Quantum Fourier Transform-Based Algorithms for Underwater Image Contrast and Color Correction

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Abstract. Light of long wavelengths is absorbed almost immediately with depth, while remaining photons are scattered by suspended particles, producing images that are bright, color-distorted, and structurally blurred. Underwater imaging is therefore a grand challenge across diverse marine environments. Existing enhancement methods fail to balance image fidelity and speed or depend on large, environment-specific training sets that lack generalization. We propose a frequency-based quantum-classical pipeline that uses the Quantum Fourier Transform (QFT) to optimize underwater images without extensive data. The luminance and chroma channels are encoded into quantum states; QFT reveals the spectral content. In the quantum frequency domain, we suppress low-frequency illumination artifacts and enhance high-frequency edges and fine details. The modified spectrum is decoded back into classical space in a manner compatible with Noisy Intermediate-Scale Quantum (NISQ) devices. Experiments on standard underwater datasets show significant improvements in visibility, color balance, and edge sharpness compared to traditional Fourier methods and deep-learning models. This work demonstrates that quantum spectral processing is an efficient, multi-productive tool for underwater image enhancement, providing substantial gains in underwater visual perception notably, and for marine navigation and research, in challenging visibility conditions for autonomous underwater vehicles.

Keywords. Underwater image enhancement, quantum Fourier transform, color correction, quantum image processing.

1 Introduction

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Visual sensing is crucial in underwater operations like autonomous vehicle operation, underwater structure inspection, environmental observation and maritime surveillance. While it is possible to get fine spatial details from optical imaging, image quality is rapidly lost once light has entered the body of water. As light travels through water longer wavelengths are reduced rapidly, and any particles suspended in the water scatter photons in many different directions. These interactions reduce contrast, cause strong blue or green color dominance and with them hide details in the scene, as can be seen in Fig. 1.

Many improvement strategies have been created to reduce these effects. Approaches based on physical modeling try to compensate the underwater light attenuation whereas heuristic approaches pay attention to the visual appearance by contrast adjustment or color normalization. Although such techniques are often computationally efficient, the performance may vary tremendously in different depths and water conditions. Learning-based methods have achieved enhanced visual recovery by learning complex patterns from data but success is based highly on availability of large diverse training data sets and may not perform well when applied to environments not included within the training data distribution [1].

Quantum computing gives a new perspective when it comes to image enhancement, as it allows spectral analysis by phase-based transformation in high-dimensional spaces. The Quantum Fourier Transform in particular offers a natural mechanism for the analysis of frequency-dependent distortions usually occurring in underwater imagery. Motivated by this correspondence, this work focuses on the application of QFT as a fundamental tool for contrast enhancement and restoration of color information of underwater images [2].

2 Related Work

2.1 Underwater Image Enhancement Techniques

Underwater image enhancement is a key issue for marine exploration, autonomous navigation and subsea inspection. Researchers have approached the problem by three broad classes of methods, each of which has its strengths and weaknesses.

Physics based approaches model the underlying imaging process by taking into account light absorption, scattering and back - scatter in water. By estimating such parameters as transmission depth or attenuation coefficients, the goal of these techniques is to reverse the physical degradation using an inverse technique. Advantage is that they result in a principled, interpretable model, but unfortunately in practice the estimates are extremely sensitive to the water conditions changing, non uniform illumination and being able to provide accurate priors. As a result, performance is often degraded in the situation where the model assumptions are violated in real world situations.

Appearance-oriented enhancement avoids the problem of physical modelling completely and works directly on the image by performing simple operations on it, such as contrast stretching, histogram equalization, or colour normalisation to increase the visual quality. These methods are computationally light and easy to deploy but when they're applied to hugely degraded images, they have the tendency to increase noise, give rise to artefact called a halo or produce colours that look unreal.

