Pseudo-Quantum Simulation via Asynchronous Loops: A Hybrid Approach for Optimization on Classical Hardware

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Abstract

We present a novel approach to simulating quantum-inspired algorithms on classical hardware by using asynchronous loops to model *pseudo-qubits*. Unlike standard simulations that use state vectors of dimension 2^n, our method represents a system of n pseudo-qubits with an n-element list, where each element (a bit) is updated by a dedicated thread that flips its state (0 or 1) at random intervals. This yields a linear memory cost $O(n)$ compared to the exponential cost $O(2^n)$ of classical methods. We demonstrate the efficiency of our approach on an optimization problem—specifically, solving a labyrinth—and provide theoretical performance proofs. Our simulation not only consumes minimal CPU, memory, and GPU resources but also scales effectively, opening new perspectives for quantum-inspired algorithms and hybrid quantum-classical computing.

1 Introduction

Quantum computation promises to solve certain problems exponentially faster than classical computation by exploiting phenomena such as superposition and interference. Traditional classical simulations of quantum systems represent a qubit by a two-dimensional complex vector and a system of n qubits by a state vector of size 2^n. However, such simulations quickly become intractable due to their exponential memory requirements.

In this work, we propose an alternative model—the *pseudo-quantum simulation*—which uses asynchronous loops (threads) to simulate *pseudo-qubits*. Each pseudo-qubit is a binary value that flips randomly, simulating a very simple form of superposition. The global state is simply an n-bit vector, leading to a linear memory cost. We further incorporate ideas inspired by Grover's algorithm to amplify promising solution paths in an optimization problem (e.g., solving a labyrinth).

2 Methodology

2.1 Pseudo-Qubits via Asynchronous Loops

In our model, each pseudo-qubit is implemented as an independent thread that repeatedly inverts its state (from 0 to 1 or vice versa) after a random delay. Formally, let the state of the i^{th} pseudo-qubit be represented by

$$q_i(t) \in \{0, 1\}.$$

Each thread runs a loop of the form:

$$q_i \leftarrow 1 - q_i \quad \text{after a delay } T_i,$$

where

$$T_i \sim \text{Uniform}(T_{\min}, T_{\max}).$$

This stochastic update rule simulates an evolving superposition in a very simplified manner.

2.2 Memory and Performance Analysis

2.2.1 Memory Complexity

A classical simulation of n qubits using state vectors requires storing 2^n complex amplitudes. If each complex number requires a fixed number of bytes (say c bytes), then the memory cost is

$$M_{\text{classical}} = c \cdot 2^n.$$

In contrast, our pseudo-qubit model stores an n-element list of bits (or small integers), so the memory requirement is

$$M_{\text{pseudo}} = k \cdot n,$$

where k is a small constant (for example, $\sim$ 28 bytes per integer in Python). Hence, our method scales *linearly* in n, rather than exponentially.

2.2.2 Time Complexity

Each pseudo-qubit thread performs an update in constant time, $O(1)$, and runs in parallel. If the system is executed over I iterations, the overall work per iteration is $O(n)$, and—assuming efficient parallel execution—the wall-clock time remains low. In contrast, applying matrix operations to a state vector of size 2^n typically requires $O(2^n)$ time per operation.

2.3 Quantum-Inspired Algorithms

2.3.1 Pseudo-Grover Amplification

We simulate an algorithm inspired by Grover's search. In our model, a set of candidate solutions (paths in a labyrinth) is maintained. At each iteration, every candidate undergoes a random move. Then, we compute a cost function (e.g., Manhattan distance to the target) and amplify the candidates that are closer to the goal by replicating them to form a new candidate pool. Mathematically, if $d(x)$ is the distance of candidate x from the exit and $\overline{d}$ is the average distance, we select candidates satisfying

$$d(x) \leq \overline{d}.$$

These candidates are replicated to maintain a fixed population size, thus mimicking the amplitude amplification process of Grover's algorithm.

