theta} \quad (26)$$

and

$$p_1 = \theta \left(\frac{1}{2}e^{-\theta} - \frac{1}{2}e^{-2\theta} + \frac{1}{6}e^{-3\theta} \right) + \frac{1}{4}e^{-2\theta} - \frac{1}{9}e^{-3\theta}. \quad (27)$$

The sum in Eq. (25) extends over all N_{seg} time segments where f_i denotes the instantaneous signal frequency in the

i -th FFT segment.³ The factors F_+ and $F_{\times}$ are the detector response functions [38], while A_+ and $A_{\times}$ are defined as $A_+ = \frac{1+\cos^2(i)}{2}$ and $A_{\times} = \cos(i)$. The noise power spectral density is denoted by S_n .

The factor CR_{thr} defines the critical ratio threshold for candidate selection, balancing sensitivity and false-alarm probability. In our tests with simulated signals, we adopt $CR_{\text{thr}} = 7$, which provides a good compromise between the two (see Appendix C). While in principle the optimal CR_{thr} could depend on analysis parameters such as T_{obs} and T_{FFT} due to differences in the number of effective trials, a simple theoretical estimate is difficult. We therefore determined the threshold empirically via injection studies, ensuring a false-alarm probability below 1% across the parameter space. In a real search, CR_{thr} could be adjusted for different follow-up strategies, but always following the same procedure to control the false-alarm rate. Finally, Γ denotes the chosen confidence level, i.e., the fraction of repeated trials in which a signal with amplitude $h_{0,\min}$ would be recovered, and erfc^{-1} is the inverse complementary error function.

The corresponding maximum distance can be obtained by equating the gravitational-wave strain, Eq. (3), to the sensitivity, Eq. (24), obtaining

$$D_{\max} = \frac{4\pi^2 G}{c^4} \frac{I\epsilon}{\mathcal{A}_{\min}}. \quad (28)$$

Figure 7 shows the theoretical sensitivity of the GFH-v2 pipeline computed using these equations, with real O4a

³In previous works [24,60], the quantity $\mathcal{F}_i$ was introduced to denote the scaling of the signal amplitude with frequency. For newborn magnetars, the signal amplitude scales as f_i^2 , so we directly replace $\mathcal{F}_i^2$ with f_i^4 here for clarity.

data [49,50] and actual search parameters as inputs. The left panel shows the minimum detectable strain $h_{0,\min}$, while the right panel shows the corresponding maximum distance $D_{\max}$ as a function of the initial frequency f_0 for a few representative ellipticities. For this estimate, we use power spectral densities (PSDs) derived from the full O4a dataset for both LIGO detectors. The PSDs are computed from the SFDB data [46] by averaging the power spectra of the individual FFT segments belonging to science time, applying basic data-quality vetoes and a weighted averaging procedure that reduces the influence of noisier spectra [44]. At each frequency we then take the maximum PSD value between LIGO Hanford and LIGO Livingston to obtain a conservative sensitivity estimate.⁴

The trend of these plots can be understood from the underlying sensitivity equations Eqs. (24)–(28). The curve for $h_{0,\min}$ generally increases with frequency due to the f_0^2 scaling in Eq. (24). However, the overall trend results from a combination of competing effects: higher ellipticity increases the signal amplitude but also shortens the optimal coherence time T_{FFT} (see Sec. IV A 1), which degrades the sensitivity. The net outcome of these opposing factors is the behavior observed in the plots. The impact of the real detector PSDs, which are not flat, introduces small frequency-dependent variations in the sensitivity, producing small-scale fluctuations in the curves. These PSD-induced variations are smaller than the main f_0^2 -driven trend and do not qualitatively alter the observed sensitivity behavior.

VI. EMPIRICAL SENSITIVITY

The theoretical sensitivity derived in the previous section assumes data follow a Gaussian distribution. Although this assumption can be reasonable to a first approximation, typical detector data often show non-Gaussianity both in time and in frequency. It is thus important to estimate the search sensitivity in a more empirical way, which takes in full consideration the characteristics of the data.

