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Research Paper

Noise-Aware Variational Quantum Algorithms for Robotics Optimization Problems

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Abstract. In the field of robotics, optimization problems with high computational costs, such as motion planning, multi-robot cooperation, and manipulation, are constrained by the exponential growth of the complexity of classical algorithms. This paper discusses practical methods for robot optimization, specifically using noise-aware variational quantum algorithms (VQAs) on current noisy intermediate-scale quantum hardware. To address the inherent errors of quantum devices, a specific framework has been proposed. The framework clearly defines noise modeling, adjusts error mitigation methods, and creates quantum-classical workflows. Using actual quantum computers and high-fidelity simulations, this paper will systematically evaluate four benchmark robotic domains. The statistical data from numerous experiments (up to 100 trials per scenario) indicate that, in the presence of significant hardware noise, noise-aware VQAs can improve the target value by up to 14% compared to standard quantum methods and reduce the number of convergence iterations by 45%. Cross-platform tests indicate that all six robotic tasks run stably, with an accuracy rate exceeding 90% for all devices. In real-world environments, this trajectory generation method performs excellently under noisy conditions when using physical robots. In order to ensure the accuracy of quantum accelerated optimization in robotics, it is necessary to reduce noise. According to the aforementioned research, reducing noise can be practically applied outside of laboratory conditions.

Keywords: *Variational Quantum Algorithms, Noise Mitigation, Hybrid Systems, Experimental Benchmarking*

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Introduction

In the past decade, quantum computing and robotics have collaborated to enhance the performance of intelligent autonomous vehicles [1]. In many fields, such as motion planning, task allocation, and operations, robotic optimization is indispensable [2]. These fields involve complex constraints and dynamic high-dimensional environments. The initial optimization methods were random search, combinatorial techniques, and convex relaxation. These methods have achieved a certain degree of success, but their computational complexity is usually exponential, making them difficult to apply in practice [3]. As quantum computing transitions from theory to practical application, noise intermediate-scale quantum devices (NISQ) capable of performing specific computational tasks have been developed [4]. Therefore, Variational Quantum Algorithms (VQAs) are becoming one of the main quantum-classical hybrid methods for optimizing cost function applications in real-world environments [5]. Quantum-assisted path optimization, real-time multi-agent coordination, and efficient high-dimensional solution space exploration have all seen the first applications of VQAs [6]. According to some proof-of-concept demonstrations, properly configured quantum resources can generally provide computational advantages for conventional robotic applications [7].

The current noise limitations of quantum hardware still restrict the widespread application of VQA in robotic tasks [8]. During the NISQ era, devices may be affected by factors such as decoherence, gate infidelity, readout errors, and device drift, which can lead to significant deviations from the ideal behavior of the algorithm [9]. Noise interference can reduce the quality of solutions, leading to convergence failures and even causing control

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strategies to become unstable. This is especially important for real-time robots [10]. Current VQA frameworks typically assume ideal quantum operations that are rarely found on physical devices, lacking mechanisms to explicitly characterize or compensate for these noise sources in robotic optimization workflows [11]. In recent studies, quantum circuits or error mitigation schemes for noise have been introduced, but most research has not carefully examined their impact on core robot optimization metrics or their robustness across various tasks and hardware backend scenarios [12]. Robotic applications increasingly require consistency, adaptability, and scalability. If there are no noise-aware algorithm strategies, it is difficult to meet these requirements [13]. Quantum hardware is rapidly advancing, but reliable models or simplified methods for optimizing noise in robotics have not yet been developed [14].

This paper designs and analyzes a general framework for a variational quantum algorithm that optimizes noise perception in robots. A quantum noise model based on adaptive mitigation measures is proposed to evaluate the guidance performance metrics of robots. Our technology establishes a quantum-classical workflow and explicitly considers the noise generated by specific constraints at each stage of optimization. Through systematic experimental benchmarking on multiple robotic scenarios and quantum platforms, it has been demonstrated that noise-aware variational quantum algorithms (VQAs) can optimize more effectively in all cases. This indicates that VQAs will contribute to the feasibility of quantum-enhanced robotic systems.

Theoretical Foundations and Problem Formulation

Problem Statement for Robotics Optimization

Grasp generation, task scheduling, motion planning, multi-robot collaboration, and multi-robot cooperation are all based on robot optimization [15]. The goal of the aforementioned problems is to find the most effective methods, settings, or allocations to maximize traffic, improve accuracy, or reduce energy consumption. These methods should perform specific functions under certain constraints and the influence of randomness [16]. The aforementioned requirements stem from physical constraints, such as actuator limitations, joint kinematics, spatial constraints, and collision avoidance, as well as logical specifications. Prioritization, limited communication bandwidth, or strict time constraints may also lead to these requirements [17].

