Analog Quantum Image Representation with Qubit-Frugal Encoding

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In this work, we introduce a fundamentally new paradigm for quantum image representation tailored for neutral-atom quantum devices. The proposed method constructs a qubit-efficient image representation by first applying a cartographic generalization algorithm to a classical edge-extracted input image, yielding a highly optimized sparse-dot based geometric description. While ensuring the structural integrity of the image, this sparse representation is then embedded into the atomic configuration of Aquila (QuEra Computing Inc.), modeled through the Bloqade simulation software stack. By encoding visual information through physical atom placement rather than digital basis-state coding, the approach avoids the costly state-preparation overhead inherent to digital quantum image processing circuits. Additionally, pruning sparse dot images, akin to map feature reduction, compresses representations without fidelity loss, thereby substantially reducing qubit requirements when implemented on an analog neutral-atom quantum device. The resulting quantum-native images have been successfully evaluated through matching tasks against an image database, thus illustrating the feasibility of this approach for image matching applications. Since sparse-dot image representations enable seamless generation of synthetic datasets, this work constitutes an initial step towards fully quantum-native machine-learning pipelines for visual data and highlights the potential of scalable analog quantum computing to enable resource-efficient alternatives to energy-intensive classical AI-based image processing frameworks.

INTRODUCTION

Just recall the past few days, whether at home, in the office, or any familiar environment where the same people appear regularly. How do we recognize them? We rarely rely on a full-frontal view of their faces. Instead, our brain quickly identifies them based on other cues: body structure (build), height, rear, side profiles (partial facial views), general posture, complexion and sometimes accompanied with voice. Inspired by this natural recognition process, we began developing an image processing technique to identify objects/humans based on their edges. The end goal of this approach being the substantial reduction of qubit requirements in the NISQ era.

Quantum image processing (QImP)

Quantum image processing (QImP) [1] is concerned with incorporating the advantages of quantum mechanical properties to represent images in a quantum computer and then, based on that image format, implement various image operations. Due to the parallel computing derived from quantum state superposition and entanglement, QImP has natural advantages over classical image processing towards exponential rise in speed of execution. For quantum image processing, quantum image representation (QImR) plays a key role, which substantively determines the kinds of processing tasks and how well they can be performed. Under QImP, Edge extraction is an indispensable task. With the sharp rise in the image data, real-time storage & processing has become a limitation for classical edge extraction algorithms

Why Quantum in ML (Image Processing)?

Machine learning (ML) comes under the umbrella term of AI (Artificial Intelligence), applying specifically to the cases dealing with processing of large datasets & classification/regression problems. Quantum machine learning (QML) has emerged as a promising direction due to the computational advantages provided by quantum mechanics. However, relying on classical image preprocessing while only applying quantum techniques at the feature-generation/learning stages, limits the potential benefits. To fully exploit quantum superposition, entanglement, and the natural ability of quantum systems to represent and manipulate pixel correlations in parallel, a quantum-native approach to image representation and processing is necessary. Quantum image processing, particularly for tasks such as edge detection and other structural operations, offers a pathway to computational efficiency and could outperform classical methods in select scenarios, making it an important component of energy-efficient next-generation QML pipelines.

Motivation for QML/QImP

Classical machine learning methods, particularly kernel-based classifiers, often face fundamental scalability limitations when applied to data with highly nonlinear and high-dimensional structure, as the explicit construction and evaluation of complex feature spaces rapidly becomes computationally prohibitive. Quantum machine learning offers a principled alternative by exploiting the exponentially large Hilbert space of quantum systems as a natural feature space, enabling the efficient realization of rich, nonlinear kernel functions throug quantum state preparation and entangling operations. As demonstrated by Havlíček et al. [2], quantum-enhanced feature maps can induce class separability that is difficult or infeasible to replicate using classical kernels of comparable computational cost. This observation motivates the study of quantum-native learning models that leverage quantum interference and entanglement to construct expressive similarity measures, providing a pathway toward quantum advantage in supervised learning tasks on near-term and future quantum hardware.