To empirically estimate the sensitivity of the pipeline, we performed simulated signal injections into O4a data across representative values of frequency and ellipticity. For each injection set, we determined the minimum detectable strain amplitude (or equivalently, the maximum distance) as that strain such that 90% of the signals were successfully recovered.

A. O4a data characteristics

Our test dataset is drawn from the first portion of the LIGO-Virgo-KAGRA fourth observing run (O4), hereafter O4a, spanning May 24, 2023, to January 16, 2024 [49,50]. Relative to O3, O4a marked a significant advance in

instrument performance, with substantial upgrades to the interferometers [62].

During this period, the Virgo detector [63] was not operating due to commissioning activities aimed at improving its sensitivity. KAGRA [64] and GEO 600 [65] were operating but remained less sensitive than the LIGO instruments [66] and thus, the present study uses only data from the two LIGO detectors (Hanford and Livingston). Figure 8's left panel shows the average noise power spectral densities of the two detectors computed over the full O4a dataset.

We selected a 20-day window starting from August 20, 2023 [Modified Julian Date (MJD): 60176.991] as the input data for the empirical sensitivity evaluation. The GFH-v2 pipeline determines the effective observation time T_{obs} individually for each signal, based on its initial frequency f_0 and ellipticity ϵ (see Fig. 5). Only this effective duration is used in the analysis. For the upper ellipticity subinterval considered in the empirical sensitivity study (Sec. VID), the chosen 20-day segment fully contains the evolution of the signals. The science segments within this window [50] are shown in the right panel of Fig. 8.

B. Signal injections

We performed simulated signal injections into the time-domain reduced-analytic series derived from O4a SFDB data, as described in Sec. IV B, using the parameter ranges defined in Sec. IV A (Table I). The full ellipticity range ($\epsilon \in [3 \times 10^{-4}, 3 \times 10^{-3}]$) was divided into five representative subintervals, each spanning comparable logarithmic intervals to follow the gradual change in signal amplitude and spindown behavior across the full range while keeping the computational cost manageable. For each subinterval, and at a fixed source distance, injections were carried out in steps of 10 Hz, with approximately 150 signals uniformly distributed in each frequency interval across the full f_0 range.⁵ The ellipticity for each signal is drawn randomly from a uniform distribution within the selected subinterval. Other physical parameters, including the inclination angle and polarization angle, are sampled from uniform distributions within their respective ranges (e.g., $\cos i$ uniformly in $[-1, 1]$). This procedure was repeated for different source distances to trace the detection horizon.

For the empirical sensitivity evaluation (Sec. VID), only the upper ellipticity subinterval ($\epsilon \in [2.5 \times 10^{-3}, 3 \times 10^{-3}]$) is used, corresponding to the strongest signals. The effective observation time T_{obs} for each injected signal is determined by its f_0 and ϵ (see Fig. 5), ensuring that the signal is fully contained within the 20-day O4a data window described in Sec. VIA. The FFT coherence times T_{FFT} were set consistently with the definitions in Sec. IVA.

⁴This calculation provides a general reference sensitivity of the pipeline using the full O4a dataset and is not tied to the specific data segment used in the injection studies presented in Sec. VI.

⁵The exact number of injections varies between 120 and 180, depending on the frequency band; additional injections were performed in certain frequency intervals.

