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Quantum Image Edge Detection Using the Qiskit Image Processing Library

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Abstract**—**Finding the edges in an image is still a fundamental part of picture analysis. This report takes a deep dive into how quantum computers could tackle this problem, with a practical focus on using the Qiskit ecosystem. We formalize two of the most common quantum image encoding methods (FRQI and NEQR) and show how to build quantum circuits that perform edge detection. A key part of our analysis is a realistic comparison of classical and quantum time complexities, where we are careful to include the often-overlooked costs of state preparation and readout. We also analyze how real-world quantum noise might distort the results and show diagrams for the FRQI layout, a sample circuit, and the entire processing pipeline. We wrap up by suggesting which real-world applications might be the first to benefit from this technology and what research is still needed to bridge the gap from theory to practice.

Index Terms**—***Quantum image processing, FRQI, NEQR, Qiskit, edge detection, quantum noise, time complexity.*

I. INTRODUCTION

Edge detection is all about finding the important outlines in an image. It is a key step that powers everything from medical scan analysis and robotic vision to satellite imaging and quality control in factories. The classical methods for this (like Sobel, Prewitt, and Canny) are well-understood and very efficient.

So, why bring quantum computing into it? The hope is that quantum mechanics offers a new set of tools—like superposition, entanglement, and amplitude processing—that could give us an edge for certain types of vision tasks.

II. QUANTUM IMAGE REPRESENTATIONS

A. *Quantum Image Representations*

Before we can do anything, we have to get our classical image into a quantum state. This is the first and biggest hurdle. Let's look at the two most common ways to do this, FRQI and NEQR, to see how they work and what their pros and cons are.

1) *FRQI: Flexible Representation of Quantum Images*

FRQI is clever. For a $2^n \times 2^n$ image, it uses $2n$ qubits to store all the pixel locations (x, y) and just one extra qubit to store the intensity (like grayscale value) for that pixel. It saves the intensity value as an angle, θ_i, on that single qubit.

The full state for the entire image (with $N = 2^{2n}$ pixels) is a big superposition of every pixel:

$$|\Psi_{\text{FRQI}}\rangle = \frac{1}{\sqrt{N}} \sum_{i=0}^{N-1} \big(\cos\vartheta_i\,|0\rangle + \sin\vartheta_i\,|1\rangle\big) \otimes |i\rangle \tag{1}$$

Here, $|i\rangle$ is the quantum state representing the (x, y) coordinate, and the $(\cos\vartheta_i|0\rangle + \sin\vartheta_i|1\rangle)$ part is the intensity qubit for that coordinate. To build this state, you first put the location qubits into a uniform superposition (so they represent all locations at once) and then apply a series of controlled rotations to set the correct intensity angle for each location.

a) State preparation cost: This is the catch. A naive approach to setting every pixel's angle requires $O(N)$ controlled operations, which is slow. While there are more advanced, tree-like methods to speed this up [16], this preparation cost is often the dominant factor in the entire algorithm.

2) *NEQR: Novel Enhanced Quantum Representation*

NEQR takes a more straightforward approach. It also uses $2n$ qubits for the pixel location, but instead of one clever angle-based qubit for the intensity, it uses a whole register of q qubits to store the pixel's value as a standard binary number.

The state looks like this:

$$|\Psi_{\text{NEQR}}\rangle = \frac{1}{\sqrt{N}} \sum_{i=0}^{N-1} |I_i\rangle \otimes |i\rangle \tag{2}$$

where $|I_i\rangle$ is the q-bit binary state (e.g. $|10110010\rangle$) for the intensity at location $|i\rangle$. This is much more like classical digital storage.

a) State preparation cost: This is also expensive, costing $O(N \cdot q)$ operations in a simple approach. Its main advantage is that reading the data out is deterministic—you just measure the intensity qubits. With FRQI, you have to sample the amplitudes, which is probabilistic.

3) *FRQI vs NEQR: a compact comparison*

Below is a direct comparison of the two methods (Table 1).

