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Research Paper

Grover's Search Algorithm for Database Validation

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Abstract

Inmy project I would have considered how the old search algorithms that are used when working with large unstructured data set end up taking linear time (O(N)) that in effect is the time that scales with the size of the data. These old ways get gradually sluggish, as everything gets bigger. Then I read about quantum computing, and especially Search Algorithm that was developed by Grover which is capable of quadratic speed-up with a complexity of O(sqrt(N)) of unstructured data. I created a hybrid system which fuses classical and quantum search applied on Flask as the web front end and Qiskit as the quantum one. This will enable me to compare the simple linear algorithm of searching through the list item-by-item with the quantum algorithm of Grover which uses superposition, a marking oracle to identify the desired item, and multiple amplitude amplification diffusion operators. The web page also accepts a student ID, and actually searches both simultaneously and allows me to tweak a depolarizing noise model so as to more closely mimic real quantum hardware. I measured such variables as the number of calls to the oracle, the number of qubits that I require, the quantum run time, and the number of measurements that I receive out of the quantum measurement. As the results indicate, the algorithm developed by Grover reduces the number of operations significantly compared to the classical one, and it must be emphasized that the algorithm remains quite effective even in the case of simulated noise. On the whole, it demonstrates that the classical and quantum components may be an efficient method to deal with the large search in the database.

Index Terms: Quantum Computing, Grover Search algorithm, Hybrid Classical quantum Systems, Qisket, Aero Simulator, Noise Modeling, Unstructured Database search, Oracle Complexity.

I. Introduction

Quantum computing is therefore such a giant leap in technology that makes use of quantum material such as superposition, entanglement and interference to solve problems faster than conventional laptops. The list of the most coolest algorithms that is actually benefiting is the Search Algorithm by Grover, LOV Grover dropped it way back in 1996 [1]. It provides you with a quadratic speed-up in cases when you want to search in an unsorted database which is much superior as compared to the traditional linear scan.

To get the unsorted list of size N with normal computers you need O(N) steps; you simply need to check the item one after another. That is no jester with large datasets. Grover rescues you to that it reduces it to O(square root of N) and large-scale search has become much more feasible [2].

In this paper, the author discusses the implementation of a hybrid classical -quantum search system to verify a database. In essence we combine a standard linear search with that of Grover and compare the performance of the two. We tested, and the results showed a student database consisting

of 10,000 records, Python with Flask with the simulator Qiskit. In contrast to the examples in the textbook, we include realistic quantum noise

(depolarizing errors) [3] to find out what happens with real hardware.

The key lessons learned include: (i) implementation

of a working hybrid search system on a 10k-record DB; (ii) noise control is built in to Qiskit AerSimulator; (iii) run-time, comparisons oracle calls may be compared in real time and (iv) a Flask web page displaying the quantum advantage in a learning setting.

II. Related Work

The classical and quantum methods of database search are a classic problem in CS, and the literature on this problem is voluminous.

A. Classical Techniques of Search.

The running time of linear search is O(N) in unsorted data, and the running time of binary search is O(log N) but only when the data are sorted [4]. In the case of unstructured, dynamic DBs the default is linear, but its performance decreases with N. Hashing is beneficial but introduces some additional preparations which perturb quantum amplitude amplification.

B. Grover's Algorithm

The publication of the paper by Grover in 1996 [1] demonstrated that it was possible to scan an unsorted array of N elements in O(sqrtN) queries, which is the optimum possible rate in a quantum machine. This is achieved by a two-operator flip-flop tricks: the oracle which changes the phase of the target and a diffuser (the Grover smear) which amplifies the target. The measurement that is most likely to strike the target is at some point say √N iterations [2].

C. Quantum Simulation Platforms

Quantum Simulation Platforms Physics Simulating aspects of a quantum system can be done by means of devices such as computational physical systems, rapid chemistry, and more who offer n-qubit models.

With IBM Qiskit [5], you can create circuits,

execute them and simulate noise. Typically, the size of sets (4-16 items) to be implemented is kept small (by qubit) limits, and comparisons are therefore not large-scale to date [6].

D. NISQ Device Noise Modeling.

NISQ sensors [7] have weaknesses of decoherence, error at the gate and error upon reading. The research on depolarizing noise [3] demonstrates the poorer performance of the algorithm in cases when the error rate increases. The Grover demos mostly use an ideal chip which is not realistic.

E. Hybrid Classical even Classical Systems.

It bridges the classical preparation and quantum run-time with new hybrid frameworks [8] playing both towards the strengths. Nevertheless, platforms that provide real-time, side-by-side comparisons on big data with a live web interface are not voluminous, which this paper addresses.