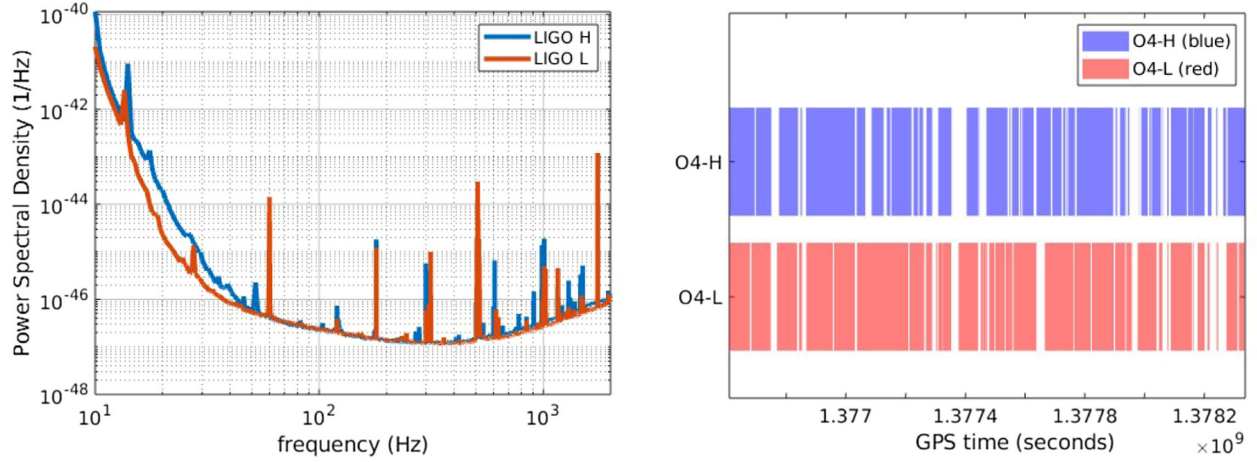


FIG. 8. Overview of the LIGO O4a dataset used in this study. Left: average noise spectral densities of both detectors computed over the full O4a dataset. Right: science segments from the two LIGO detectors (Hanford and Livingston) over the 20-day analysis window starting on August 20, 2023, which is used for the injection studies in Sec. VID.

All injections are assumed to start at the beginning of the dataset for simplicity. In more realistic scenarios, the signal start time may not coincide with the beginning of the analyzed data. Allowing for different starting times introduces an additional trials factor, which can slightly reduce sensitivity. In future work, we plan to scan over a discrete grid of possible start times, choosing a step size that balances parameter-space coverage, computational cost, and minimal sensitivity degradation.

C. Candidate selection

The injected datasets were analyzed with GFH-v2, and candidates were selected from the resulting Hough maps. To systematically cover the parameter space, the Hough map was divided as follows: the x_0 parameter was divided into a number of blocks determined by the number of injections and width of the spindown band covered by the signal.⁶ The k axis was divided such that each block is approximately square shaped, containing the same number of bins along x_0 and k . Within each block, the bin with the highest map count was selected as a candidate. A second candidate was chosen only if it was sufficiently far away from the first (in this case, by six bins in x_0) to reasonably select candidates of different origin.

Coincidence checks were performed across detectors and with respect to the injected parameters to identify common candidates. Since only x_0 and k were varied in this study, coincidences were evaluated using a threshold of $d_{\text{coin}} = 2$. In previous implementations, additional parameters such as

braking index and sky position were included in the search, requiring a higher threshold.

D. Detection efficiency and sensitivity

Following the candidate selection, we determine the detection efficiency for each signal initial frequency, defined as the fraction of injected signals that are successfully recovered with $CR \geq CR_{\text{thr}}$ and coincident across the detectors (see Appendix C for details on how CR_{thr} was chosen using injection tests on real O4a data).

For this analysis, we restrict the study to the upper ellipticity subinterval ($\epsilon \in [2.5 \times 10^{-3}, 3 \times 10^{-3}]$) defined in Sec. VIB, which corresponds to the strongest signals in the considered parameter space. Lower ellipticities result in proportionally smaller detectable distances without significantly affecting the efficiency curves. We note that averaging over this small ellipticity subinterval produces only minor differences in the resulting sensitivity estimates.⁷

To estimate the empirical maximum detectable distance, D_{max} , we identify the point at which the detection efficiency curve crosses the 90% recovery level. For each frequency, injections are sorted by increasing distance, and their corresponding efficiencies are evaluated. The first distance value at which the efficiency falls below 90% is taken as the upper bracketing point, while the immediately preceding distance value, that yields an efficiency above 90%, is taken as the lower bracketing point. The crossing

⁶In the injection study, the number of blocks along the x_0 axis was scaled with the number of injected signals to control the candidate density. In a real search, a fixed partitioning scheme is used instead (e.g., 100 blocks in x_0).

