Progress in the Search for Continuous Gravitational Waves from Binary Pulsars and a Proposed Approach to Machine-Learning Detection

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The goal of this paper is to both document our progress towards developing a software-injection algorithm which can be used to analyze continuous waves from binary sources in real data noise, and to provide a clear and accessible discussion of the way continuous wave data can be processed using spectrograms, which display data in the time-frequency domain, and power spectra, which utilize the frequency-power domain. We consider the ways that waves from binary sources differ from isolated ones when viewed in these different parameter spaces, and the variation in binary source waves that we must consider in our detection procedures. This is an important prerequisite for understanding the Rome group's existing continuous wave search algorithm, which relies on the characterization of binary source waves as a 'double horn' shape which appears firstly in the wave's power spectrum. We also foresee the necessity of a machine learning algorithm to be used to eventually distinguish between real detected signals and false positives which are the result of instrumental artefacts. We thus discuss a potential search method that such an algorithm could utilize to search for binary waves in the frequency domain.

I. INTRODUCTION

In September of 2015, the first detection of gravitational waves was confirmed by the advanced LIGO interferometers [2]. This detection, due to the coalescing of two black holes, established the blossoming of the field of gravitational wave astronomy. Using gravitational wave detections, we expect to be able to observe features of astrophysical systems invisible to us using only electromagnetic observation techniques. In addition to the transient waves of the type detected in 2015, continuous waves form an undetected, yet auspicious class of signals. Continuous gravitational waves are predicted to be emitted by rapidly rotating Neutron stars (NSs), both from isolated cases and from binary pairs of NSs [3]. The Rome group at La Sapienza focuses on the detection of binary pairs of neutron stars. This forms a promising class of signals, as an order of 10^8 of these objects are expected to exist in the Galaxy [1]. However, traditional detection methods used for transient waves are not effective for detecting continuous waves from binary pulsars. This is partially due to the weakness of such continuous signals, and thus the increased integration time necessary to recover them. Therefore, one major challenge in these continuous wave detections is accounting for computational efficiency and minimizing computational cost.

Another challenge faced is the strength of the detector noise, including instrumental lines, which obstruct true detections by suggesting many false positives. In existing literature, the Rome group has successfully designed an algorithm that can detect injected binary signals in Gaussian white noise, but which is not perfectly able to distinguish signal peaks from those due to data noise [5]. Thus, in the presence of instrumental lines this algorithm would return false detections. This has motivated a quest for a machine learning algorithm that could train the algorithm when a detection is false through repeated trials and methods of artificial intelligence.

In this paper, we outline a process that has been refined and simplified to inject simulated signals from binary pulsars into Gaussian noise, and eventually real detector noise and data. Developing this algorithm is a preparatory step to testing a future machine algorithm to do detections in the time-frequency domain in both real and whitened noise.

We also discuss an alternate method with which a machine learning algorithm could work on detection in a frequency-power domain, by viewing the signal as a Power spectrum. Through analyzing the power spectrum, it is easier to see how the wave signal is affected by variation in orbital parameters of the source binary. It is also clear that waves from isolated sources and those from binary sources appear as very different shapes in the frequency domain, confirming that different algorithms that are specific to detections from each source type is necessary.

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II. INJECTIONS OF BINARY SOURCE SIGNALS

We have fixed an algorithm that works to inject fake signals from binary pulsar sources in existing data or noise. This algorithm has been fixed for simplicity, as existing codes which do these injections are more computationally intense and require the use of other intermediate file types which this algorithm doesn't require. This process inputs a short fast-Fourier Transform database (SFDB), which is created by dividing the data in time series into interlaced chunks of length T_{FFT}, or the chosen coherence time. This T_{FFT} must be chosen to be small enough as to confine the signal power into a frequency bin [5]. The algorithm then outputs the injections in the form of peakmaps, which represent data in the time-frequency domain. Peakmaps are created by selecting only the time-frequency peaks which are above a given threshold which is chosen to filter out average leveled noise[5]. It is these peakmaps that the Rome group's existing algorithm works on, as they take the filtered peaks and apply a set of filters in order to exaggerate a signal in the presence of noise [5].