Table 1. Comparison of FRQI and NEQR Encoding Methods

Feature	**FRQI**	**NEQR**
Qubit Count	Stingy ($2n{+}1$). Uses 1 qubit for intensity.	Hungry ($2n{+}q$). Uses q qubits for color depth.
Retrieval	Probabilistic via sampling.	Exact, deterministic bit-by-bit.
Native Ops	Global, wave-like transforms.	Bitwise math; ideal for digital filters.
Noise Sensitivity	High (analog angle-based).	More robust (digital bit flips).

III. QUANTUM EDGE DETECTION METHODS

With the image loaded, how do we actually find the edges? Here are the main strategies.

A. *Hadamard-Based (QHED-like) Amplitude Probe*

Using the FRQI state (1), we exploit the Hadamard trick. The goal is to compare the intensity $|\varphi_i\rangle$ of pixel i with its neigh-

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bour j. The Hadamard gate is a natural "difference" operator:

$$H = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

If two neighbouring pixel states can be interfered and a Hadamard applied, the amplitude on the $|1\rangle$ state is proportional to their difference. A large amplitude signals a sharp edge.

a) Circuit idea: A circuit conditioned on location $|i\rangle$ performs an operation with neighbour $|j\rangle$, typically using controlled-shift operations or small local patches.

B. NEQR Bitwise Sobel

The classical Sobel filter slides a 3×3 kernel over the image to find the gradient. With NEQR, pixel values are already in digital format. Quantum arithmetic circuits (reversible adders) compute the Sobel gradients G_x and G_y for all pixels simultaneously in superposition. The edge magnitude $|G| \approx |G_x| + |G_y|$ is then thresholded.

High-level NEQR Sobel steps: (1) For each index $|i\rangle$ in superposition, load the intensities of its 8 neighbours into temporary registers. (2) Use quantum add/subtract circuits to compute G_x and G_y. (3) Approximate the magnitude and apply a threshold. (4) Measure to obtain the edge map.

C. Hybrid Patch-Based Approaches

Since controlling operations on a large $|i\rangle$ register is expensive, a practical NISQ-era approach breaks the image into small patches (e.g. 8×8), processes each patch on a small quantum computer, and stitches the results classically, dramatically reducing qubit and gate requirements.

IV. RELATED WORK

Quantum image processing (QIP) has evolved significantly from theoretical inception to practical circuit implementations. The field began with the development of efficient storage mechanisms, primarily FRQI and NEQR [1,2]. While FRQI offered a qubit-efficient method by encoding intensity into amplitudes, it suffered from probabilistic measurement limitations. This led Zhang et al. [2] to propose NEQR, which uses a basis-state representation allowing deterministic retrieval at the cost of increased qubit requirements.

Building on these foundations, researchers shifted focus toward algorithmic primitives such as filtering and edge detection. Early work by Cavalieri and Maio [4] demonstrated theoretical exponential speedup, though this often neglected state-preparation overhead. More recent studies addressed these bottlenecks; Shubha et al. [11] explored "Quantumized" edge detection that optimises circuit depth for specific image types, while Xu et al. [10] implemented the Kirsch operator using quantum arithmetic for higher-precision directional edges.

In the current NISQ era, focus has pivoted to hybrid architectures. Geng et al. [12] proposed a hybrid quantum-classical edge detector that offloads heavy arithmetic to classical processors while leveraging quantum interference for feature extraction. Works such as Billias et al. [25] are pushing toward utility-scale experiments validating these algorithms on real hardware, identifying that quantum error mitigation [21] is critical for usable results.

V. METHODOLOGY

Our methodology utilizes a formal mathematical framework to compare quantum encoding schemes and evaluates computational efficiency through end-to-end complexity analysis. We move beyond simple processing speedups to consider the critical overheads of state preparation and measurement, while also modelling the degradation of edge fidelity under realistic quantum noise conditions.

The core objectives are:

1. *Encoding Method Comparison:* Establish formal mathematical distinctions between FRQI and NEQR, contrasting qubit requirements and retrieval mechanisms.
2. *End-to-End Time Complexity:* Rigorously evaluate total runtime, incorporating the often-overlooked costs of image loading (state preparation) and data retrieval (measurement).
3. *Noise Impact and Mitigation:* Quantify edge-detection fidelity degradation under realistic noise models and identify necessary error mitigation techniques.