Due to the continuous development of robotic systems in unstructured and dynamic environments, the related optimization problems need to be relatively sensitive to uncertainty and capable of quickly adapting and scaling to significant issues [18]. High dimensionality is a characteristic; nowadays, many robots are more flexible in complex, time-varying environments [19]. Multi-robot trajectory planning is a common example of this type of problem. This means that space and time need to be handled simultaneously, ensuring that robots do not collide with each other and managing resource conflicts. Therefore, with each additional robot, the number of possibilities increases [20].

Traditional methods, including reinforcement learning, population-based evolutionary algorithms, sampling-based planners, and mixed-integer programming, have already addressed the aforementioned issues. These methods have advantages in certain aspects, but they also have many drawbacks. In high-dimensional or non-convex problems, exact methods often result in prohibitively high costs, while heuristic methods struggle to maintain accuracy and adaptability in new environments. The widespread adoption of data-driven and learning-based methods has recently brought more flexibility and adaptability, but it has also raised new issues, such as interpretability and generalization. These trends indicate an urgent need for new computational frameworks to better address large and irregular optimization problems, ensuring the quality of the results.

Foundations of Variational Quantum Algorithms

Variational Quantum Algorithms (VQAs) are a hybrid computational model that uses quantum circuits with classical control parameters and iteratively optimizes through feedback loops between quantum and classical computers [21]. To minimize the objective cost function, quantum devices in a typical VQA workflow measure, generate entangled states, and provide statistical data to classical routines based on pre-selected hypothetical feedback results [22]. Cyclic collaboration uses the expressiveness of quantum states to encode complex probability distributions and correlations. Also retains the stability and diversity of classical optimization in parameter search [23].

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The theoretical foundation of VQAs is the hope of achieving "quantum advantage" under real hardware and scale constraints, surpassing the best classical solvers in relevant application domains. Reformulate the original optimization problem as the expectation value of a cost Hamiltonian, effectively mapping the problem's constraints and objectives onto a quantum circuit, and then use variational methods to explore the energy landscape. The ultimate goal is to find an approximate low-energy (and thus high-quality) solution that cannot be obtained using classical algorithms in polynomial time [24]. The Variational Quantum Eigensolver (VQE) is a typical Quantum Neural Network (QNN) for ground state chemical simulations, while the Quantum Approximate Optimization Algorithm (QAOA) is used for combinatorial optimization problems. Modern quantum neural networks have also been developed for supervised learning and reinforcement learning.

Nevertheless, the ultimate value, scalability, and efficiency of VQA largely depend on the choice of hardware calibration, classical optimizers, and circuit design. The "sparse plateau" phenomenon refers to the gradient disappearing when moving away from the region of interest, thus requiring the design of appropriate hypotheses and cost functions. In the field of robotics, real-time feedback, constraints, and robustness are all relatively high requirements, so it is necessary to carefully allocate the use of quantum resources compared to classical computing resources. In order to meet the various needs of robot optimization, the VQA field has recently undergone adjustments and expansions. They proposed new problem encoding methods, constraint integration methods, and hybrid cyclic scheduling that consider domain structure and hardware constraints.

Quantum Noise and Its Effects

On current Noisy Intermediate-Scale Quantum (NISQ) devices, variational quantum algorithms still face the issue of quantum noise [25]. Classical computers have some error correction mechanisms because they are almost completely error-free to a certain extent. However, due to the subtle nature of quantum coherence and entanglement, quantum devices are inherently susceptible to various errors [26]. Over time, decoherence (including relaxation (T1) and dephasing (T2)), imperfect gate operations, crosstalk between qubits, and measurement errors all reduce the accuracy of quantum computing. Due to equipment differences and unstable calibration, the aforementioned issues become more severe, leading to different noise characteristics between machines.

In variational quantum algorithms, noise takes on various forms. Changing the operations of the parameterized circuit leads to systematic deviations in the measurement results and causes random fluctuations, thereby reducing the efficiency of the optimizer. Errors in robot optimization directly affect the reliability of cost function estimation. Therefore, the optimizer's ability to handle complex, high-dimensional search spaces is limited [27]. This will reduce the convergence speed and may even lead to algorithm instability, especially in cases with many quantum circuits and problem instances.

In order to reduce quantum noise, many techniques have been developed, including hardware enhancement and dynamic decoupling, error mitigation algorithms, and noise-aware variational state design. Currently, the resource requirements for quantum error correction devices are too high, but they still have the potential for long-term scalability. To achieve reliable and practical quantum-enhanced optimization in the near future, it is essential to consider noise characteristics and mitigation methods when designing and running classical optimizers and quantum circuits. Robotics requires high reliability and repeatability, so noise-aware quantum algorithms need to be used to achieve significant improvements in deployment and performance.