In order to inject the correct signal, we must consider the modulation effects from both the motion of Earth and of the binary source pair on the expected observed waveform. The effect of the modulation due to the motion of the Earth on the expected waveform can be found in the references [4].

A. Binary Source Modulation

In order to inject a continuous wave signal from a binary pulsar source, we must consider the modulation on the wave signal that we would receive as an observer if the emitting source was in binary orbit. To do this, we characterize binary sources using a modified version of the five Keplerian orbital parameters. These include eccentricity, argument of periapsis, time of ascension node, orbital period, and a factor called a_p which is calculated as

$$a_p = asin(i)/c \tag{1}$$

with a being the the semi-major axis and i the inclination angle.

The modulation of the wave signal due to binary source motion is analyzed through an addition of Binary Romer Delay. In contrast to an isolated pulsar, gravitational waves from an orbiting pulsar will not be observed with a constant frequency by a stationary observer. We analyze the new waveform by considering a pulsar in orbit, such that in its frame of reference it is emitting waves of constant frequency. As the pulsar orbits its binary companion, it emits these waves at varying distances from the observer, such that the distance that the wave must travel to meet us varies periodically. This difference in distance is analytically equivalent to a stationary source pulsar emitting waves with a corresponding difference in time.This 'time delay' with which we observe incoming continuous waves from binary sources is called Binary Romer Delay. We consider a small eccentricity approximation, and define

$$\psi(t) = \frac{2\pi}{P}(t - t_{asc}) \tag{2}$$

with P being the orbital period and t_{asc} the time of ascension node. Then, Binary Romer Delay can be calculated by

$$\frac{R}{c} = a_p(sin\psi(t) + \frac{\kappa}{2}sin2\psi(t) - \frac{\eta}{2}cos2\psi(t)) \tag{3}$$

with $\kappa = ecos\omega$ and $\eta = esin\omega$ where ω is the frequency [4]. Subtracting this time delay from a standard time vector, we are able to account for the binary source modulation.

III. VISUALIZING CONTINUOUS WAVES USING POWER SPECTRA

Power spectra allow us to analyze signals in the frequency-power domain. Understanding the variation in the shape of the signal in the power spectrum helps us understand the variation that a future machine learning based detection algorithm should be able to reconcile. They also illuminate clearly the source of the 'double horn' shape used for detection in white noise in the Rome group's existing work [5].

A. Isolated Pulsars

In our first test we inject a simple sine wave into Gaussian white noise, in order to illuminate the process of creating a Power Spectrum and in order to eventually compare with modulated signals. The injected sine wave of the form $\Psi = Asin(2\pi ft)$ simulates an isolated pulsar rotating at a fixed frequency with no modulation. The lack of modulation implies that both the source and the observer are fixed in space. This signal is injected into white noise, and a Fourier Transform coherence time is chosen. The choice of this coherence time will affect the visibility of our signal, as we will later explore. The dataset is divided into sections of coherence time length, and a Fast Fourier Transform (FFT) is applied to each section. (Note that we don't use interlaced bin times in this test, but this is another option for more robust detection in real data). This converts the data from the time-space domain to the time-frequency domain, as the FFT returns the set of frequencies that the signal in that coherence time bin can be decomposed into. For our simple sine wave, only a single frequency stands out. This frequency is constant in time, such that the FFT will return the same strongest frequency in every coherence time bin. A spectrogram is created by combining the

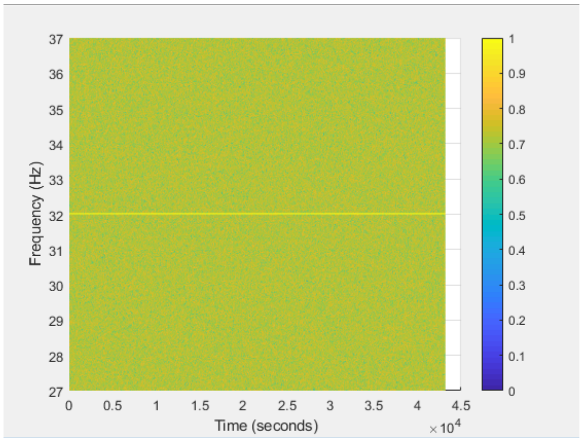

FIG. 1. A spectrogram for an isolated pulsar rotating at constant frequency and with no signal modulation.