⁷In practice, results are always evaluated separately for each ellipticity subinterval rather than averaged over the full range ($\epsilon \in [3 \times 10^{-4}, 3 \times 10^{-3}]$), ensuring that the dependence on ϵ is properly captured. Here, we present the sensitivity for the upper subinterval to illustrate the maximum detection horizon achievable by the pipeline. In a real search, upper limits are also computed separately for each ellipticity subinterval.

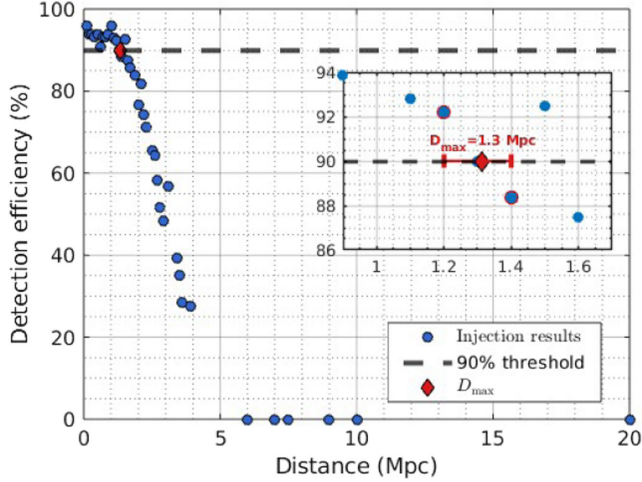


FIG. 9. Detection efficiency curve for a representative frequency ($f_0 = 1400$ Hz) in the upper ellipticity subinterval, $\epsilon \in [2.5 \times 10^{-3}, 3 \times 10^{-3}]$, using $CR_{\text{thr}} = 7$. The maximum detectable distance, D_{max} , is determined by linear interpolation at the 90% recovery level, with horizontal bars representing the errors derived from the bracketing distances.

point, D_{max} , is then obtained by linear interpolation between these two values. This procedure is based directly on the discrete set of injection results and does not assume any particular functional form for the efficiency curve. Although one could estimate the 90% crossing using a smooth fit to the data, the approach adopted here avoids extrapolation beyond the data points and provides a simple and data-driven estimate. The associated uncertainty on D_{max} is derived from the spacing between these neighboring distance points, defining asymmetric error bars.

Figure 9 illustrates a representative example of a detection efficiency curve for a single frequency, showing how D_{max} and its associated uncertainty are determined.

Figure 10 presents the comparison between the empirical maximum detectable distances obtained from injection studies and the corresponding theoretical sensitivity estimates across the analyzed frequency range. Overall, the empirical sensitivity follows the theoretical trend, although deviations up to a factor of ~ 2 are observed in certain frequency bands. In some bands, the empirical D_{max} falls below the theoretical prediction, typically in regions affected by strong spectral features, such as suspension violin modes and their harmonics [67] (as highlighted by the shaded gray regions in Fig. 10). These disturbances raise the local noise level and reduce the recovery efficiency, leading to a lower measured sensitivity relative to the theoretical expectation.

Conversely, at some frequencies, the empirical sensitivity exceeds the theoretical one, sometimes by factors of 1.5–2. One possible explanation is that the theoretical sensitivity curve is based on a conservative assumption: at each frequency, it uses the maximum of the LIGO Hanford