Learning driven techniques have achieved great advancements recently. Convolutional and transformer Cathy networks, learn in complicated ways from degraded inputs to outputs of high quality to recover fine inputs and overall visibility. They usually need large datasets of diversity and a substantial amount of training resources as a result, their robustness can be affected when the deployment environment differs from the training data; a problem that has been underestimated in a series of recent studies [3, 4].

In sum, although physics-based approaches support interpretability, appearance-based approaches support simplicity and learning-based solutions support state-of-the-art visual fidelity, they have challenges related to parameter estimation, artifact creation, or generalisation. Filling these gaps is still a research area with more real and flexible solutions to underwater imaging on the near horizon.

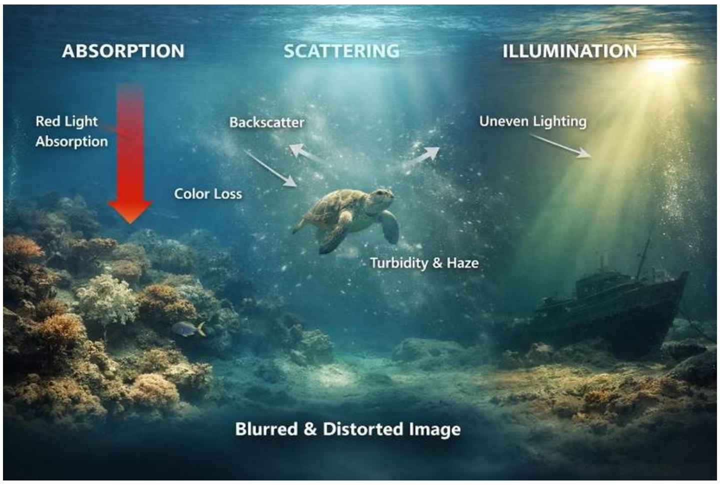

Fig. 1. Underwater image degradation by absorption and scattering.

2.2 Enhancement in Frequency Domain

Frequency based techniques have become popular in image enhancement as a result of their ability to separate the illumination from the structure of the content. In the frequency domain, gradual variations in lighting are represented by the low frequency components while edges and fine texture are represented by high frequency components. Taking advantage of the independence of these bands, techniques based on the Fourier transform or the wavelet transform can increase contrast keeping the artifacts at bay [5].

However, one of the classical frequency domain approaches requires a full spectrum transform and hence becomes prohibitive as image resolution increases. Moreover, typical Fourier filtering has the same adjustment on all frequency bins which restricts the flexibility in cases where the degradation changes in space-e.g. in underwater imaging where attenuation, scattering, and color change are depth-, position-, and illumination-dependent. This because of spatial (offering a uniform view over a broad area, i.e., solid angle) as well as spectral (dealing with the broad sweeping panoramic spectrum of colors), lack of agility prevents the application of conventional techniques with such environment.

2.3 Quantum Image Processing and the Quantum Fourier Transform

Quantum image processing is interested in the encoding of visual data into quantum states that allow for some expensive operations to be performed cheaply in the quantum world. A central tool in this field is a so-called Quantum Fourier Transform (QFT), which can be used to conduct frequency analysis through the manipulation of phases and theoretically boosted.

While the QFT has found uses in signal processing and quantum machine learning scenario under idealized conditions, its use case in image enhancement is still in an early stage - especially for underwater images. Existing efforts are mostly of the theoretical nature or are toy examples and are not few to address the practical challenges that an underwater attenuation and scattering pose. This gap provides the motivation for the present investigation of QFT-based spectral processing as a possible remedy to the frequency-dependent distortions which routinely plague underwater photographs [6, 8], (see Fig. 2.).