VI. TIME COMPLEXITY ANALYSIS

A quantum algorithm might look fast on paper, but we must count the entire process—from loading the image to getting the answer out. Let the image have $N = M^2$ pixels and q bits of colour depth.

A. Classical Baseline

A classical Sobel filter runs in $O(N)$, performing a constant number of operations per pixel. This is the benchmark to beat.

B. FRQI Full Pipeline

a) State preparation $T^{\text{prep}}_{\text{FRQI}}$: The naive loading approach requires $O(N)$ rotation gates:

$$T^{\text{prep}}_{\text{FRQI}} = \alpha N \tag{3}$$

b) Quantum processing $T^{\text{proc}}_{\text{FRQI}}$: A global Hadamard on the intensity qubit is $O(1)$. The neighbour-comparison step costs at least $O(\log N)$.

c) Measurement/readout $T^{\text{meas}}_{\text{FRQI}}$: Reconstructing the full N-pixel edge map requires $\Omega(N)$ measurements.

d) Total:

$$T^{\text{total}}_{\text{FRQI}} = O(N) + O(\log N) + O(N) \approx O(N) \tag{4}$$

There is no asymptotic speedup over the classical pipeline.

C. NEQR Full Pipeline

a) State preparation: $T^{\text{prep}}_{\text{NEQR}} = \alpha' Nq \quad [O(Nq)$ cost].

b) Quantum processing: Arithmetic circuit depth d_{arith} depends on q, not N, giving $O(d_{\text{arith}})$.

c) Measurement: $O(N)$, same as FRQI.

d) Total:

$$T^{\text{total}}_{\text{NEQR}} = O(Nq) + O(d_{\text{arith}}) + O(N) \approx O(Nq)$$

This is linear in N, same as classical, but slower by constant factor q.

D. When Quantum Advantage May Emerge

Quantum advantage may emerge when: (1) only a global property is needed (e.g. "does any edge exist?"—answerable in sublinear time); (2) the image is already in a quantum state

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(e.g. from a quantum sensor); (3) the quantum transform has a significantly smaller constant factor.

VII. QUANTUM NOISE ANALYSIS

Real quantum computers are noisy. Qubits lose coherence and gates introduce errors. We model noise with standard channels applied to density matrix ρ:

A. Noise Channels

a) Depolarising noise (probability p):

$$\mathcal{E}_p(\rho) = (1-p)\,\rho + p\,\frac{I}{2} \tag{5}$$

b) Amplitude damping (γ): Models qubit decay $|1\rangle \to |0\rangle$ (energy loss):

$$E_0 = \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{1-\gamma} \end{pmatrix}, \quad E_1 = \begin{pmatrix} 0 & \sqrt{\gamma} \\ 0 & 0 \end{pmatrix}$$

c) Phase damping / dephasing (λ): Destroys superposition off-diagonal elements without bit flips; deadly for interference-based algorithms.

B. Effects on Edge Detection

Noise attacks edge signals by: (1) attenuating amplitude differences, making edges "fade"; (2) mixing states, causing false-positive spurious edges; (3) flipping readout bits, adding salt-and-pepper noise to the edge map.

We quantify performance using *edge fidelity* F_e, the correlation between the ground-truth classical edge map E_{gt} and the noisy quantum output E_q. As error rate increases, F_e drops sharply (see Fig. 1).

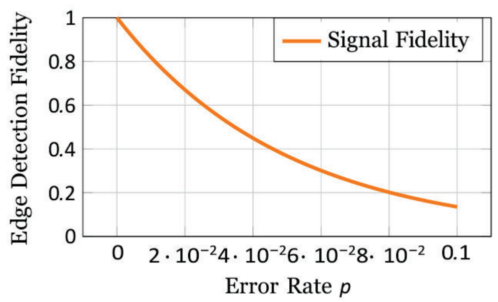

Figure 1. Conceptual degradation of edge fidelity as physical error rates increase. Without error mitigation, fidelity drops sharply.

C. Mitigation Techniques

- **Zero-Noise Extrapolation (ZNE):** Run the circuit at several amplified noise levels, then extrapolate back to the zero-noise limit.
- **Probabilistic Error Cancellation:** Learn the noise model and stochastically apply "inverse" gates to cancel errors.
- **Readout Mitigation:** Calibrate the probability that $|1\rangle$ is misread as $|0\rangle$ and correct final counts via a calibration matrix.
- **Shallow Circuit Design:** Fewer gates (especially slow two-qubit gates) reduces exposure time to noise.

