Applying Quantum State Preparation Algorithms to Gravitational Wave Data Analysis

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Abstract. Quantum state preparation is an important part of quantum computing, and ensuring gravitational wave template waveforms can be loaded efficiently is essential for preserving the advantages quantum algorithms could offer. Here, we look at improving the efficiency of amplitude encoding for gravitational waveforms by considering an approximation of the inspiral section. By inducing a small error into the Grover-Rudolph algorithm, we can reduce the number of quantum logic gates required as the number of qubits grows. This means that we can encode templates into a quantum processor in a form that requires modest numbers of both qubits and gates, opening the door to development of algorithms accessible to near-term quantum devices.

1 Introduction

Quantum algorithms, that is algorithms designed to run on computers operating on the principles of quantum rather than classical mechanics, offer a speed-up over classical techniques for certain tasks. Such devices were proposed as early as the 1980s [1–3], with the now famous examples of Grover's search algorithm [4] and Shor's factoring algorithm [5], both proposed in the 90s, cementing interest in the field. The past decade in particular has seen rapid technical progress [6–8], and although current devices are too error-prone to implement scalable quantum computing, impressive progress has been reported on implementing the error-correction techniques needed to make this a reality [9, 10]. It is still unclear for which computational tasks quantum computing will offer a tangible benefit over classical techniques, and only recently has gravitational wave data analysis been considered as a possible application area [11–19].

The first step of gravitational wave data analysis is detecting whether a signal is likely to be present in a segment of data. Matched filtering is the standard technique to achieve this [20, 21], although more recent work employs machine learning [22, 23]. Matched filtering searches a template bank, calculating a signal to noise figure of merit for the data with each template, and returns matches above a specified threshold. It has been shown that replacing a brute force search with Grover's search algorithm could offer a quadratic speed up [11, 13]. Further research improved on these techniques, reducing the number of qubits required by using quantum Monte Carlo integration with quantum amplitude amplification [14]. Quantum Machine Learning (QML) has also been explored as a potential approach for signal detection algorithms; quantum variational rewinding utilises a quantum circuit along with classical training techniques for time series anomaly detection [15]. If it is determined likely that a signal is present, Bayesian analysis is used to estimate the source parameters. With upwards of 15 parameters in gravitational waveform models, these algorithms are very computationally expensive, and recent work has therefore proposed the use of quantum algorithms [16, 17].

There are therefore many possibilities for quantum computing to help with gravitational wave data analysis. However, there are some caveats to these potential speed ups. The waveforms used are often made of millions of data points. Loading the classical data into a quantum computer requires large numbers of qubits or large circuit depths [18]. Not properly accounting for the cost of encoding the data can, in some instances of processing classical data on a quantum computer, negate any potential quantum speed up [24]. Solving the problem of preparing quantum states representing classical data is therefore a crucial application.

There are many different types of encoding: basis encoding emulates classical encoding where each qubit represents a binary digit, e.g. $0101 \to |0101\rangle$ [25]. This was employed in the original proposal to use Grover's algorithm for matched filtering [11], but leads to memory requirements which are still far out of reach of current technology. Here we will focus on amplitude encoding, a particularly space-efficient type of encoding in which classical data is encoded as the amplitudes of a quantum state, requiring only n qubits to encode 2^n datapoints.

There have been previous attempts to encode gravitational waveforms into the amplitudes of quantum states. Hayes et al. proposed a method for encoding a waveform by splitting the waveform into amplitude and phase components [12]. This encoded the amplitude of the waveform using the Grover-Rudolph algorithm [26] and training a quantum GAN, with the phase information of the model encoded separately. Other methods have looked at using QML models to encode binary black hole mergers [19].

In this work, we encode the amplitude of the inspiral stage of a binary black hole system in the frequency domain. We implement the method of [27], which accepts a small error in the Grover-Rudolph algorithm to reduce the number of gates needed to encode the waveform with respect to previous work [12, 26]. Although the waveform phase is arguably more important to the astrophysics, encoding the amplitudes is a necessary first step, so we focus on this problem. We show a significant reduction in circuit size while maintaining good fidelity of state preparation.