Early evidence [3,4,5] suggests that annealing/analog quantum computers can be integrated into quantum-classical AI workflows, which could potentially enhance model efficiency and performance. From optimizing energy grids and data center placement to reducing GPU power consumption and enhancing AI model performance, annealing/analog quantum computing offers a promising path forward.

An analog quantum computer like the QuEra's Aquila [6] is a neutral-atom quantum device with currently up to 256 qubits (atoms). Its power consumption is reported as less than 7 kW for the full system. It is less than 0.05 percent of the power required by a classical supercomputer [7]. Projections for future QuEra systems with significantly more qubits (e.g., 10,000) indicate similar power levels around 7 kW, suggesting that power usage in neutral-atom architectures like Aquila does not scale with the number of atoms. This is unlike classical computing, where power often scales more linearly with processing elements. While the QuEra computer is efficient, quantum computers from manufacturers such as IBM, Rigetti, Google, and D-Wave also consume approximately 10-25 kW.

Moreover, MIS (Maximum Independent Set) problems are solved instantly & natively by QuEra's analog quantum computer Aquila [8], using Rydberg blockade whereas even with heuristic or approximation algorithms (e.g. simulated annealing, greedy algorithms), solving large MIS instances on classical supercomputers can take hours to days for graphs with hundreds of nodes, thereby consuming enormous amounts of compute power. MIS is used in ML-related tasks like feature selection, graph-based clustering, and resource allocation in networks.

In ML, optimization is the process of systematically adjusting the model's parameters (the weights w and bias b) to minimize the loss function. As hardware improves (e.g., higher fidelities, error correction), these systems are poised to tackle larger ML optimization tasks, such as quantum kernel methods and variational algorithms. Quantum optimization can be utilized, particularly with the analog ones like neutral atom machines, which are naturally good at finding low-energy states of a system. This can be directly mapped to finding the minimum of a loss function (where the minimum loss is the "lowest energy state"). Once the image is in Quantum computer, we can also use quantum reservoir computing (QRC) for machine learning since it uses much less training data (~300 images are enough), much less training cycles, thus conserving energy & water. Moreover, it doesn't suffer from the vanishing gradient problem since it does not use the "Gradient Descent" approach [4,9].

For certain types of complex optimization problems (like training very specific neural network architectures or solving combinatorial problems in clustering), quantum algorithms have the potential to find good solutions much faster than classical computers. Certain subroutines in AI/ML (linear algebra, kernel methods, sampling, optimization) have quantum algorithms with provable speedups. If real, usable quantum ML algorithms replace classical heavy compute, then in principle the same task could be solved with far fewer computational steps → less energy.

Cartographic Generalization

Cartographic generalization (CG) [10,11] denotes the systematic simplification of spatial data while preserving its essential geometric structure. Traditionally developed within cartography to enable the depiction of geographic entities such as roads, rivers, and coastlines across varying map scales, CG ensures interpretability without sacrificing structural accuracy.

CG includes a broad class of algorithms, including line simplification, smoothing, aggregation, and displacement techniques. One of the most influential line simplification techniques in CG is the Ramer–Douglas–Peucker (RDP) algorithm [11], originally proposed by Urs Ramer (1972) and later refined by David Douglas and Thomas Peucker (1973). The RDP algorithm operates on the principle of recursive distance thresholding: given a polyline represented by a sequence of points, the algorithm iteratively removes intermediate points that contribute minimally to the overall shape, based on their perpendicular distance from a baseline connecting two endpoints. Points exceeding a specified tolerance are retained as significant vertices, while others are discarded, resulting in a simplified yet structurally consistent representation. The enduring appeal of RDP lies in its computational efficiency, geometric interpretability, and parameter-based control over the degree of simplification. By adjusting the distance threshold, users can tune the algorithm to balance precision with data compactness. This makes RDP an indispensable tool not only in cartography but also in computer vision, robotics, and image-based shape abstraction, where maintaining the perceptual essence of an object with fewer data points is critical.