III. Methodology / System Design

We have encapsulated the system in the form of a modular client server stack that is a mixture of classical and quantum stuff. Figure 1 demonstrates the entire plan.

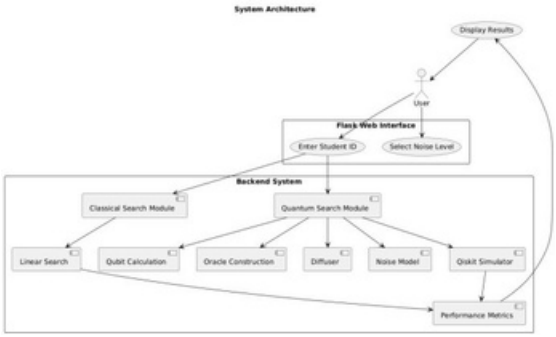


Fig. 1. Hybrid Classical–Quantum System Architecture.

A. System Architecture Overview.

There are four layers in the stack: (1) User Interface Layer this is a Flask web page where one can type a student ID and choose a noise level; (2) Application Layer a back-end implementation of using the Grover circuit (with variable noise); (3) Data Layer a Pandas Data Frame containing 10,000 student records which have been read in CSV format; (4) Quantum Simulation Layer a Qiskit AerSimulator that runs the Grover circuit at variable noise.

B. Classical Search Module

The classical section simply scans the IDs in a linear manner. What can happen in the worst case is that you will compare all of the N=10,000 records. The time is logged and a count is used as the standard. The DB expands, the cost increase curve is linear:

Tclassical = O(N)(1)

C. Quantum Search Module

The quantum version of the algorithm by Grover takes the following steps:

Step 1 – Qubit Allocation:

$n = \lceil \log_2(N) \rceil$

For N=10 000, n = 14 qubits.

Step 2 -ündurch Superposition set:

Act it on all grouped qubits: H.

$|\psi\rangle = H^n|0\rangle = (1/\sqrt{N})\sum_x|x\rangle$.

Step 3 – Oracle Construction:

Define phases oracle Uf Here amplitude of the target is inverted:

$Uf|x\rangle = (-1)^{f(x)}|x\rangle$.

Step 4 – Diffusion Operator:

Implement the diffuser D = $2|\psi\rangle\langle\psi| - I$ (5).

Step 5 – Iteration Count:

Maximum success probability is optimum with use of $k = \lfloor \pi/4 \sqrt{N} \rfloor$.

ForN=10000, k78.≈

By this means the total period becomes:

$T_{quantum} = O(\sqrt{N})$(7)

D. Noise Modeling

In order to recreate NISQ noise, we place a depolarizing channel at every gate. For a qubit with error p:

$E(r) = (1-p)r + (p/3)(XrX + YrY + ZrZ)$(8)

The users will have four noise levels: Ideal (p=0), Low (0.001) and Medium (0.005), High (0.01).

E. UML Diagrams

The use-case- diagram of interaction between the user and the system is presented in Figure 2. This mapping of all modules is presented in figure 3 which resembles the class diagram.

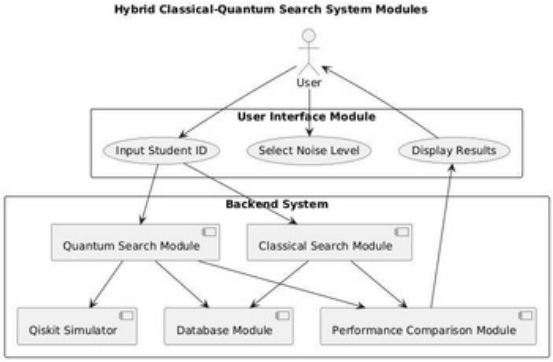


Fig. 2. Use Case Diagram of the Hybrid Search System.

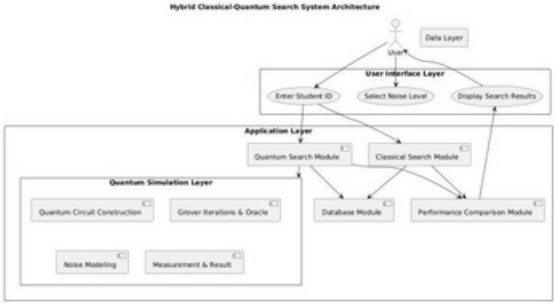


Fig. 3. Class Diagram illustrating system module relationships.