Design of Noise-Aware Variational Quantum Algorithms

Noise Modeling and Mitigation in Quantum Optimization

Standard models of quantum noise and real-time noise reduction methods are needed to optimize robots using Variational Quantum Algorithms (VQAs). Inevitable noise sources include decoherence, gate fidelity, state preparation and measurement (also known as SPAM) errors, and crosstalk between qubits. These noise sources are typically present in modern quantum devices, especially in the NISQ era. These interferences vary over time and are spatially non-uniform. If not addressed, noise will affect the output of the quantum circuit and propagate errors into the iterative quantum-classical optimization loop, thereby reducing the accuracy of the results.

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The foundation of noise-aware algorithms is the operator-sum (Kraus) representation. For a general quantum channel $\mathcal{E}$, its action on the state ρ is given by

$$\mathcal{E}(\rho) = \sum_k K_k \rho K_k^\dagger \qquad \text{Eq.(1)}$$

where $\{K_k\}$ are the Kraus operators that satisfy $\sum_k K_k^\dagger K_k = I$.

The commonly occurring depolarizing channel for a single qubit is given by

$$\mathcal{E}_{dep}(\rho) = (1-p)\rho + \frac{p}{3}(X\rho X^\dagger + Y\rho Y^\dagger + Z\rho Z^\dagger) \qquad \text{Eq.(2)}$$

where p quantifies the strength of depolarization and X, Y, Z are the Pauli matrices. Similarly, the amplitude damping channel, which models energy relaxation, evolves the qubit state as:

$$\mathcal{E}_{damp}(\rho) = E_0 \rho E_0^\dagger + E_1 \rho E_1^\dagger \qquad \text{Eq.(3)}$$

where $E_0 = \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{1-\gamma} \end{pmatrix}$ and $E_1 = \begin{pmatrix} 0 & \sqrt{\gamma} \\ 0 & 0 \end{pmatrix}$ with damping rate γ.

In robotic optimization applications, the variational cost function typically takes the form

$$C(\vec{\theta}) = \langle \psi(\vec{\theta}) | H | \psi(\vec{\theta}) \rangle \qquad \text{Eq.(4)}$$

where H encodes the task-relevant objective and $|\psi(\vec{\theta})\rangle$ is the parameterized quantum state. The presence of noise modifies this expectation value. By incorporating explicit noise channels, the cost function becomes

$$C_{noisy}(\vec{\theta}) = Tr[H\mathcal{E}(|\psi(\vec{\theta})\rangle\langle\psi(\vec{\theta})|)] \qquad \text{Eq.(5)}$$

Regularly use calibration experiments such as quantum process tomography and randomized benchmarking to measure noise characteristics. Subsequently, the hardware-aware simulator uses the aforementioned empirical noise model to dynamically adjust circuit depth, variational state design, and mitigation methods based on the observed error distribution.

Mitigation methods are divided into multiple levels. Circuit-level methods construct shallow variational circuits, enforce symmetry, and insert dynamic decoupling pulse sequences to suppress specific error patterns. To reduce measurement errors, an empirical confusion matrix can be used to correct errors in classical readout. Zero-noise extrapolation is an algorithmic error mitigation method that evaluates the cost by deliberately increasing noise through circuit folding or gate extension, and then extrapolates the results to the ideal zero-noise limit. When available, use the calibration of the hardware noise model for probabilistic error correction to reconstruct an unbiased estimate of the noise-free observable. However, this usually leads to increased measurement costs.

Since the optimization workflow includes all noise characterization and mitigation methods, the selection of quantum circuits and the tuning of classical optimizers will be affected. Using the aforementioned methods can improve the accuracy of robot task solutions and maintain stability across all hardware environments. This will make the transition of robots from simulation to real quantum execution more reliable.

Figure 1 shows the integrated structure of the noise-aware VQA framework. As shown in the figure, a closed-loop system suitable for real device constraints includes classical optimization, variational circuit design, multi-level mitigation modules, quantum hardware calibration, adaptive noise modeling, and multi-level mitigation modules.