LITERATURE REVIEW

Most of the previous research has demonstrated the theoretical potential of quantum computing for image processing tasks in the digital quantum paradigm. They have made use of QImRs like FRQI (Flexible Representation of Quantum Images), QPIE (Quantum Probability Image Encoding), NEQR (Novel Enhanced Quantum Representation), which scale up qubit requirements with image size [12]. Subsequently, quantum circuits are employed to simulate low resolution images, particularly emphasizing exponential speedups over classical methods

Notably, Yao et al. (2017) [1] presents an NMR (Nuclear Magnetic Resonance) based approach applying quantum edge detection on a 4×4 image, using real quantum hardware. The novelties are the use of QPIE for image representation & the using the Quantum Hadamard Edge Detection (QHED) algorithm for detecting image boundaries with a single-qubit operation requiring O(1) time, regardless of image size, outpacing classical O(N) methods. Nevertheless, for processing real-world images, qubit scarcity & NMR noise present serious challenges in this approach. Cavalieri and Maio (2020) [13] proposed an improved QHED using central finite differences but validated it through simulations (e.g., 100,000 measurements on 32x32 images). Also, the use of SWAP ckts has been employed for image matching tasks. While this represents a significant step forward, the final edge detection results suffer from severe quality issues due to inherent decoherence, gate noise, and error propagation when implemented on actual gate-based quantum hardware. They noted barriers like insufficient qubits on platforms such as IBM Quantum, emphasizing the need for future hardware advances. As a result, the techniques remain inadequate for practical use.

Using QuEra's Aquila, Milan et al.[4] introduce QRC after representing heavily downsized images using an analog QImR. They encode downscaled tomato leaf images from the PlantVillage dataset using position modulation in a 9×9 atom array (81 qubits total), but this setup maps to an 8×9-pixel resolution (72 pixels or features). Pixel values adjust vertical inter-atom distances (bonds) between rows, requiring one extra atom row for the 8-pixel rows across 9 columns thus, features = (atom rows - 1) × atom columns. The paper's position encoding scheme scales up qubit requirement linearly with pixel count: Larger images require bigger atom arrays (more qubits) to embed more features via inter-atom bonds, e.g., 81 qubits for 72 pixels in 8×9 resolution, 108 qubits for 96 pixels in 8×12. QuEra's updates confirm this trend, with 256-qubit arrays handling 200-300 pixels for vision tasks, though hybrid classical downscaling remains key for practicality. However, the caveat is, that a 300-pixel image is insufficient for most real-world applications.

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In contrast, our approach Sparse Dots Representation (SDR) overcomes these limitations by leveraging an analog quantum computing paradigm, specifically using QuEra's neutral atom quantum device (Aquila). The dynamics of its Rydberg atom array under global laser driving and interactions can be expressed with the following Hamiltonian [6]:

$$H(t) = \frac{\Omega(t)}{2} \sum_{j} \left(|g_j\rangle\langle r_j| + |r_j\rangle\langle g_j| \right) + \sum_{j<k} V_{jk} n_j n_k - \sum_{j} \left[\Delta_g(t) + \alpha_j \Delta_l(t) \right] n_j \tag{1}$$

where:

- $\Omega(t)$ is the Rabi frequency of the global laser drive.
- V_{jk} denotes the interaction energy between atoms j and k in the Rydberg state.
- n_j is the Rydberg number operator for atom j.
- $\Delta_g(t)$ is a global detuning term.
- $\Delta_l(t)$ is a local detuning contribution scaled by site-dependent factor α_j.