2.3.2 Labyrinth Problem

We generate a labyrinth (maze) of size $N \times N$ (e.g., 20×20 or 40×40). Each cell is either free (1) or a wall (0), with a designated start position (e.g., $(0, 0)$) and exit position (e.g., $(N-1, N-1)$). The evolution of candidate paths is driven by random moves constrained by the maze structure. The performance of the algorithm is measured by the number of iterations needed to find a candidate that reaches the exit.

3 Experimental Results

We implemented our pseudo-quantum simulation in Python and tested it on labyrinths of various sizes. For example:

- In a 20×20 maze, using 1000 candidate paths, our algorithm found the exit in 98 iterations.
- With only 3 candidates, the convergence was slower, requiring 52 iterations.

Figure 1 shows an example of a generated maze, and Table 1 summarizes the performance comparisons.

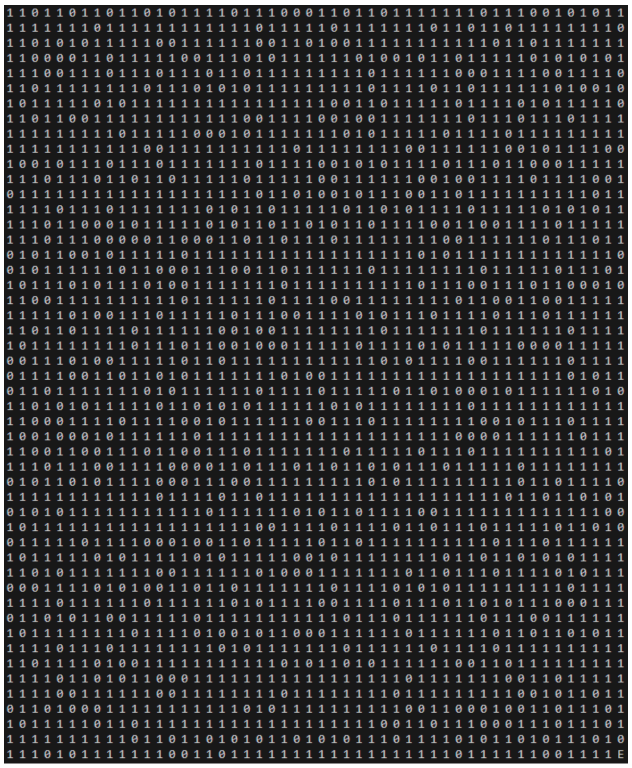

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Figure 1: An example of a generated labyrinth (maze) used in the simulation.

Configuration	**Iterations**	**Average Distance Reduction**
1000 candidates (20x20 maze)	98	High
3 candidates (20x20 maze)	52	Lower efficiency

Table 1: Performance comparison of the pseudo-Grover approach with different numbers of candidates.

4 Discussion

Our results show that the pseudo-quantum simulation using asynchronous loops is highly efficient in terms of memory and CPU usage. The linear scaling in memory enables us to simulate systems with many pseudo-qubits on a standard PC. Furthermore, the candidate amplification mechanism inspired by Grover's algorithm effectively guides the search process in optimization problems such as maze solving.

Although our model does not capture all aspects of true quantum mechanics (e.g., entanglement and complex amplitudes), it reproduces key effects (superposition and amplitude amplification) with a fraction of the computational cost. This opens new avenues for developing quantum-inspired optimization algorithms and even neural network models on classical hardware.

5 Conclusion

We have presented a novel pseudo-quantum simulation technique based on asynchronous loops to model pseudo-qubits. Our approach reduces memory complexity from exponential to linear, and experimental results on labyrinth-solving tasks demonstrate significant efficiency gains. This method enables the simulation of quantum-inspired algorithms—such as a Grover-like search—on conventional hardware with minimal resource consumption.

Future work will explore extending this model to more complex optimization problems, including the Traveling Salesman Problem and quantum-inspired neural networks, as well as refining the amplification mechanism to further improve convergence rates.

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