Exploring the research scope in Satellite Imagery Using Quantum Image processing - A comprehensive Review

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Abstract

Quantum computing (QC) promises to revolutionize data-intensive fields due to its potential for exponential speedups and novel computational paradigms. Satellite image processing (also called Earth Observation, EO) is one such domain, where large volumes of high-dimensional data (e.g., multispectral or hyperspectral images) challenge classical methods in terms of computation, memory, and latency. In this review, we survey the state-of-the-art at the intersection of quantum computing and satellite image processing. We first outline quantum image representations, key quantum algorithms proposed for image processing (e.g., edge detection, segmentation, classification), and quantum machine learning (QML) models. We then examine recent studies that target Earth observation data, including resource estimation and hybrid quantum-classical architectures. Next, we delineate the major challenges (hardware, encoding, noise, scalability) and propose potential solutions, focusing on suitable quantum algorithms and hybrid strategies. Finally, we discuss future directions and research opportunities.

Index Terms: Quantum image processing, satellite imagery, Earth observation, Quantum machine learning, Quantum algorithms, Remote sensing.

1.0 Introduction

Satellite imagery plays a central role in modern global monitoring systems, supporting applications such as climate change assessment, land-use classification, disaster management, precision agriculture, and military surveillance. With the increasing deployment of high-resolution passive and active sensors—ranging from multispectral imagers to hyperspectral sensors and synthetic aperture radar (SAR)—satellite data has become richer, more complex, and extremely large in volume. For instance, hyperspectral images may contain hundreds of narrow spectral bands, yielding millions of high-dimensional feature vectors per scene. Processing such datasets using traditional algorithms has become computationally demanding, especially in scenarios requiring real-time or large-scale analysis. Classical image processing and machine learning methods have advanced significantly, yet they confront inherent constraints including memory bottlenecks, energy consumption, algorithmic inefficiencies, and the curse of dimensionality. Quantum computing (QC) offers a fundamentally different computational paradigm capable of addressing these challenges by exploiting quantum superposition and entanglement to process high-dimensional data more efficiently. Theoretical studies suggest speedups in similarity search, optimization, and linear-algebra-based operations—core components of remote sensing tasks.

In this context, Quantum Image Processing (QIP) has emerged as a promising sub-discipline, focusing on encoding, storing, processing, and analyzing image data using quantum systems. Foundational efforts include the development of quantum image representations such as the Flexible Representation of Quantum Images (FRQI) and the Novel Enhanced Quantum Representation (NEQR), which allow pixel values and spatial coordinates to be encoded into quantum states. These representations enable the implementation of quantum operations for tasks such as edge detection, segmentation, filtering, and classification. As recent work begins applying QIP concepts to real satellite imagery, new hybrid quantum-classical frameworks, quantum machine learning models (e.g., QCNNs), and quantum optimization techniques are being explored. Although the field remains nascent and quantum hardware is constrained by noise and limited qubit counts, early results indicate potential advantages for remote sensing use cases.

This paper expands on these developments by providing a comprehensive review of QIP research with a focus on satellite imagery. We analyze classical-to-quantum image encoding methods, relevant quantum algorithms, use-cases in Earth observation, technical challenges, and future pathways toward achieving quantum advantage in remote sensing.

2.0 Background and Quantum Foundations

A. Quantum Computing Basics

Qubits and Quantum States At the heart of quantum computing lies the qubit, the quantum analogue of the classical bit. Unlike a classical bit, which can exist in one of two states—0 or 1—a qubit can exist in a superposition of both states simultaneously, represented as $|\psi\rangle=\alpha|0\rangle+\beta|1\rangle$, where α and β are complex numbers that satisfy the normalization condition $|\alpha|2+|\beta|2=1$. This property allows quantum computers to perform computations on multiple states. simultaneously, offering a form of parallelism that is exponentially more powerful than classical computing as shown in Figure 2.1. However, Issues such as coherence, noise, and gate errors remain central challenges.

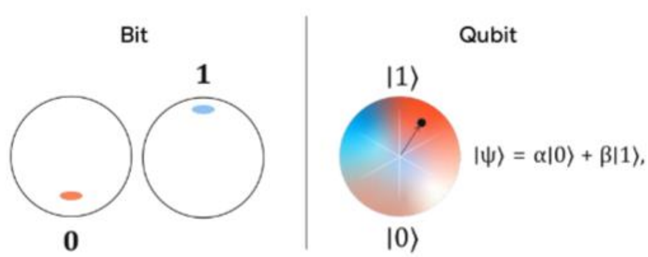

Figure 2.1

B. Quantum Image Representation

A core question in quantum image processing (QIP) is how to encode a classical image into a quantum state. Several proposals have been proposed:

1. Flexible Representation of Quantum Images (FRQI): Encodes pixel positions in basis states and pixel values in amplitude.
2. Quantum Probability Image Encoding (QPIE): Encodes probabilities.
3. Other schemes: more compact amplitude-based encodings.