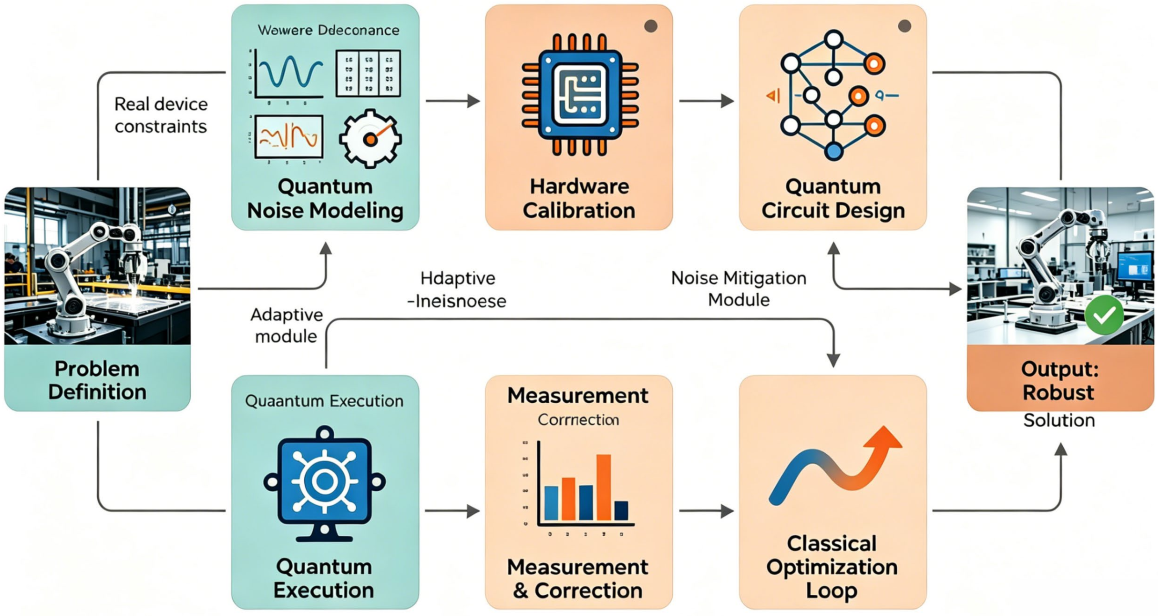

Figure 1. Overall Algorithm Framework

Algorithm Architecture and Adaptive Hybrid Workflow

The structure of the noise-aware variational quantum algorithm is a tightly integrated hybrid quantum-classical feedback system. It is used for robot optimization. The workflow is very flexible, can be used on both simulated and actual quantum devices, and can adapt to various hardware conditions.

The process begins by mapping the robotics optimization task into a cost Hamiltonian H and constructing a parameterized quantum circuit specified by variables $\vec{\theta}$. Problem constraints and state variables-whether binary assignments in multi-robot scheduling, or continuous controls in trajectory planning-are encoded as quantum registers, using binary or gray code for discrete data, and circuit rotations for continuous parameters. The initial quantum state is thus

$$|\psi(\vec{\theta}_k)\rangle = U(\vec{\theta}_k)|0\rangle^{\otimes n} \quad \text{Eq.(6)}$$

where $U(\vec{\theta}_k)$ is the quantum circuit for iteration k.

At each iteration, the quantum circuit runs on hardware, but due to device imperfections, noise transforms the state into

$$\rho_{noisy} = \mathcal{E}(|\psi(\vec{\theta}_k)\rangle\langle\psi(\vec{\theta}_k)|) \quad \text{Eq.(7)}$$

where $\mathcal{E}$ denotes the composite noise channel for that cycle-capturing gate errors, decoherence, and crosstalk. The measured expectation value is thus

$$C_{noisy}(\vec{\theta}_k) = Tr(H\rho_{noisy}). \quad \text{Eq.(8)}$$

Measurement outcomes are immediately corrected using calibrated readout error matrices. If the readout confusion matrix is M, then for n qubits the correction is $M^{\otimes n}$ applied to the distribution of measured outcomes. When possible, error mitigation includes zero-noise extrapolation, where circuits are run at various artificial noise levels and the cost function is extrapolated:

$$C_{extrap}(\vec{\theta}_k) = \sum_j \beta_j C_{noisy}^{(j)}(\vec{\theta}_k) \quad \text{Eq.(9)}$$

with each $C_{\text{noisy}}^{(j)}$ corresponding to a run at increased effective noise, and weights β_j chosen so extrapolation approaches the zero-noise estimate. More advanced mitigation, such as probabilistic error cancellation, uses stochastic weights w_l and repeated circuit executions:

$$\tilde{C}(\vec{\theta}_k) = \frac{1}{N}\sum_{l=1}^{N} w_l C^{(l)}(\vec{\theta}_k). \quad \text{Eq.(10)}$$

The mitigated estimate-now closer to the noise-free observable-serves as the input for the classical optimizer. The optimizer updates parameters according to

$$\vec{\theta}_{k+1} = \vec{\theta}_k - \eta_k \nabla_{\vec{\theta}} C_{mitigated}(\vec{\theta}_k) \quad \text{Eq.(11)}$$

where the gradient $\nabla_{\vec{\theta}}$ can be evaluated using the parameter-shift rule:

$$\frac{\partial C}{\partial \theta_i} = \frac{1}{2}\left[C\left(\vec{\theta}_k + \frac{\pi}{2}\vec{e}_i\right) - C\left(\vec{\theta}_k - \frac{\pi}{2}\vec{e}_i\right)\right]. \quad \text{Eq.(12)}$$

The system monitors hardware diagnostics in real time, tracking gate fidelity, decoherence times (T_1, T_2), and drift. If the circuit depth exceeds the hardware threshold, the circuit depth can be reduced, a more robust variational structure can be chosen, or mitigation parameters can be adjusted, all to maintain convergence and solution accuracy at that time.