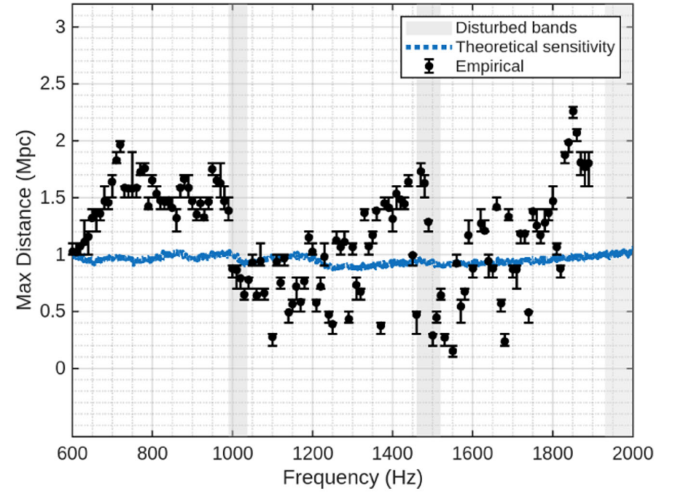


FIG. 10. Comparison between the empirical maximum distance obtained from signal injections and the theoretical sensitivity estimate across the analyzed frequency range, for the upper ellipticity subinterval $\epsilon \in [2.5 \times 10^{-3}, 3 \times 10^{-3}]$, using a 90% confidence level and $CR_{\text{thr}} = 7$. The theoretical sensitivity here uses a 10-day PSD corresponding to the effective duration of the injections in the upper ellipticity subinterval, taking the maximum value between H1 and L1 detectors to remain conservative. The shaded gray regions indicate frequency bands affected by instrumental disturbances [67], which lead to a degradation of the empirical sensitivity.

(H1) and LIGO Livingston (L1) detector PSDs. This choice effectively corresponds to adopting the noisier of the two detectors at that frequency and therefore provides a conservative estimate of the noise level. As a result, the predicted sensitivity is slightly underestimated.

Overall, the comparison indicates that the empirical results are consistent with theoretical expectations at the order-of-magnitude level, capturing the main trends while naturally reflecting real data variations.

VII. CONCLUSION

In this work, we have presented an enhanced methodology for the detection of tCW signals using the updated GFH-v2 pipeline. This approach introduces astrophysically motivated parameter constraints, optimized choices of coherence and observation times, and computational improvements that significantly enhance both sensitivity and computational efficiency. Using real O4a LIGO data and simulated tCW signals describing newborn magnetar emission, we demonstrated the pipeline's ability to recover signals over a broad parameter space and to produce empirical sensitivities consistent with theoretical expectations at the order-of-magnitude level. These results establish GFH-v2 as a robust and efficient framework for directed searches for tCW signals in current and future observing runs.

The pipeline has already been applied in a real directed search targeting the nearby core-collapse supernova SN2023ixf, detected in May 2023. This analysis was carried out using data from LIGO Engineering Run 15 (ER15), which was conducted shortly before the start of the O4 observing run. We used the subset of ER15 data segments approved for LIGO-Virgo-KAGRA Collaboration (LVK) publications [50]. The source localization provided by electromagnetic observations enables a well-constrained directed search using the framework developed in this study. Results from that analysis will be presented in a forthcoming publication.

In future work, we plan to extend this study in several directions. First, we will relax the assumption that all signals start at the same time and test different start times to see how this affects detection efficiency. We also plan to include a wider range of magnetar spindown models, considering different braking indices [39] and possible fallback accretion effects, to check how robust the method is under various physical conditions [7,29,30]. Additionally, we plan to implement an adaptive Hough approach, where the contribution of each time segment is weighted according to the detector noise level and the beam pattern, following the method described in Refs. [18,44].

Moreover, a promising direction is to develop a hybrid pipeline that combines GFH-v2 with a machine-learning based tCW search. Recent studies have demonstrated that convolutional neural networks can efficiently identify tCW signals and generate reliable triggers at very low computational cost [68,69]. In this framework, the ML pipeline can rapidly scan large portions of parameter space to generate candidate triggers, which are then followed up by GFH-v2 for a detailed and sensitive analysis. This approach could enable efficient all-sky searches for long transient signals, combining speed and sensitivity.

Finally, the GFH-v2 framework can also be applied to search for other long-duration sources, such as postmerger remnants, using data from future observing runs with the advanced LIGO, Virgo, and KAGRA detectors.

Overall, the results presented here demonstrate that the GFH-v2 pipeline provides a sensitive, efficient, and astrophysically informed framework for long-transient gravitational-wave searches, representing an important step toward probing the physics of newly born magnetars and other rapidly evolving compact objects with gravitational waves.