2 Quantum State Preparation

Quantum state preparation refers to the task of preparing a specified quantum state in a quantum computer. We are interested specifically in amplitude encoding, in which a list of floating point numbers $\{g_y\}$ are encoded in a quantum state as:

$$|\Psi\rangle = \sum_{y=0}^{2^n-1} g_y |y\rangle, \tag{1}$$

where $|y\rangle$ are n-qubit computational basis states [28] and $\sum_y g_y^2 = 1$. We will consider $\{g_y^2\}$ to be a discretisation into 2^n points of a probability distribution $g^2(x)$, defined on the domain $0 \le x \le 1$ and satisfying $\int_0^1 g^2(x)\mathrm{d}x = 1$. Despite being very space efficient, the circuits required to implement amplitude encoding grow exponentially. The Grover-Rudolph algorithm is a well understood method for encoding efficiently integrable probability distributions and works by iteratively discretising the distribution by halving it each time, Fig (1). These sections are then used to calculate an angle [26]. These angles are then put into a circuit made of rotational Y gates conditional on previously encoded qubits [29]. As each section of the distribution is halved at each level m, this results in 2^m sections, and therefore the circuit grows exponentially as more qubits are encoded. For 9 qubits this would require 511 multi-qubit controlled rotational gates.

Marin-Sanchez, et al. proposed a way to reduce the number of gates required by accepting a small error ϵ in encoding [27]. This method works by noting that beyond a certain level $k(\epsilon)$, the angles generated between different sections are so similar that, instead of requiring 2^m conditional gates it is possible to use a single gate [27]. It is shown in [27] that the difference between angles at a given level may be bounded by a parameter η, defined as:

$$\eta = \sup_{x\in[0,1]} |\partial_x^2 \log g^2(x)|. \tag{2}$$

The level $k(\epsilon)$ at which we can switch to a single gate, as a function of the selected acceptable error ϵ is then given by:

$$k(\epsilon) = \max\{\lceil -\frac{1}{2}\log_2(4^{-n} - \frac{96}{\eta^2}\log(1-\epsilon))\rceil, 2\}. \tag{3}$$

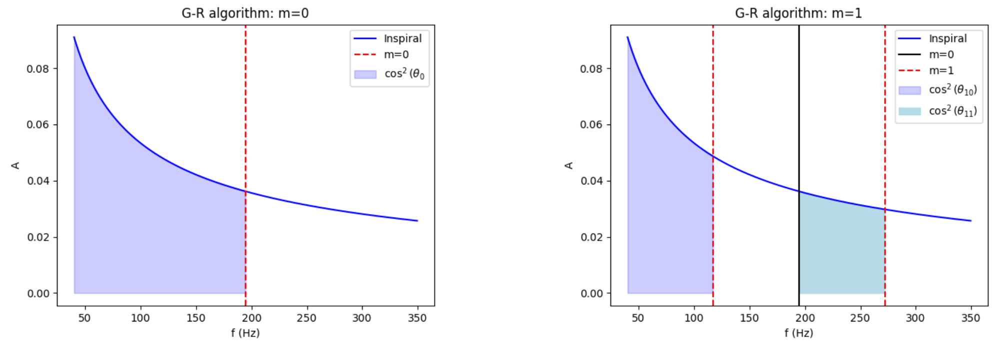

Figure 1: Left: the first level (m=0) and Right: the second level (m=1) of the Grover-Rudolph (G-R) algorithm for discretising a distribution to generate angles.

Once we have calculated $k(\epsilon)$ we can construct our circuit, initially by using the Grover-Rudolph circuit [26] up to level $k(\epsilon)$, then at level $k(\epsilon)+1, ..., n$ we switch to single rotational Y gates.

3 Inspiral example

This method is designed to work for analytically representable distributions and we therefore select the inspiral section of a binary black hole merger, which has the following form in the frequency domain:

$$\tilde{A}_N(f) = \frac{Q\mathcal{M}^{5/6}}{D} f^{-7/6}\,, \tag{4}$$

where $\mathcal{M}$ is the chirp mass, D is the luminosity distance to the source and Q is dependent on the geometry of the detector and source system [30]. To express this in the form required, related to a probability distribution defined on the domain $x \in [0, 1]$, we write $f = f_{min} + x(f_{max} - f_{min})$, and define:

$$g(x) \propto (f_{min} + x(f_{max} - f_{min}))^{-7/6} \tag{5}$$

where the constant of proportionality is determined by the normalisation of the probability distribution $g^2(x)$ [1]. We select a frequency range of $40 - 170$Hz which will include the relevant range for the inspiral part given a spinless ($\beta = \sigma = 0$), near equal-mass system of $m_1 = 35M_\odot$ and $m_2 = 30M_\odot$. This is encoded in $n = 9$ qubits, resulting in a discretisation of the waveform into 512 points. The analytical