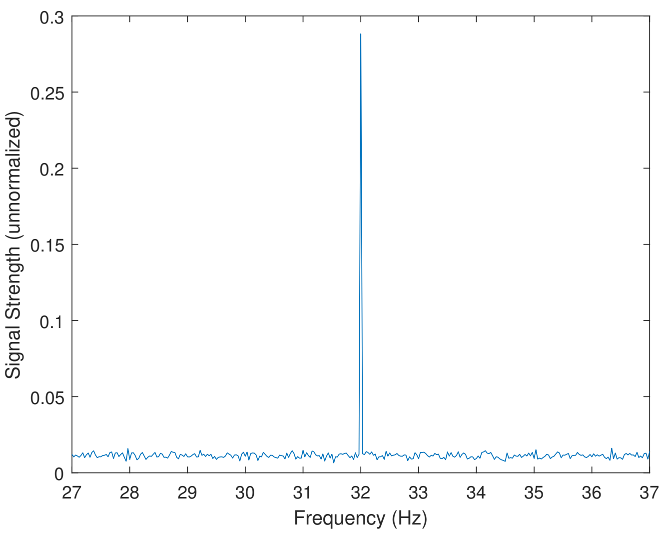

FIG. 2. A power spectrum plot for an isolated pulsar rotating at constant frequency and with no signal modulation.

FFT data from each coherence time bin into one plot, such that we have time on the abscissa and frequency on the ordinate and the signal strength at each frequency is distinguished by a color map. This spectrogram is shown in Fig. 1. Taking the time average across all repeated bins of coherence time, we arrive at a Power Spectrum plot as in Fig.2., in which we can see the signal in the frequency domain. In this case, there is a strong single peak at the frequency of the injected wave.

B. Binary Pulsars

We use the same characterization of binary sources discussed in section II to find the spectrogram for a binary source wave. We add the binary modulation given by the Binary Romer delay, and inject our new signal by adding it to white Gaussian noise. We then follow the same process as before, where we divide the data into sections of the length of the FFT coherence time and perform FFTs on each section, recombining the sectioned plots at the end. We obtain the spectrogram shown in Fig. 3. We now see an oscillating frequency which is characteristic of the binary source motion.

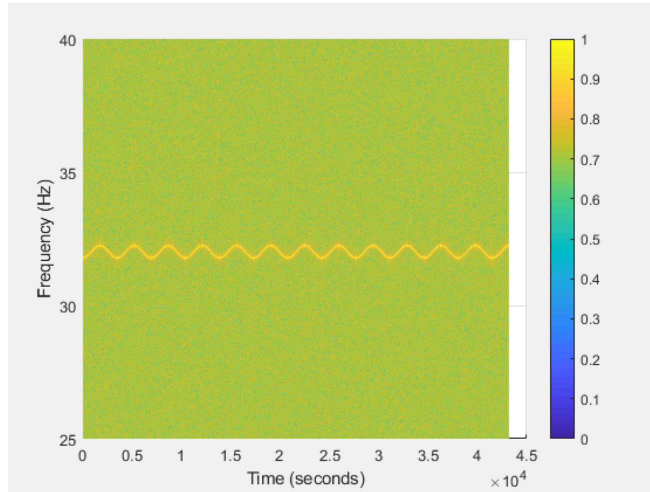

FIG. 3. A spectrogram for a binar pair of pulsars.