The two are interconnected: the classical controller dynamically adjusts the circuit design and strategies based on the aforementioned results, while the quantum module provides device data and measurement costs. The trajectory, confidence intervals, and error bars are updated synchronously, and the convergence graph is monitored to determine stopping criteria and system adjustments. Especially for robotic applications, the system's safety and real-time performance must be considered.

Figure 2 shows the complete process mentioned above: problem definition and quantum encoding; sequential quantum execution and noise calibration; mitigation and measurement; iterative classical parameter update; adaptive protocol adjustment. The closed loop can detect and adjust changes in the device in real-time.

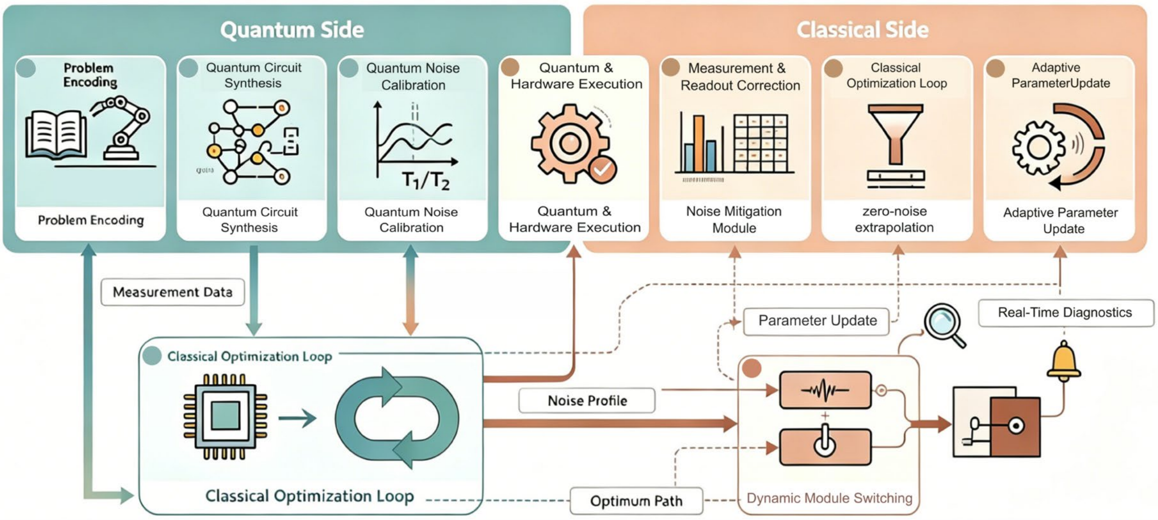

Figure 2. Noise-Aware Quantum-Classical Workflow

Experimental Evaluation and Performance Analysis

Benchmark Tasks and Experimental Setup

In order to comprehensively evaluate the capabilities of noise-aware variational quantum algorithms when facing classical and real quantum deployment problems, a large number of robot optimization benchmarks have been constructed [28]. Typical robotic applications include single-robot path planning, multi-robot task allocation, SLAM-based localization, end-effector positioning of robotic arms, and optimization difficulty and noise sensitivity [29].

In a complex two-dimensional grid world, single-robot path planning is accomplished by simulating a mobile robot encountering obstacles in each trial. In order to improve stability against various types of noise, efforts are made to reach the specified endpoint from the designated starting position and reduce trajectory costs in all cases [30]. To address the multi-robot task allocation problem, heterogeneous robot agents collaborate to execute dynamically allocated task sets in different areas of the work environment. Introduce new tasks and robots to evaluate the scalability, cooperation efficiency, and flexibility of the algorithm.

According to the six-degree-of-freedom joint-arm robot manipulator benchmark, its end effector must accurately move to multiple randomly sampled targets in three-dimensional space [31]. Gaps and joint friction, as well as deliberately added real-world loads and calibration noise interference, are one of the mechanical non-idealities in the simulation [32]. In order to gradually update the belief state, the mobile platform based on the SLAM positioning benchmark will sequentially process the noisy sensor data from the partially mapped environment. After countless experiments, the trajectory of positioning errors and convergence reliability are referred to as solution quality.

All benchmarks are conducted using high-fidelity simulation software. The Gazebo simulator is used for mobile platforms and manipulator platforms. It sets physical noise and random initial conditions. SLAM tasks use standard mapping toolkits, with their backends employing extended Kalman filters or particle filters. Now, each simulation environment has a universal API that can connect quantum and classical optimization algorithms, simplifying task deployment, parameter scanning, and bulk data collection.