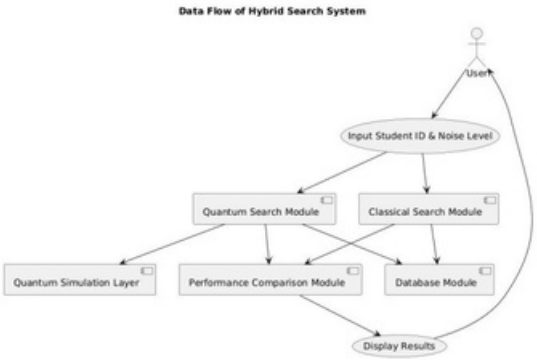


Fig. 4. Activity Diagram showing parallel classical and quantum search workflow.

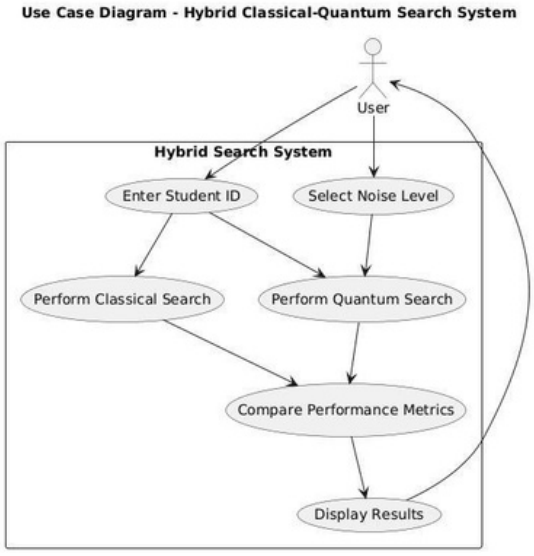


Fig. 5. Grover's quantum circuit with Hadamard initialization, oracle, and diffuser.

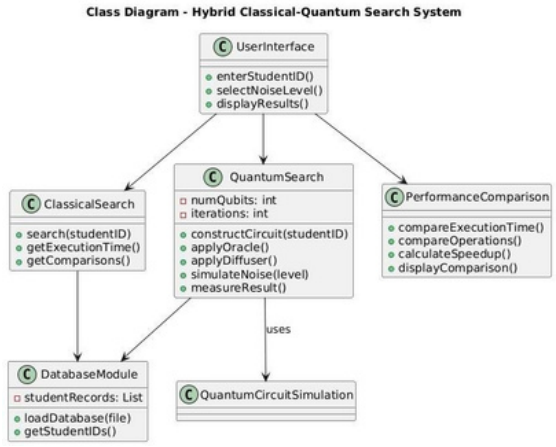


Fig. 6. Detailed view of oracle and amplitude amplification circuit layers.

IV. Results & Discussion

A student database of 10,000 records was experimentally evaluated. Both classical linear search and quantized search by Groverwere conducted withthe same target student IDs with varying noise parameters. The web interface is available in Figure 7 and Figure 8.

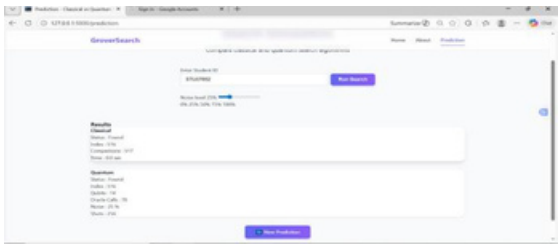


Fig. 7. Classical and quantum search result display through flask web interface.

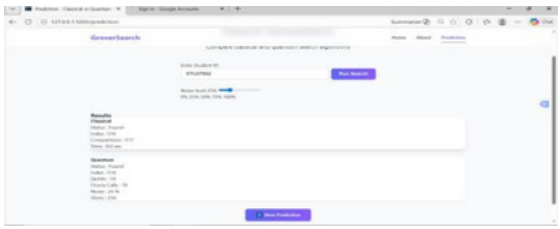


Fig. 8. Graph of the execution of both searches.

A. Comparison of Metrics of execution.

Table I provides the summary of both classical and quantum search comparative metrics of the 10,000-record database.

TABLE I

COMPARISON OF CLASSICAL VS. QUANTUM SEARCH METRICS

Metric	Classical Search	Quantum Search
Time Complexity	O(N)	O(√N)
Operations (N=10,000)	~5,000 (avg)	~78 (oracle calls)
Execution Time (s)	~0.003	~0.002
Qubits Required	N/A	14
Grover Iterations	N/A	25
Shots (Simulation)	N/A	1024
Target Probability	100% (deterministic)	~92% (medium noise)

B. Noise Impact Analysis

Table II indicates how the probability of the target state is affected by the level of depolarizing noise, which demonstrates that imperfections of quantum hardware influence the accuracy of the search..