ACKNOWLEDGMENTS

This work is partially supported by ICSC—Centro Nazionale di Ricerca in High Performance Computing, Big Data and Quantum Computing, funded by European Union—NextGenerationEU. This research has made use of data or software obtained from the Gravitational Wave Open Science Center ([70]), a service of LIGO Laboratory, the LIGO Scientific Collaboration, the Virgo Collaboration, and KAGRA. LIGO Laboratory and Advanced LIGO are funded

by the United States National Science Foundation (NSF) as well as the Science and Technology Facilities Council (STFC) of the United Kingdom, the Max-Planck-Society (MPS), and the State of Niedersachsen/Germany for support of the construction of Advanced LIGO and construction and operation of the GEO600 detector. Additional support for Advanced LIGO was provided by the Australian Research Council. Virgo is funded, through the European Gravitational Observatory (EGO), by the French Centre National de Recherche Scientifique (CNRS), the Italian Istituto Nazionale di Fisica Nucleare (INFN), and the Dutch Nikhef, with contributions by institutions from Belgium, Germany, Greece, Hungary, Ireland, Japan, Monaco, Poland, Portugal, and Spain. The construction and operation of KAGRA are funded by Ministry of Education, Culture, Sports, Science and Technology (MEXT), and Japan Society for the Promotion of Science (JSPS), National Research Foundation (NRF) and Ministry of Science and ICT (MSIT) in Korea, and Academia Sinica (AS) and the Ministry of Science and Technology (MoST) in Taiwan. We also acknowledge the Amaldi Research Center, for the clusters hosted in Rome INFN, where we have stored the LIGO/Virgo data used in this research and run part of the present analysis. We thank the INFN-CNAF computing staff for the resources we have used in this analysis and for their constant support. We further acknowledge Iuri La Rosa and Luca Rei for their constructive review and insightful feedback for the pipeline.

DATA AVAILABILITY

The data that support the findings of this article are publicly available [49,50].

APPENDIX A: QUANTITATIVE COMPARISON OF GFH IMPLEMENTATIONS

Figure 11 shows a comparison of the computing times for the original GFH and the GFH-v2 implementations. The test dataset covers an 800-Hz-wide frequency band and a 9 h time window, analyzed with $T_{\text{FFT}} = 2$ s. The tests were performed on an Intel Xeon E5-2620 machine (16 cores, 2.1 GHz, hyperthreading). While the original implementation runs on a single thread, GFH-v2 exploits multithreading.

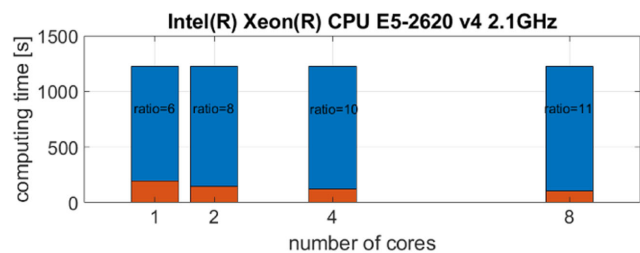


FIG. 11. Computing time comparison between the old GFH and GFH-v2 implementations. Blue bars: old code (single thread). Red bars: GFH-v2 (multithreaded).

The blue and red bars indicate the computing time for the old and new codes, respectively, as a function of the number of cores used. The results demonstrate that GFH-v2 achieves a speedup of roughly 1 order of magnitude compared to the original implementation.

APPENDIX B: THEORETICAL SENSITIVITY EQUATION

In this appendix, we give some details on the derivation of the sensitivity formula, Eq. (25), directing the reader to Ref. [60] for more details. The sensitivity computation consists of several steps and starts from two basic quantities: the probability of selecting a noise peak (local maxima above the threshold θ) in the peakmap, $p_0 = P(\theta; 0)$, given by Eq. (26), and the probability of selecting a peak when a signal with spectral amplitude λ (in units of the equalized spectra) is present, $p_\lambda = P(\theta; \lambda)$. Details of the original computation, for CW signals, can be found in Ref. [44], while its extension to long-transient signals is given in Ref. [24]. Under the assumption of Gaussian noise, the probability of selecting a peak in the peakmap in presence of a signal with spectral amplitude λ is

$$p_\lambda = \int_{\theta}^{\infty} p(x; \lambda) \left(\int_0^x e^{-x'} dx' \right)^2 dx, \quad (\text{B1})$$