VIII. EXPERIMENTAL DESIGN AND SIMULATIONS

A. Datasets and Preprocessing

- Simple 8×8 and 16×16 images (squares/circles on black backgrounds).
- Small 16×16 crops from real images (BSD500 dataset, sample MRI scans).
- All intensities normalised to $[0,1]$.

B. Pipelines Implemented

- FRQI + Hadamard probe: encode the image, apply the Hadamard probe, and sample the results.
- NEQR + Bitwise Sobel: encode the image, run the quantum Sobel arithmetic circuits, and measure.
- Hybrid patching: split the image into 8×8 patches and run them sequentially.

C. Simulator and Noise Models

We used Qiskit's `aer_simulator` with custom depolarising and amplitude-damping noise models. In each run, we measured edge fidelity F_e, precision, and recall against a ground-truth map from a classical Canny filter.

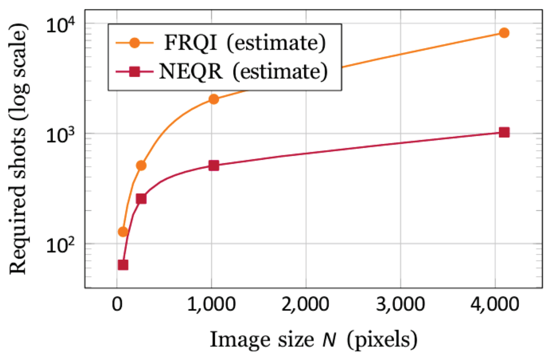

Figure 2. Illustrative shot budget vs. image size. Distinct colours differentiate FRQI and NEQR scaling behaviours.

IX. REAL-WORLD APPLICATION MAPPING

While fully fault-tolerant quantum computers are required for broad advantage, specific domains may see earlier benefits.

A. Healthcare: Diagnostic Imaging

Medical imaging (MRI, CT, PET) relies heavily on edge detection for organ segmentation and tumour identification. Quantum interference patterns may be more sensitive to subtle amplitude differences at soft-tissue boundaries. Additionally, quantum algorithms can process raw quantum-sensor data directly, skipping the classical conversion step that introduces quantisation noise.

B. Space: Remote Sensing and Earth Observation

Satellite imagery involves vast datasets with unique challenges. Synthetic Aperture Radar (SAR) images suffer from speckle noise; quantum edge detectors using global properties may separate true topological features (ice-shelf cracks, coastline shifts) from coherent noise better than local convolutional filters. Key challenges include data-latency bottlenecks (state-preparation is $O(N)$) and the prohibitive energy/thermal requirements of superconducting qubits for onboard processing.

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X. CONCLUSIONS

This report walked through the practical steps of quantum edge detection, starting from FRQI and NEQR image encoding and examining the real-world costs of state preparation, processing, and readout. For full-image-to-full-image tasks, these quantum algorithms do not offer an asymptotic speedup over classical $O(N)$ methods and are likely much slower in practice. We also showed how noise degrades performance and what mitigation strategies can help.

Key findings:

- **State preparation is the bottleneck.** Without practical QRAM, an end-to-end speedup is unlikely.
- **Measurement is the other bottleneck.** Global-query models that avoid reading the full image back out are a more promising direction.
- **Noise sensitivity:** FRQI (analog) is fragile; NEQR (digital) is more robust but qubit-hungry. This trade-off is a major challenge.
- **Real hardware validation** is needed. Most QIP results rely on simulators; experiments on actual noisy hardware are scarce.

The most likely path to quantum advantage is not replacing classical filters but finding niche problems where the input is already quantum or only a single global image property is needed.

I. DIAGRAMS (FRQI, CIRCUIT, FLOWCHART)

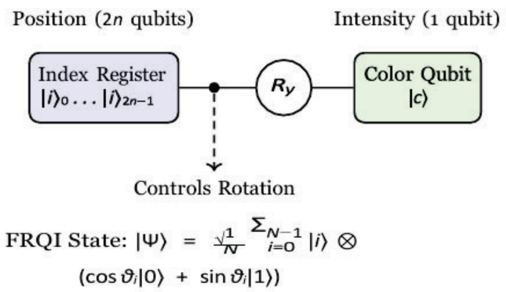

Figure 3. FRQI conceptual diagram: the position register controls a rotation on the single intensity qubit to encode pixel values as amplitudes.