Ruan, Xue et.al present opportunities and challenges regarding QIP representations, arguing that while quantum parallelism grants advantages, some claims of "quantum superiority" are overstated. Furthermore, research has explored transformation from classical to quantum images and noise mitigation strategies in the encoding process.

3.0 Literature in Quantum Image Processing

3.1 Classical Image Processing Tasks on Quantum Computers

1. **Edge Detection**:
   - Xi-Wei Yao et al. (2017) propose encoding a grayscale image into a quantum state (amplitudes) and devise a quantum edge detection algorithm that remarkably requires a *single-qubit operation*, independent of image size.
2. **Improved Edge Detection Algorithms**:
   - Shubha, et al. (2024) introduced a modified quantum Hadamard Edge Detection (QHED) algorithm combined with FRQI encoding to handle non-binary images more accurately.
3. **Image Classification**:
   - Dang, et al. (2018) propose a *quantum k-nearest neighbor (kNN)* algorithm for image classification. They extract classical feature vectors, load them into a quantum superposition, compute similarity in parallel, and use a quantum minimum search. Their complexity is $O(\sqrt{kM})$ vs. classical $O(kM)$, showing a quadratic speed-up.
4. **Quantum Convolutional Neural Networks (QCNN)**:
   - Prajapat, Tomar, Kumar, Kumar, and Vasilakos (2025) propose a QCNN model for image classification, showing that combining quantum circuits and deep learning can yield efficient processing.

3.2 Reviews and Surveys of Quantum Image Processing

- Ebrahimpour et al. (2024) provide a comprehensive survey of quantum computing in image processing, covering compression, enhancement, pattern recognition, recovery, and future directions. AIAI Journal+1
- Sungheetha (2023) surveys applications and challenges specifically in quantum image processing, noting both promise and practical bottlenecks. IRO Journals
- Mamatha et al. (2024) analyze advanced image processing tasks via quantum computing, emphasizing scalability and hardware constraints. IJISAE

3.3 Quantum Computing for Satellite / Remote Sensing (Earth Observation)

- Otgonbaatar et.al (2023) present a detailed review in *IEEE Transactions on Quantum Engineering*, specifically for satellite image processing, estimating quantum resource requirements and assessing hybrid HPC + QC architectures for Earth observation data. IEEE Transactions on Quantum Engineering+2IEEE Transactions on Quantum Engineering+2

More recently, Sebastianelli, et al. (2024) introduces a *quanvolutional neural network* (quanvolution = quantum convolution) model that directly targets Earth observation data. The authors report up to **5% accuracy improvement** over classical methods in remote sensing tasks, with a parameter-efficient design and no need for training quantum kernels. arXiv. However, Comparison among various Quantum Image Representation Approaches is shown in Table 3.1.

Table 3.1: Comparison among various Quantum Image Representation Approaches

Quantum Image Representation Approach	Key Features	Advantages	Challenges
Flexible Representation of Quantum Images (FRQI)	Encodes image information using amplitude and phase of quantum states	Efficient storage of image data	Requires complex quantum circuits for operations
Novel Enhanced Quantum Representation (NEQR)	Uses a binary sequence to encode pixel values directly into quantum states	Higher fidelity in representing image details	Increased resource requirements (more qubits)
Quantum Image Processing (QIP)	Utilizes quantum algorithms to perform image transformations	Potential for faster processing times compared to classical methods	Still in early stages of development; hardware limitations

3.4 Quantum Simulation & Evaluation

- Hasegawa et.al. (2024) evaluate quantum image processing workflows on classical hardware using *GPU-based quantum simulations* (e.g., cu Quantum). Their experiments verify that many quantum image-processing algorithms can be simulated, exploring performance and resource tradeoffs.

4.0 Challenges in Applying Quantum Computing to Satellite Image Processing

Exploring literature, the main challenges are:

1. **Encoding High-Dimensional Satellite Data**:
Satellite images (especially hyperspectral data) have many bands and high resolution. Representing each pixel's spectral vector in a quantum state is nontrivial. Quantum image representations (e.g., FRQI) may be poor.

2. **Quantum Resource Constraints**:
Quantum circuits require qubits, gates, and coherence time. As shown by Otgonbaatar et al, resource estimation (e.g., number of *T-gates* after transpiration) is critical. IEEE Transactions on Quantum Engineering+1

3. **Noise / Error**:
Real quantum hardware (especially NISQ) suffers from decoherence and gate errors. These errors can degrade encoded image data and algorithmic performance.

4. **Scalability and Circuit Depth**:
Deep circuits for complex tasks (e.g., quantum convolution, segmentation) may exceed coherence time, making them infeasible on current hardware.

5. **Hybrid Architecture Complexity**:
Deciding how to partition processing between classical HPC and quantum resources is challenging. Suboptimal partitioning could eliminate quantum advantage. Otgonbaatar et al. investigate this trade-off. IEEE Transactions on Quantum Engineering

6. **Benchmarking and Validation**:
There is a lack of standard datasets and benchmarks for evaluating quantum image-processing on EO data. Also, simulating quantum algorithms (e.g., via cu Quantum) has limits.