where x is the value of the noise spectrum. This equation corrects an error in Ref. [44] [Eq. (19)], where the inner integral had as argument $p(x; \lambda)$, instead of $p(x; 0)$. By computing the integral of Eq. (B1), under the small signal approximation, we find

$$p_\lambda = p_0 + p_1 \lambda, \quad (\text{B2})$$

where p_0 is given by Eq. (26) and

$$p_1 = \theta \left(\frac{1}{2} e^{-\theta} - \frac{1}{2} e^{-2\theta} + \frac{1}{6} e^{-3\theta} \right) + \frac{1}{4} e^{-2\theta} - \frac{1}{9} e^{-3\theta}, \quad (\text{B3})$$

which corresponds to Eq. (27). The expression for the minimum detectable λ now reads [cf. Eq. (66) in Ref. [44]]

$$\lambda_{\min} = \sqrt{\frac{p_0(1-p_0)}{N_{\text{eff}} \times p_1^2}} (CR_{\text{thr}} - \sqrt{2} \text{erfc}^{-1}(2\Gamma)). \quad (\text{B4})$$

By following the same steps as in Ref. [44] and considering the case of a signal with finite duration, we arrive at the expression for the theoretical sensitivity of the GFH-v2 algorithm, given in Eq. (25). Note that Eq. (26) replaces Eq. (34) of Ref. [24], not only because of the difference in the expression for the coefficient p_1 but also because in Eq. (25) the dependence on the detector radiation pattern is explicit, while in Ref. [24], an average

over time (and the source parameters) is assumed. This is not correct when the signal duration is smaller than about one sidereal day, in which case no time average can be taken.

APPENDIX C: SELECTION OF THE CRITICAL RATIO THRESHOLD

The critical ratio threshold, CR_{thr} , determines the balance between search sensitivity and false-alarm control in the candidate selection stage.

A lower threshold increases the number of recovered signals but also raises the rate of false alarms, while a higher threshold reduces false alarms at the cost of missing weaker signals.

To identify an optimal choice, we performed a set of injection tests on real O4a LIGO data at a fixed source distance of 1000 Mpc, using the same procedure as described in Sec. VI, analyzing the recovery fraction which is in this case the corresponding false-alarm rate for different values of CR_{thr} .

Figure 12 shows the false-alarm fraction versus frequency for different CR_{thr} values. As expected, the false-alarm rate decreases rapidly with increasing threshold. We found that values below $CR_{\text{thr}} \approx 5$ lead to a significant rise in false coincidences, while values above 7 begin to substantially reduce the recovery efficiency for weaker signals.

Based on these tests, we adopted $CR_{\text{thr}} = 7$ as a compromise providing a stable false-alarm rate across the full frequency range while maintaining good detection efficiency.

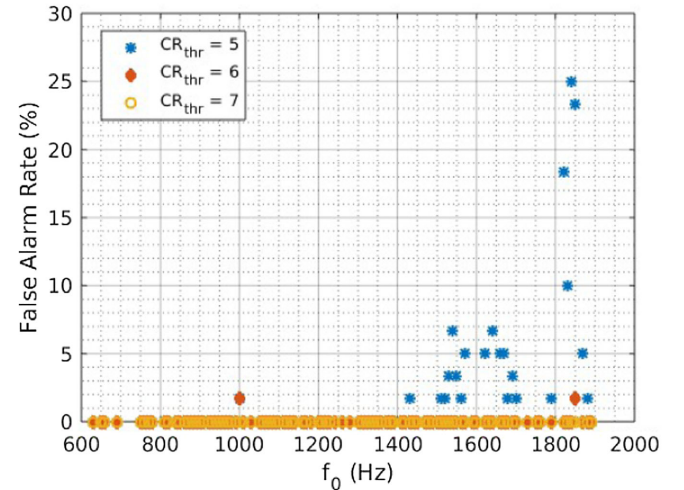


FIG. 12. False-alarm rate as a function of frequency for different critical ratio thresholds CR_{thr} . Most points are zero for higher thresholds (6 and 7), illustrating that the chosen $CR_{\text{thr}} = 7$ effectively suppresses false alarms across nearly all f_0 , whereas $CR_{\text{thr}} = 5$ shows a non-negligible false-alarm fraction.

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