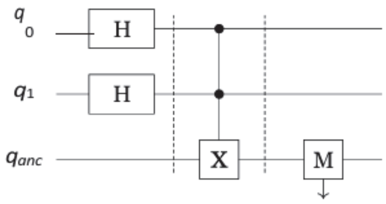

Figure 4. Schematic quantum circuit for edge detection: superposition creation (H), neighbour-checking oracle (Controlled-X), and measurement.

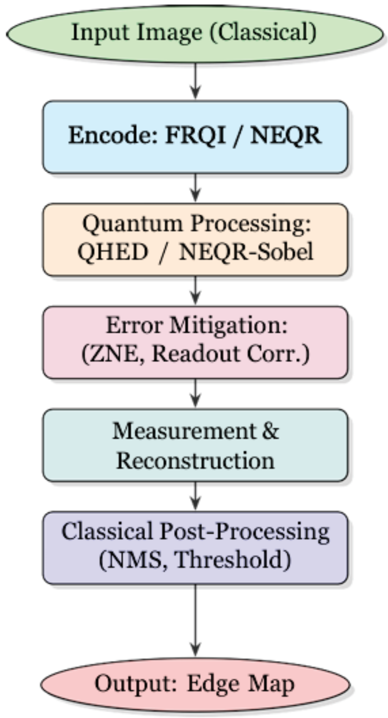

Figure 5. High-level pipeline: Input Image $\rightarrow$ Quantum Processing $\rightarrow$ Error Mitigation $\rightarrow$ Measurement & Reconstruction $\rightarrow$ Classical Post-Processing $\rightarrow$ Edge Map.

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II. QISKIT EXAMPLE CODE

The following self-contained Qiskit example demonstrates FRQI-style encoding for a small image and a Hadamard-based edge probe. This code uses the Aer simulator.

Listing 1. Qiskit FRQI + Hadamard probe (example)

```
from qiskit import QuantumRegister, ClassicalRegister,
     QuantumCircuit
from qiskit_aer import AerSimulator
from qiskit.compiler import transpile
from qiskit.circuit.library import RYGate
import numpy as np

def frqi_angles_from_image(img):
    # Map pixel values [0,1] -> angles [0, pi/2]
    angles = (np.pi / 2.0) * img.flatten()
    return angles

def build_frqi_circuit(angles):
    n_pixels = len(angles)
    n_idx = int(np.ceil(np.log2(n_pixels)))
    qidx = QuantumRegister(n_idx, 'idx')
    qint = QuantumRegister(1,     'int')
    c    = ClassicalRegister(1,   'c')
    qc   = QuantumCircuit(qidx, qint, c)

    # Put index register into uniform superposition
    qc.h(qidx)
    qc.barrier()

    # Naive controlled rotations for small N
    for idx, theta in enumerate(angles):
        if theta > 0:
            bits = format(idx, f'0{n_idx}b')[::-1]
            for i, b in enumerate(bits):
                if b == '0':
                    qc.x(qidx[i])
            cry = RYGate(2 * theta).control(n_idx)
            qc.append(cry, qidx[:] + [qint[0]])
            for i, b in enumerate(bits):
                if b == '0':
```

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```
                qc.x(qidx[i])
        qc.barrier()
    return qc

if __name__ == '__main__':
    # Sample 4x4 image: centre square
    img = np.zeros((4, 4))
    img[1:3, 1:3] = 1.0
    print("Input␣Image:\n", img)

    angles = frqi_angles_from_image(img)
    qc = build_frqi_circuit(angles)

    # Hadamard probe on intensity qubit
    qc.h(qint[0])
    qc.measure(qint[0], c[0])

    backend = AerSimulator()
    t_qc = transpile(qc, backend)
    job = backend.run(t_qc, shots=1024)
    counts = job.result().get_counts()
    print("\nMeasurement␣counts:", counts)
```

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