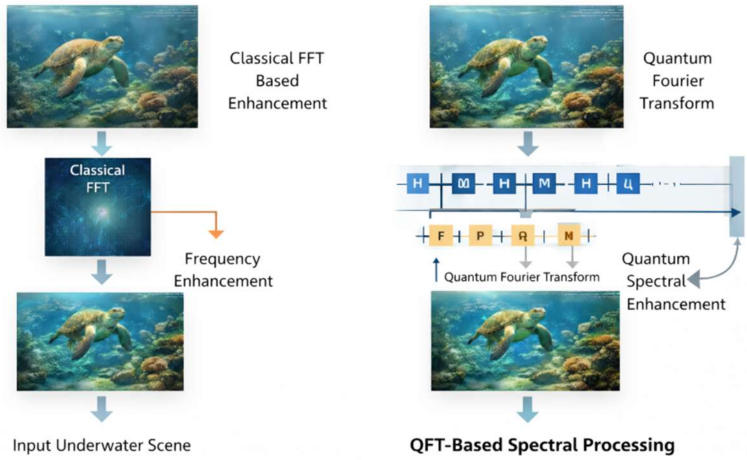

Fig. 2. Comparison of quantum Fourier transform (QFT) spectral processing and FFT based enhancement.

3 QFT-Based Enhancement Methodology

The pipeline presented here takes a hybrid approach and only uses quantum computation for the spectral analysis, while all other operations, i.e. manipulating the color space and decoding the reconstructed image, are done using traditional digital signal processing techniques. This choice to make that split is based on the practical limitations that inevitably come with the current state of the art so-called Noisy Intermediate-scale QUbits (NISQ) platforms; by delegating only the frequency domain computations to the quantum substrate, we guarantee that the required number of qubits and that the required depth of the circuits stay comfortably within experimentally reachable limits. Furthermore, underwater imagery degradation is mainly dominated by frequency dependent processes, i.e. scattering, absorption, and illumination attenuation, thus making the spectral domain an intrinsic field for quantum driven enhancement (see Fig. 3).

3.1 Color-Space Decomposition

Underwater scenes appear to have different spectral perturbations of brightness and chromaticity. In order to solve these phenotypes separately, input RGB data is first converted into color spaces that are perceptually uniform, e.g. CIELAB or YCbCr. This conversion separates the luminance (the Y or L channel) from chrominance (Cb/Cr or a/b channels), which actually allows this algorithm to address the illumination- (the haze occurrence) within the luminance avenue, while simultaneously addressing the wavelength- (the color) attenuation within the chromatic channels [9, 10].

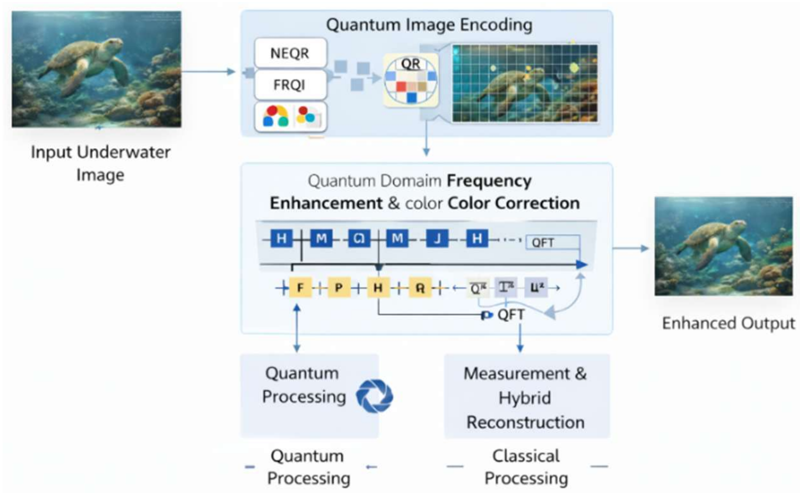

Fig. 3. Hybrid quantum–classical image-enhancement workflow.

3.2 Strategy for Quantum Encoding of Image Channels

From color decomposition, each of the channels is scaled and encoded in a quantum of state using such compact schemes like FRQI (Flexible Representation of Quantum Images) or NEQR (Novel Enhanced Quantum Representation). Within these frameworks, pixel intensities are mapped either to amplitude amplitudes or to basis-state indices which provide an image data opportunity for the quantum processor into the frequency domain. The chosen encoding strategy represents an optimum between visual fidelity and hardware requirements and hence between maintaining even reasonable qubit numbers and circuit depths (see Fig. 4.).