7. **Misleading Claims of Quantum Superiority**:
As Ruan, Xue, and Shen argue, not all claims of exponential speedup are realistic under practical constraints. OUCI

5.0 Possible Solutions and Suitable algorithms

Given the challenges, literature and theory point to several possible strategies and algorithms:

A. Hybrid Quantum-Classical Architectures

- **Partitioning tasks:** Use classical pre-processing (e.g., down sampling, PCA) to reduce data dimensionality, then apply quantum circuits on the compressed representation. For instance, classical PCA followed by Quantum Principal Component Analysis (QPCA) can reduce the effective qubit count.
- **Hybrid training:** Parameterized quantum circuits (PQCs) / variational quantum algorithms (VQAs) can be trained using classical optimizers, as in variational quantum classifiers or QCNNs.

B. Quantum Algorithms for Core Tasks

1. **Quantum Edge Detection**:
- Use amplitude-encoded image representations (like FRQI) together with single-qubit operations to detect edges with quantum speed-up. The Phys. Rev. X method is a key example. Physical Review Journals
- Modify QHED with more flexible encodings (e.g., FRQI), as in the work by Shubha et al. arXiv
2. **Quantum Classification / Clustering**:
- **Quantum kNN**: Using quantum parallelism to compute similarity and then quantum minimum search yields a quadratic speed-up. arXiv
- **Quantum Convolutional Neural Networks (QCNN)**: For EO images, one can design QCNNs tailored to remote sensing features. The *Quanv4EO* model is promising: quanvolution layers followed by quantum circuits processing spectral/spatial patches. arXiv
- **Quantum PCA (QPCA)**: Use QPCA to reduce dimensionality of hyperspectral data before further processing.
3. **Quantum Optimization / Segmentation**:
- Formulate segmentation as a **QUBO** (Quadratic Unconstrained Binary Optimization) problem and solve using **QAOA** (Quantum Approximate Optimization Algorithm). Such an approach can be particularly useful for partitioning land cover, change detection, or clustering pixel groups.
- Alternatively, use **quantum annealing** (if hardware available) for segmentation or clustering tasks.

C. Error Mitigation and Circuit Optimization

- **Error mitigation techniques**: Use techniques such as zero-noise extrapolation, mitigation via calibration, dynamical decoupling, or circuit cutting. For example, *quantum circuit cutting* decomposes large circuits into smaller ones to reduce resource needs.
- **Shallow circuit design**: Focus on minimal-depth circuits, small, parameterized gates, and low entanglement — critical for NISQ devices.

- **Encoding optimizations**: Use more compact encodings, compress information before loading, or hybrid encoding to minimize qubit usage.

D. Simulation and Benchmarking

- Use classical simulators optimized for quantum circuits (e.g., GPU-based simulators like *cuQuantum*) to prototype and evaluate algorithms before deploying on real QC hardware. Hasegawa *et al.* demonstrated this approach. Fukushima Laboratory
- Develop EO-specific quantum benchmarking datasets (e.g., small patches of multispectral or hyperspectral images) that can be used to compare quantum vs classical performance.

6.0 Scope of Future Research Directions

1. **Scalable Quantum Representations**: Research on new quantum image encoding schemes explicitly tailored for high-dimensional EO data (e.g., hyperspectral bands) to minimize qubit overhead.
2. **Hybrid Learning Frameworks**: Develop variational quantum circuits that incorporate domain knowledge from remote sensing (e.g., spatial-spectral correlations) and classical deep learning.
3. **Resource-efficient Quantum Circuits**: Design PQCs for image processing with minimal T-gates, shallow depth, and noise robustness.
4. **Quantum Segmentation & Change Detection**: Extend QAOA-based methods for segmentation, and dynamic circuits for detecting temporal changes in satellite images.
5. **Quantum Benchmarking for EO**: Establish standard quantum benchmarking protocols and datasets for satellite imagery to compare quantum methods fairly.
6. **Error Mitigation in Remote Sensing Use Cases**: Explore advanced error mitigation strategies specifically in image processing pipelines.
7. **Hybrid HPC+QC Deployment Strategies**: Explore architectures where large-scale EO processing is distributed between HPC clusters and quantum accelerators, optimizing performance, cost, and resource utilization (extending analyses like those in Otgonbaatar et al.).

7.0 Conclusion

Quantum computing holds significant promise for satellite image processing (Earth observation), offering potential advantages in speed, dimensionality reduction, and novel processing paradigms. However, as the literature shows, many challenges remain—from encoding and hardware limitations to error, resource constraints, and hybrid architecture design. Current research (e.g., quantum edge detection, QCNNs, resource-estimation for

EO datasets) provides proof-of-concept and initial benchmarks but realizing practical quantum advantages in real-world EO tasks will require careful algorithmic design, efficient encoding, error mitigation, and hybrid computation strategies. Future work combining quantum algorithm development, realistic simulation, and hardware-aware deployment may pave the way for quantum-enhanced remote sensing workflows.

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