In the proposed sparse-dot framework, visual information is encoded directly through the physical placement of neutral atoms rather than via digital basis-state representations. The spatial arrangement of atoms corresponding to the sparse dot pattern is implicitly captured by the distance-dependent interaction energy term "V_{jk}" in the Rydberg Hamiltonian (Eq.(1)), which naturally reflects the geometric relationships within the image. As a result, image structure is embedded in the system's many-body dynamics without requiring explicit position encoding or costly state-preparation circuits, making the approach well suited for analog quantum devices such as Aquila.

SDR is the only representation that does not scale up with image resolution (Table 1), rather the number of qubits used for representation depends upon the precision required in the application. It is user defined & directly compatible with analog neutral-atom hardware, enabling geometry-native quantum image processing unavailable to FRQI, NEQR [17], or QPIE. Through a spatial-encoded representation of Edge-extracted megapixel-size images, our method can encode structurally relevant edge information using sparse point clouds, without the resource overhead or noise sensitivity of gate-based systems. This not only enables real-world image sizes to be represented compactly, but also allows for quantum simulation of large and complex image structures with high fidelity.

S.No.	**QImR**	**Qubits reqd. for a 2^nx2^n pixel image**	**Features**
1	FRQI	$(2n + 1)$	Probabilistic
2	QPIE	$(2n)$	Probabilistic
3	NEQR	$(2n + q)$; $q \geq 1$	Deterministic, Suffers from State Preparation problem
4	Analog QImR [4]	$> 2^n$	Qubit requirement is too high
5	SDR	Independent of 'n'; Flexible and user defined (always$< 2n$)	Deterministic, No State Preparation problem

Table 1: Comparison of major QImR techniques with SDR

WORKFLOW

For most industrial automation tasks, the image contours are sufficient enough to deliver matching/classification results. Since edge-extracted images would not require exploiting the full features in an image, this project aims to substantially reduce the required number of qubits. This reduction has been achieved by developing a new analog quantum image representation (QImR) technique i.e. SDR.

The SDR approach is shown in the following figure 1. The incoming image undergoes a Sobel- based edge extraction, then the edges are replaced with equidistant dots. The RDP algorithm is then used to minimize the number of dots representing the image. This is often accomplished by varying the perpendicular distance tolerance parameter epsilon(ε) in RDP [9]. This highly optimized image representation is referred to as "Sparse Dot Image" in this paper. We then encode the Sparse-Dot edge map directly into the atomic array of the quantum device, using Bloqade SDK [14]. This approach is a complete novelty in the quantum regime, as it allows us to map any arbitrary image on to the physical atomic array, with dramatically reduced number of qubits, without losing the geometry of the image. The Rydberg Hamiltonian of the device corresponding to the particular atomic arrangementundergoes time-evolution with tailored waveforms for Rabi-drive & Detunings.