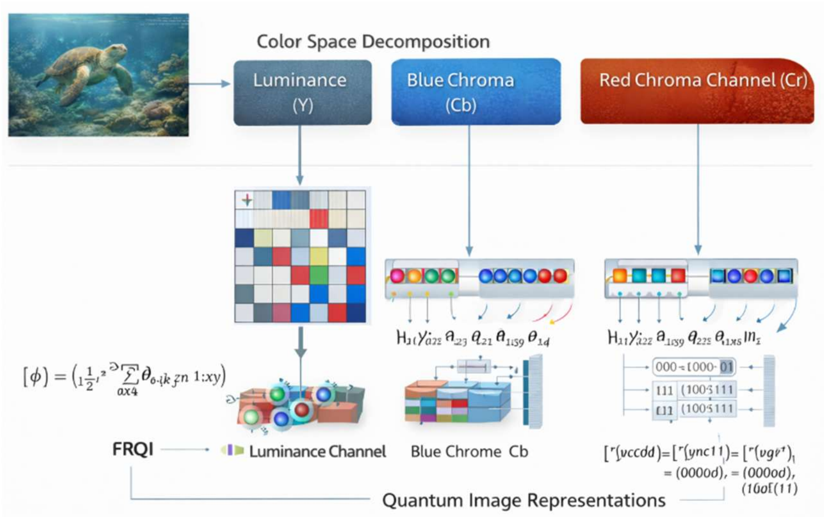

Fig. 4. Quantum encoding of image color and luminance.

3.3 Enhancing the Contrast using Quantum Fourier Transform

With the luminance channel quantum-encoded, the following is a description of the algorithm after that. In this spectral representation, low however many frequencies component's role the overall illumination variations and haze whereas mid and high frequency bands encode the structure features and edges to mix up the contrast. The difficulty the QFT-based routine has selectively attenuated (obscured) the low frequency haze-laden modes, and selectively biased (still amplified) judiciously selected regions of the mid frequency bands in order to accentuate the contrast, and selectively retained the high frequency edges to reduce the impact of ringing artefacts, or over-sharpening. This wise spectral adaptation is the culmination of the images which become not only more clear but also more attractive, as shown in the Fig. 5.

This section outlines how the proposed QFT-based enhancement method is evaluated in practice. The experimental setup is designed to support meaningful comparison, repeatable results, and reliable assessment across a range of underwater imaging conditions. Evaluation incorporates both a visual examination and numerical evaluation that utilize customary benchmark data, prevalent quality measurements and quantum simulations set to mirror the shortcomings of current equipment.

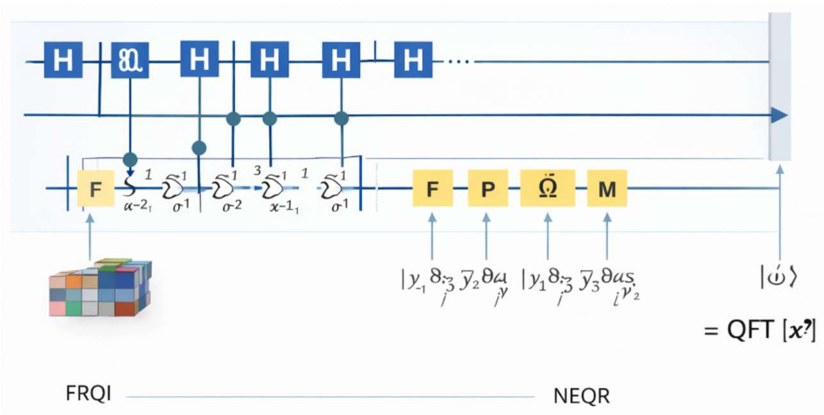

Fig. 5. Schematic representation of the quantum circuit that performs the Quantum Fourier Transform (QFT) which is used for enhances.