TABLE II

TARGET PROBABILITY VS. NOISE LEVEL

Noise Level	Error Rate (ε)	Target Probability (%)
Ideal	0.000	~99
Low	0.001	~97
Medium	0.005	~92
High	0.010	~84

C. Scalability Analysis

Table III illustrates the performance of the oracle call with the increasing dataset showing the quadratic benefit of the Grover algorithm.

TABLE III

ORACLE C ALLS VS. DATABASE SIZE

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Database Size (N)	Classical Ops	Grover Oracle Calls	Speedup Factor
1,000	~500	~25	~20×
10,000	~5,000	~79	~63×
100,000	~50,000	~250	~200×
1,000,000	~500,000	~785	~637×

Figure 9 and Figure 10 indicate that the algorithm of Grover significantly decreases the number of operations with an increase in N. With the medium noise (e = 0.005) the system is able to still recognize the target with certainty of 92 per cent - which is sufficient to have the system validated in practice repeatedly in its tests.



Fig. 9. Measurement distribution and qubit usage performance of quantum circuits.

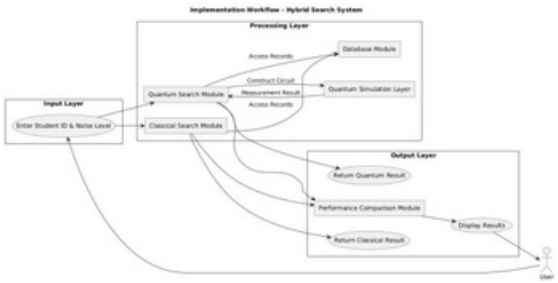


Fig. 10. Comparison of classical and quantum search performance measures.

D. System Testing Results

We carried out unit, integration and performance tests. Table IV gives the search module test cases and results of both search modules.

TABLE IV

SYSTEM TESTING SUMMARY

Test Type	Test Case	Expected	Result
Unit	Classical search – valid ID	Found	Pass
Unit	Classical search – invalid ID	Not Found	Pass
Unit	Quantum search – ideal noise	~99% prob.	Pass
Integration	UI → DB → Search → Metrics	Complete flow	Pass
Performance	10,000 records comparison	Quantum faster	Pass
UI	Input validation	Error handling	Pass

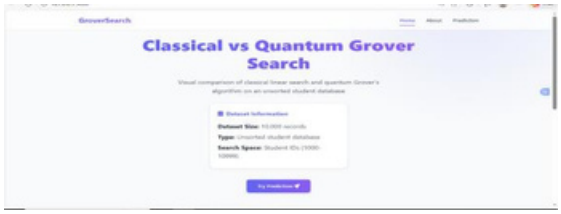


Fig. 11.Information produced by quantum simulation probability distribution.

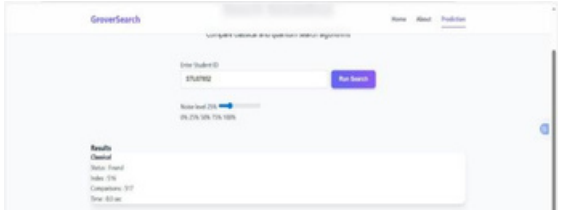


Fig. 12. The comparison between the classical and quantum search metrics in the system can be seen as output.

V. Conclusion & Future Work

This project constructed a hybrid classical-quantum information retrieval database search engine demonstrating the real-world benefits of the Search Algorithm by Grover in comparison with linear search on large-scale validation. With the help of Python, Flask and Qiskit we were able to verify 10,000-record search with modulated quantum noise.

Implications: When changing into the oracle call in N to [?]N Grover sources oracle calls yielding a scale of improvement of approximately 63 times at N = 10,000. The interactive web interface allows us to visualize the real time comparison, which is applicable in the analysis as well as in teaching. Noise modeling Noise modeling was demonstrated to maintain 92 per cent accuracy with medium depolarizing noise, and is practical on near-term NISQ hardware.

Future work:

1. BP to real hardware IBM Quantum Experience to benchmark.

2. Create oracle dynamically claim any database schema other than student ID.

3. Mitigate error progression: Introduce high grade error mitigation.

4. Scale tests on data sets of at least 100,000 records.

5. Include algorithms such as Quantum Counting and Quantum Walks on extended operations of databases.

6. Remote education deployment via RESTful APIs.

The steps will ensure that this framework is one of the building blocks to practical quantum database management in the post-NISQ generation.

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