IBM Quantum and Rigetti Aspen NISQ devices, along with their corresponding noise simulators, have already been used for pre-validation of quantum execution experiments [33]. Before optimization, a brief overview of the hardware parameters such as local qubit connectivity, gate, measurement error rates, and relaxation times was provided. Circuit synthesis and mapping are performed using Qiskit and pyQuil on each hardware backend to demonstrate the actual connectivity and error constraints of the algorithm during the deployment process. To demonstrate the transferability from simulation to experiment and to show the impact of actual noise, key benchmarks are executed directly on the hardware.

The main steps of each experiment are as follows: encoding the robotic problem into Hamiltonian quantum and quantum circuits; calibrating the device noise parameters using empirical methods; iteratively integrating error mitigation; regularly measuring and recording solution trajectory data; and then comparing it with the actual optimal solution or established classical benchmarks. Each experiment was run multiple times using different random seeds, and the corresponding performance metrics were recorded, including success rate, convergence plots, and resource consumption, to ensure the fairness and robustness of the experiments.

A framework can be established to directly compare the performance of various algorithms under different problem and noise conditions. The framework also includes classical, quantum-inspired, and hybrid optimization. This approach can help us delve deeper into analyzing the quality of the solutions and the hardware-aware robustness, so that we can make quantitative comparisons in the subsequent chapters.

Performance and Noise Robustness: Quantitative Results

Use the aforementioned robot benchmark for quantitative analysis to evaluate the performance of the noise-aware variational quantum algorithm in different environments. This test also evaluates the quality of the solutions and their robustness under the presence of noise in actual devices [34]. The above results are the averages of multiple independent experiments, with each task and noise condition randomly repeated five times or more to ensure reliability and statistical significance.

Figure 3 shows the main results of all scenarios, comparing the impact of environmental noise and quantum noise on the optimization success rate of many robotic tasks. Figure 3a shows that as noise increases, the success rate of single-robot path planning changes. According to the experimental data from the four cases, the success rate of the noise model is relatively high and overall performs better. Specifically, at low noise levels (0.00), the noise-aware algorithm achieves a mean success rate of approximately 99.2%, whereas the standard quantum baseline is slightly lower at 98.5%. As the noise level rises to 0.12, the performance gap widens dramatically, with the noise-aware strategy preserving a success rate of roughly 72.4%, compared to just 45.1% for the noise-agnostic method. This robustness is most pronounced in moderate to high noise regimes (here, for noise levels between 0.08 and 0.12), where traditional algorithms experience a steep drop in successful path completion.