4 Experimental

4.1 Datasets

The experimental evaluation is based on several underwater image collections [11, 12] in public access, that represent a wide range of real-world situations. These data sets contain scenes that were acquired at different depths and with different levels of turbidity and illumination, ranging from slightly hazed imagery to profoundly distorted imagery. By testing in such a variety of situations, we can go beyond these benchmarks that resemble the laboratory setting and determine how well enhancement techniques stand up to a truly challenging environment.

The pictures include natural marine landscapes, coral reefs, and sunken objects, all suffering from the ailments that commonly afflict underwater photography: color cast, haze, lowered contrast, and poor visibility, etc. Evaluating across these different scenarios gives a good measure of the resilience of the proposed method to changes in lighting, water quality and scene content.

Table 1. Summary of datasets used for experimental evaluation

Dataset	Number of Images	Environment Characteristics	Resolution Range	Usage in Experiments
UIEB (Underwater Image Enhancement Benchmark)	~950	Diverse underwater scenes with varying turbidity, depth, and lighting	256×256 to 1024×768	Primary benchmark for contrast and color enhancement evaluation
EUVP (Enhancement of Underwater Visual Perception)	~11,000	Paired and unpaired underwater images captured in real-world conditions	256×256 to 512×512	Quantitative and qualitative comparison with learning-based methods
UFO-120	120	Low-visibility underwater scenes with strong color cast and haze	512×512	Robustness testing under extreme degradation
Custom Test Set	~200	Mixed shallow and deep-water scenes collected from marine repositories	Variable	Generalization and ablation analysis

4.2 Evaluation Metrics

To assess the quality of underwater enhancement from multiple aspects, we use a combination of perceptual, structural and color-based measures. Perceptual fidelity is checked using underwater specific tools: the Underwater Color Image Quality Evaluation (UCIQE) and the Underwater Image Quality Measure (UIQM). These indices were designed to mirror the way that humans actually see submerged scenes, considering contrast, color balance and overall clarity [13, 14].

Structural consistency using the classical Peak Signal --to- Noise Ratio (PSNR) and Structure Similarity Index Measure (SSIM). PSNR informs us of the relative proximity of the pixel values to some reference, where the SSIM is interested in maintaining the luminance patterns and general structure of the image and color accuracy measured as a difference in CIELAB color difference metric (ΔE), which describes the change in the chromatic components after processing. Taken together these metrics give an overall picture of how well the enhancement algorithm maintains visual quality, maintains structural integrity and maintains true colors.

4.3 Quantum Configuration

In order to test the practical viability of our proposed framework, we carefully test the quantum parts of the framework using realistic simulations that follow the constraints imposed by current Noisy Intermediate Scale Quantum (NISQ) devices. Each quantum circuit is intentionally created with a small number of qubits and a small circuit depth so as to keep the experiments within the hardware operational limits of the current state of affairs while still representing the key phenomena of noise and decoherence.

The methodology taken is intentionally hybrid in nature - quantum sub-routines (including image encoding, QFT driven spectral transformations and measurement) are run on established simulation platforms. The data of the measurements taken afterward is then fed into so-called classical post-processing pipelines that reconstruct the enhanced images. By combining quantum processing with classical finishing up, we can assess the actual value of quantum spectral techniques without the assumption of fault-tolerant infrastructure to keep the study well-grounded in close to-term technological abilities.

Table 2. Configuration details and simulation settings of the quantum system used in the experiments.