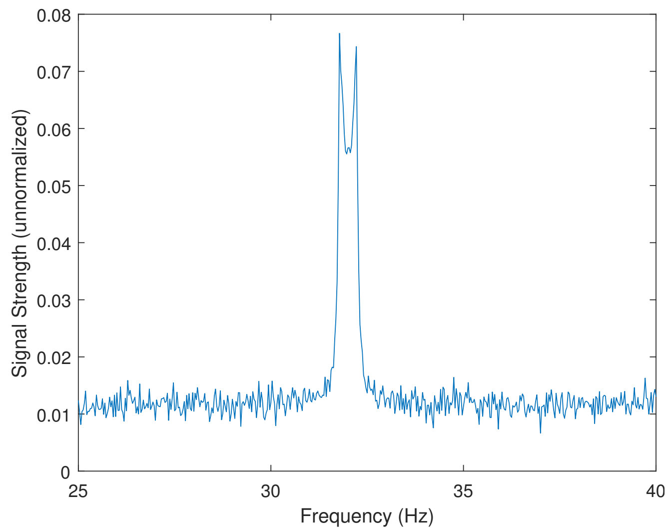

FIG. 4. A power spectrum plot for a binary pair of pulsars.

When we take the time average now, we obtain a shape characterized by a 'double horn' feature, as seen in Fig. 4. This double horn is due to the oscillating frequency discussed. Taking different orbital parameters, the qualities of this 'double horn' change. Understanding this variation is an important prerequisite for writing an algorithm that can detect waves from a wide range of potential source binaries.

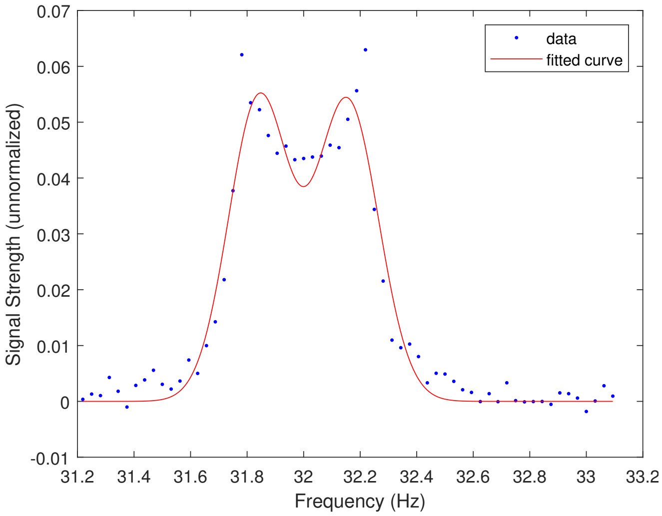

FIG. 5. Example of a double Gaussian best-fit procedure applied to the data with an injected binary signal

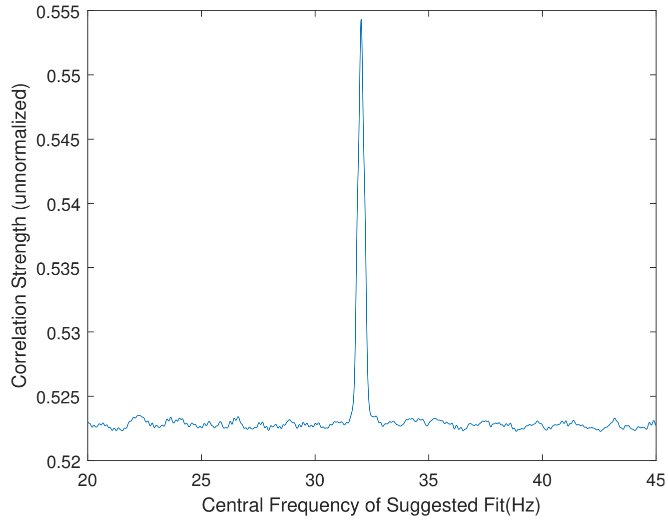

FIG. 6. Cross-correlation between a single double Gaussian, chosen randomly within manually set limits, and the data with an injected binary signal