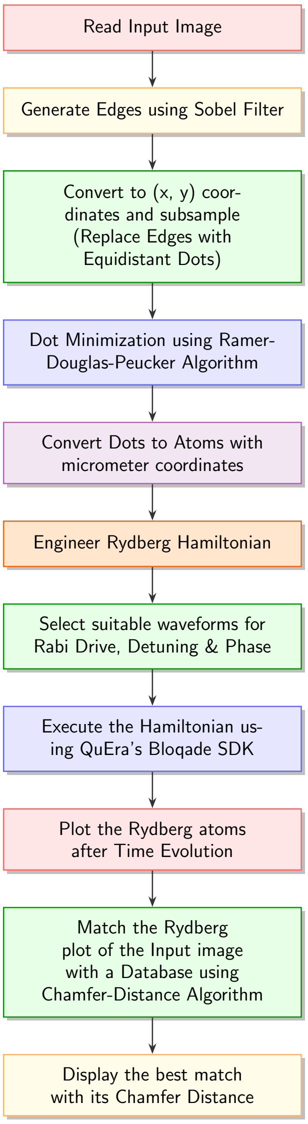


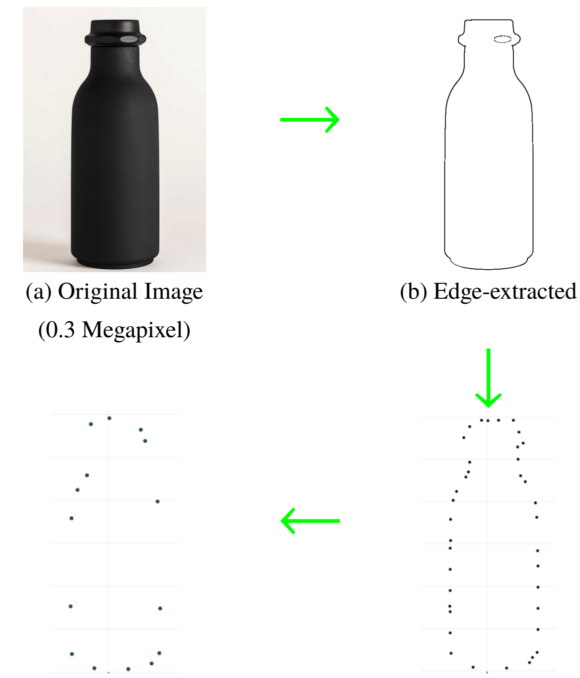
Figure 1: Project Flowchart

The resulting quantum map is compared against a dot-pattern database using Chamfer distance metric [13]. The Chamfer Distance method is well-suited to comparing the similarity between two point-clouds. It gives a distance value relative to every comparison, the least distance output being the best match to the input image.

Since AI hardware & software cannot be installed on miniature drones & medical robots, the feasible way forward would be to concentrate the AI hardware & Software in a centralized Hybrid (Quantum-Classical) computer & process the incoming sensor data from the above tethered miniature devices in parallel. The matching results obtained above on a quantum device can be sent back to the respective robots/drones/peripheral devices for real-time object identification and task management. By offloading image understanding to a centralized, hybrid processing unit, this system eliminates the need for embedded AI on each robot and demonstrates a scalable, resource-efficient model for perception in industrial robotics.

SIMULATION

The full project has been successfully implemented using the Julia language [16] & the Bloqade SDK [14]. We were able to match (simulate) all industrial value items with less than 30 atoms, often ranging between 9-21 atoms. Since neutral-atom hardware scales very easily with qubit count without any considerable increase in the energy cost, in the elaborate pipeline, these preliminary results on everyday industrial objects can be extended to human face & body contour recognition using QML. The Code & the Dataset may be made available through special request.



(a) Original Image (0.3 Megapixel)

(b) Edge-extracted

(d) Sparse-Dot version

(c) Dotted version

Figure 2: Image processing steps

Unlike digital quantum processors, which struggle to maintain coherence over long sequences of gates (especially problematic for high-resolution image tasks), analog quantum computers can naturally simulate spatially structured Hamiltonians using atom arrays with precise control over atom positions and laser-induced interactions. Our approach exploits this strength through position-based encoding of edge-derived dot patterns, allowing real-world images (up to megapixel scale) to be reduced to compact point clouds, suitable for analog simulation.

From an algorithmic standpoint, the use of classical preprocessing dramatically reduces the quantum load (Figure 2) and ensures practicality with current NISQ technology. The

Ramer-Douglas-Peucker algorithm ensures that only the most structurally significant points are retained—often fewer than 21—making the data light enough to fit comfortably within Aquila's 256-qubit limit. This compression does not compromise the semantic structure of the image, preserving key contours essential for recognition and matching

CONCLUSION & FUTURE WORK

By leveraging minimal-pixel image representations on analog neutral-atom quantum hardware, the above project aims to overcome the bottlenecks of available qubit count, energy consumption and computational scaling. Future directions for an analog-centric approach would be to use Hamiltonian energy of the atom arrangements representing images in Aquila, as matching criterion, to match an input image, from a database of images. Also, for QML tasks, QRC can be incorporated in the above study. This work envisions a transformative step toward sustainable and scalable artificial intelligence through quantum image processing.

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