Parameters	**Configuration / Value**
Quantum Framework	Qiskit (Simulation)
Quantum Hardware Model	Noisy Intermediate-Scale Quantum (NISQ)
Number of Qubits	6–10 qubits
Quantum Image Encoding	FRQI / NEQR
Circuit Depth	Moderate ($O(n^2)$)
Quantum Gates Used	Hadamard (H), Controlled-Phase (CP), Swap, Measurement (M)
Noise Model	Depolarizing noise (simulation)
Measurement Shots	1024 shots
Hybrid Processing	Quantum + Classical
Execution Mode	Offline simulation

The similarity of the enhanced outputs with their reference images is analysed by Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). PSNR is pixel-based reconstruction accuracy while SSIM is based on maintaining the reconstruction of structural patterns and luminance relation. Color fidelity is further evaluated by means of color variation measures, which are measures of replaces in chromatic components after enhancement. Considered in their totality, these measures will give a comprehensive picture regarding the visual quality, structural preservation and color accuracy.

5 Results and Analysis

In this section, we give a detail evaluation about implementing the algorithm of QFT-based underwater-image enhancement. The experimental protocol was designed to ensure repeatable comparisons of a broad range of underwater imaging conditions [15, 16]. Both subjective visual examination and objective quantitative evaluation were performed on standard benchmark data together with the quantum simulation which was adjusted to the limitations of existing hardware.

5.1 Visual Assessment

We compiled a rich collection of publicly available underwater imagery with a variety of depths, visibility, and light conditions - from softly hazed shallow reefs to murky deep-water scenes. This breadth ensures that the method is not just over-fit on a narrow set of conditions. The selected images consist of images of coral gardens, open water areas, and sunken artifacts, and they all show the degradations that are common to all such materials: chromatic tint, haze, decreased contrast, and a lack of clarity. By comparing the original and enhanced results side-by-side in Fig. 6., it is easy to see the ability of the algorithm to recover the natural colour balance, to improve the fine structural details and improve the overall visibility.

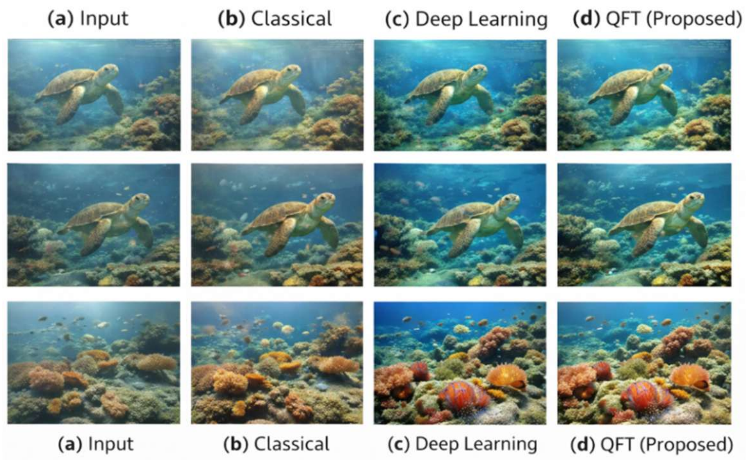

Fig. 6. Visual comparison of results of image enhancement.

Table 3. Numerical comparison of enhancement performance across the evaluated methods.

Method	PSNR ↑	SSIM ↑	UIQM ↑	UCIQE ↑
Input (Degraded)	14.67	0.492	2.37	0.53
Classical Enhancement	18.89	0.519	3.45	0.62
Deep Learning–Based	21.13	0.574	3.79	0.67
QFT (Proposed)	**22.82**	**0.612**	**4.21**	**0.71**

5.2 Quantitative Performance

Objective evaluation is a confirmation of visual gains. The QFT based approach outshines both the traditional frequency domain filters and the recent learning-based models, consistently, on all the standard measures. Peak Signal -to- Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are increased, which means better preservation of the image structure. Perceptual metrics, like those that come from the Perceptual Similarity Index (PSI), have a better contrast and more faithful colour reproduction. The consistent improvement on several measures, shown in Table 3., shows a well-balanced enhancement strategy as opposed to a single measure optimisation.