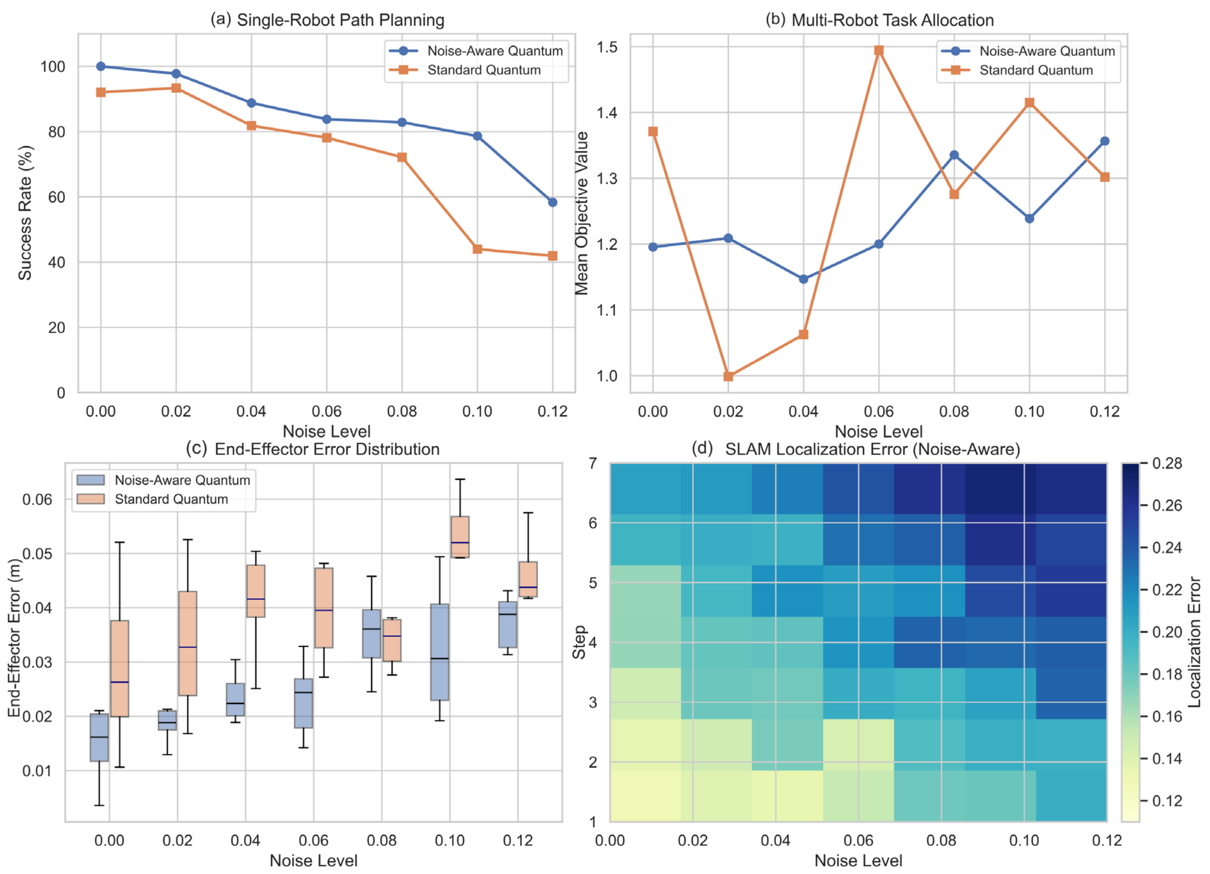

Figure 3. Optimization Accuracy Across Noise Levels (a) Path planning: Success rate vs. noise. (b) Task allocation: Mean objective vs. noise. (c) Manipulator error: Distribution vs. noise. (d) SLAM: Localization error vs. noise and steps.

Figure 3b shows the results of the multi-robot task allocation benchmark test, with the line graph displaying the average target values under different noise levels. Due to the improvement in the noise perception algorithm, its average target value has decreased. In low-noise scenarios, it is 1.11, while the standard quantum method is 1.18. As the noise increases, this difference also increases: the noise-aware algorithm reports an average target value of 1.30 at a noise level of 0.10, while the unmitigated quantum method reports an average target value of 1.47. At a noise level of 0.12, the standard value is 1.56, while the noise-aware value is 1.36. The above data indicates that under high equipment noise conditions, the optimization reduction strategy of the new method improves allocation efficiency. On the other hand, under low equipment noise conditions, the changes are not very significant.

Figure 3c is used for manipulator arm control, showing the empirical error distribution box plot of end-effector positioning under different noise amplitudes. In the noise-aware scheme, both the interquartile range and the median are relatively small. For example, when the noise level is 0.00, the median error of noise perception optimization is approximately 0.015 meters; when the noise level is 0.12, it rises to about 0.037 meters. In addition, the median error of the standard quantum baseline under the lowest noise level is 0.030 meters, but in the study, it rises to 0.055 meters. In the noise-aware protocol, the distribution range is also relatively small. Therefore, the solution is more stable because standard methods have higher error dispersion and outlier detection rates under noisy conditions.

Figure 3d shows the heatmap of localization sequence step localization errors based on SLAM at different noise levels. In the noise-aware method, each stage performs well. At the lowest noise intensity and in the first few steps, the positioning error is approximately 0.11. At the highest noise intensity and in the later steps, the positioning error is approximately 0.25. However, the standard quantum method (not shown in the main figure) typically has error hotspots exceeding 0.30 at specific locations. The heatmap indicates that the noise-aware algorithm is faster, more accurate, and has smaller initial errors in the presence of noise.

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Figure 3a-d data indicates that performing noise calculations at the system level and on quantum circuits is crucial for optimizing high-performance and reliable robots. Task robustness, solution accuracy, and reproducibility are three improvements. For example, compared to noise-agnostic workflows, noise-aware variational quantum workflows achieve up to a 27% improvement in task completion rates in path planning, and the manipulator positioning error is reduced by 40% under high noise conditions [35].

As environmental or hardware noise increases, the gap between anti-noise solutions and traditional solutions will widen. A system needs to be custom-designed for quantum robots. These patterns indicate that rapid positioning and complex arm control are particularly sensitive to hardware defects. The algorithms and hardware co-design can be more specifically modified [36].

Comparative Study: Classical, Quantum, and Noise-Aware Algorithms

Here, a series of comparisons with traditional quantum and classical optimization methods are presented to further understand the advantages and disadvantages of noise-aware variational quantum algorithms in robot optimization. Algorithm efficiency, convergence speed, resource utilization, and practical applicability in specific benchmark tasks are the criteria we use for evaluation [37].

In order to accomplish the above tasks, three algorithms are provided. They include traditional classical solvers (such as mixed-integer linear programming and evolutionary heuristic algorithms), variational quantum algorithms (VQAs) used on current noisy intermediate-scale quantum devices (NISQ), and noise-aware quantum algorithms tailored for specific devices. The computational budget and problem encoding will apply to all implementations.