IV. A POTENTIAL DETECTION STRATEGY FOR MACHINE LEARNING

In order for a future machine learning algorithm to search for continuous waves from binary systems in the power spectra, we propose one potential method, using a double Gaussian fit. The 'double horn' shape may be approximated by a function given by the addition of two Gaussians, of the form

$$G = a_1 \exp(-(\frac{x-b_1}{c1})^2) + a_2 \exp(-(\frac{x-b_2}{c2})^2) \quad (4)$$

where a1, b1, c1, a2, b2, c2 are independent parameters, and exp indicates the exponential function. The parameters a1 and a2 are proportional to the heights of the two respective peaks, b1 and b2 correspond to the central frequency of each peak, and c1 and c2 to the widths of each peak. If we assume that the source orbit has low eccentricity, we can set a1 = a2 and c1 = c2, thus reducing our number of parameters to 4 from 6, greatly reducing computational power required. An example of a double Gaussian best fit procedure can be seen on an optimized wave in Fig. 5. The signal in this case has been optimized for maximal visibility, by setting a zero argument of periapsis and a high semi-major axis, as well as a zero eccentricity as previously discusses. This plot is meant to show an example the fit of the Gaussian curve on the signal data. However, because of the multitude of noisy data points compared to signal points, applying a double Gaussian best fit procedure to random sections of data is an ineffective way for an algorithm to recognize a signal. The data points of pure noise tend dampen the best fit, often returning a nonexistent fit unless manually zoomed in to the injected signal sufficiently.

Instead, we developed a method of signal recognition which returns the four-parameter double Gaussian that optimizes a fit to the signal at the correct localized frequency. This is done by creating a four dimensional parameter space, and taking a grid across that space with desired fineness and limits, depending on the computational strength available. The grid used in this example was chosen by first performing a double Gaussian best fit, in order to determine a close enough grid so that we could minimize the computational expense of this test. The limits of the parameter space grid where chosen to be a small interval around the optimized fit parameters. The grid is made of a set of four-dimension points spanning the space, with a uniform separated by 0.01 unit in each direction.

Each 'point' is defined by the four parameters, such that it defines a single and unique double Gaussian curve. This particular double Gaussian curve is created for every point in the grid and cross-correlated with the available data.The double Gaussian is shifted across the data in the frequency domain and cross correlated at each frequency, returning a vector which contains the correlation strength for the curves at each central frequency. The example output of a single cross-correlation is given by Fig. 6., where there is a defined peak at the moment the central frequency of the double Gaussian matches that of the injected signal. By repeating this cross-correlation with every point in our four dimensional grid, we find that a single double Gaussian created correlates the most strongly with the data, as seen by the top curve in Fig. 7. Taking the parameters of the top curve's double Gaussian, as well as the frequency of its peak, we are returned with the approximate location of a suggested signal, and the approximate shape of such signal.

However, in cases where the approximate location of the wave is not known, and we are not able to construct such a limited grid as we have done as a test, a much

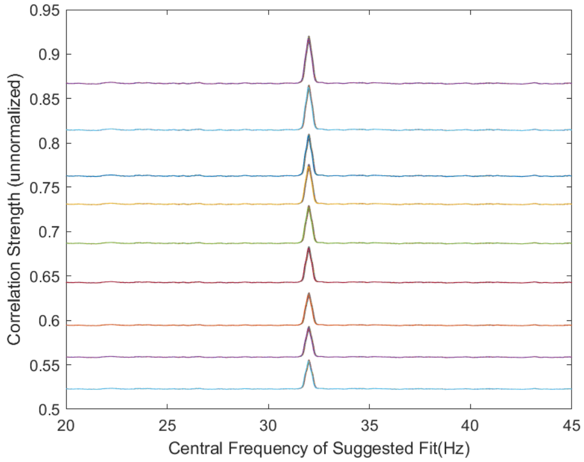

FIG. 7. Cross-correlation between a a set of double Gaussian curves which cover a grid over four-dimensional parameter space, and the data with an injected binary signal

larger section of our four-dimensional parameter space would have to be used to create an extensive set of potential double Gaussian curves. Proper tests must be performed to establish the computational budget of this process.

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