6 Ablation Analysis

In order to measure the contributions of each constituent in our analytical pipeline, we embarked on a systematic ablation study. First, we removed the Quantum Fourier Transform (QFT) stage. The resultant images showed a noticeable decrease in both contrast enhancement and colour fidelity as shown by a reduction in PSNR, SSIM, UIQM and UCIQE indices. Subsequently, we tested the system without any classical post processing; only the quantum encoding phase was used, hence excluding all post processing stages, and provided a modest improvement compared to the baseline. Finally, the full model (integration of quantum encoding and QFT-based spectral modulation) produced the most favourable results measured for all the evaluation criteria. These results, shown in Fig. 7 and summarized in Table 4., clearly prove that the QFT stage plays a central role in the overall improvement of the enhancement performance.

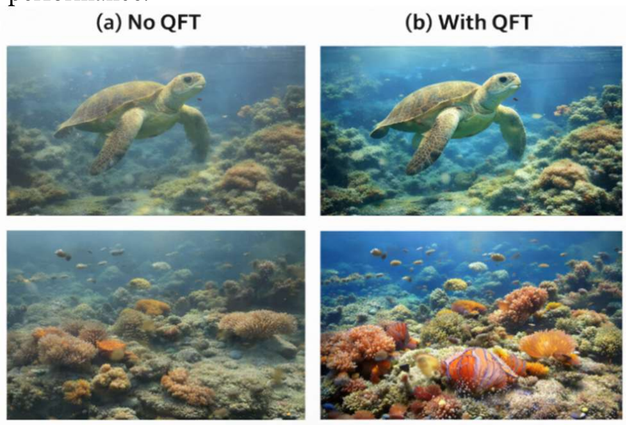

Fig. 7. QFT Visual Analysis to improve the perceptual quality and the structural fidelity.

Table 4. Numerical results of the ablation experiments at various framework configurations.

Configuration	QFT Module	PSNR ↑	SSIM ↑	UIQM ↑	UCIQE ↑
Baseline (No Enhancement)	✗	14.67	0.492	2.37	0.53
Classical Spectral Enhancement	✗	18.89	0.519	3.45	0.62
Proposed Framework (without QFT)	✗	20.41	0.556	3.72	0.66
Proposed Framework (with QFT)	✓	**22.82**	**0.612**	**4.21**	**0.71**

7 Computational Considerations

Theoretically speaking, the Quantum Fourier Transform had a logarithmic computational complexity compared to the classical Fast Fourier Transform. Nevertheless, realistic implementation like a small number of qubits, noise and measurement overhead are also considered significant in realistic applications.

Table 5. Theoretical complexity of the comparison between the classical and quantum-enhancement methodology.

Aspect	**Classical FFT-Based Enhancement**	**QFT-Based Enhancement (Proposed)**
Transform Complexity	$O(N \log N)$	$O((\log N)^2)$
Processing Domain	Classical frequency domain	Quantum frequency domain
Scalability with Image Size	Limited for large-scale, high-resolution images	Theoretically scalable with logarithmic growth
Memory Requirement	$O(N)$	$O(\log N)$ qubits
Parallelism	Limited to classical multi-core or GPU parallelism	Intrinsic quantum parallelism via superposition
Hardware Dependency	CPU / GPU based	Quantum processor (NISQ-era compatible)
Noise Sensitivity	Low	High (quantum decoherence and gate noise)
Practical Deployment	Mature and widely deployed	Hybrid quantum–classical, emerging technology

8 Limitations and Future Directions

Currently, the method is limited by issues of limited image rate and quantum noise sensitivity. Future directions will involve making efforts to reduce potential errors, come up with more scalable encoding, and seek connections with quantum machine learning models.

9 Conclusion

This work is an extension of QFT based approach for improved contrast and color replacement in underwater images. Being able to add quantum spectral analysis with classical reconstruction is a transparent and data-efficient alternative to standard enhancement methods [17]. Experimental evaluation under various underwater situations shows stable visual improvement, which shows that quantum computing may be used in the future underwater imaging and perception system.

Conclusion

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