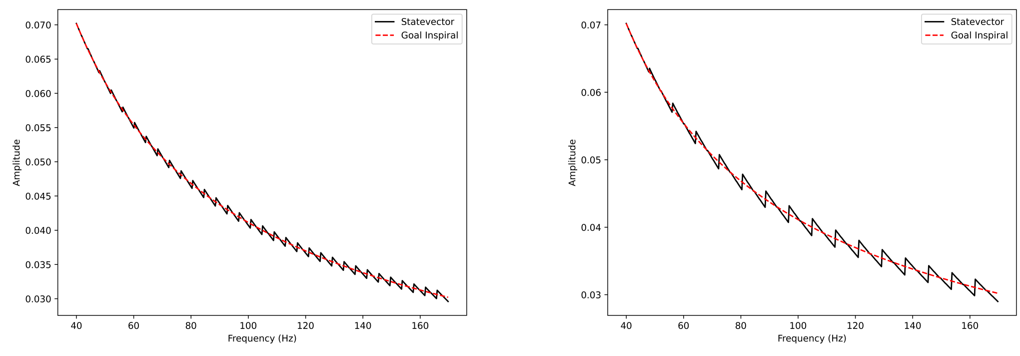

Figure 2: Comparison of the encoded state with the goal inspiral waveform. Left: $\epsilon = 0.01$, Right: $\epsilon = 0.05$.

expression, Eq (2), gives $\eta = 24.6$. We then select an error rate of $\epsilon = 0.01$ to get a $k(\epsilon)$ value of

[1] We use the binary black hole inspiral waveform as an example only, and the same method can be applied to other models, scaled to be defined on $0 \leq x \leq 1$, and to satisfy $\int_0^1 g^2(x)dx = 1$. The complexity of the circuit depends on the behaviour of $\delta_x^2 \log g^2(x)$, through the parameter η; the case in which this has singularities is considered in [27].

$\lceil 4.64 \rceil = 5$. The resulting circuit requires 5 full levels of G-R encoding before switching to a single rotation for the remaining higher order qubits. In total, the circuit uses 35 rotational Y gates, of which 31 are multi-qubit controlled gates, which break down into 596 CNOT gates. This encoding achieves a fidelity of 0.99994. We note that the resulting fidelity is much higher than anticipated from the tolerated error specified: $\epsilon = 0.01 = 1 - F$. This is because the upper bound defined by η in the difference between angles is not a tight bound in general, so the resulting circuit can be much better than the maximum error specified. Choosing $\epsilon = 0.05$ results in an even smaller circuit with 15 controlled Y gates, corresponding to 212 CNOT gates, while maintaining a fidelity of 0.99977. The amplitudes of the resulting encoded state in each case are shown alongside the desired waveform in Fig 2.

4 Comparison

Technique	Controlled Rotations	CNOT	Fidelity
Fixed Circuit ($\epsilon = 0.01$)	31	596	0.99994
Fixed Circuit ($\epsilon = 0.05$)	15	212	0.99977
G-R	512	42,324	1
QGANS [12]	N/A	100	0.983
G-R with linear piecewise [12]	N/A	23689	0.999

Table 1: Comparisons of different amplitude encoding techniques to encode the analytical example $f^{-7/6}$. Note that [12] considered encoding into $n = 6$ qubits, while here we use $n = 9$ qubits.

As summarised in Table 1, there have been other attempts to encode the inspiral section of a gravitational wave signal from a compact binary coalescence [12]. Most techniques that use the G-R algorithm require significantly larger circuits. Quantum Generative Adversarial Networks (QGANS) do offer the smallest circuit but this comes at the expense of high classical computation costs and results in the worst fidelity [12].

In conclusion, we demonstrate that by inducing a small error ϵ we can encode gravitational waveforms into quantum computers, with a drastically reduced gate complexity whilst maintaining a good overall fidelity. Further improvements are possible with refinements of the scheme outlined here, which we will report on in detail in a separate publication. Efficient encoding methods for amplitude encoded template waveforms means the ability to load and process templates using a small quantum device and low circuit depth. While further work is needed to study algorithms making use of data in this form, for example quantum neural networks [31–35], this promises to bring applications into the realm of near future quantum technology.

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