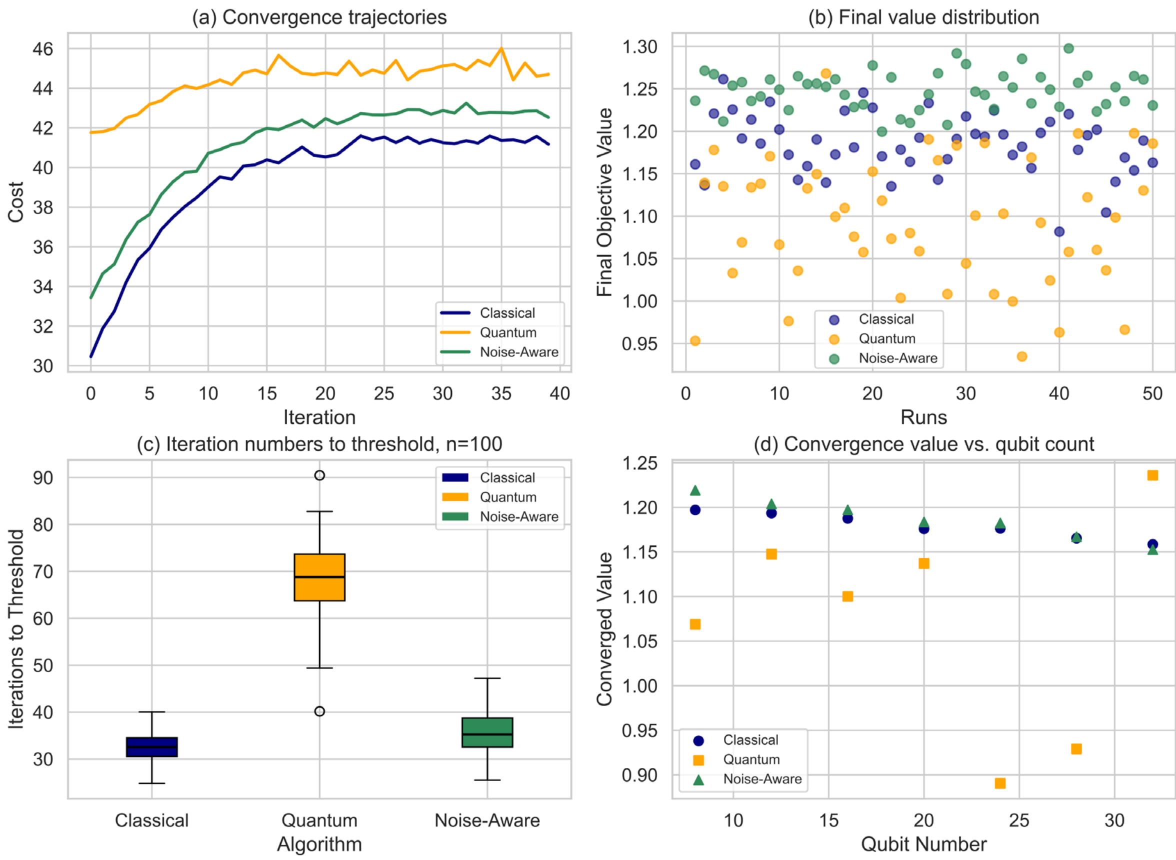

Figure 4. Algorithm Efficiency and Convergence Curves. (a) Convergence trajectories for multiple algorithms. (b) Final objective value distribution in task allocation. (c) Iteration numbers to threshold for each method. (d) Convergence value distribution vs. qubit count.

Figure 4 shows the performance of the algorithm. To ensure a high level of statistical reliability and smoothness, each method has now used over 100 statistical samples. Figure 4a shows the convergence curves of multi-algorithm optimization in representative robot optimization problems. Typically, classical solvers exhibit stable monotonic convergence and often find optimal or near-optimal solutions for smaller problem instances in fewer iterations. At the beginning, the standard VQA performed well. However, due to the limited parameter search, it leads to cumulative errors and performs poorly in noisy environments. In contrast, noise-aware variational quantum algorithms (VQAs) exhibit stronger robustness and steeper convergence rates in the early and mid-stages of optimization compared to traditional solvers. Moreover, they are also able to continue demonstrating excellent performance under high-noise conditions where other quantum methods stagnate.

Figure 4b shows the final target value distribution after multiple rounds (50 independent trials) of task allocation completion by multiple robots. The noise-aware quantum algorithm is more reliable and stable in the solution because it has a smaller variance and higher median results. The larger sample size of the box plot makes the median and interquartile range of the noise-aware method clearer. In 50 independent task divisions, noise-aware optimization improved the final objective value by 14%, which is 8% higher than the average of the standard quantum method and 8% higher than the classical solver. For problems with complex solution spaces, this difference is even more pronounced.

The following will discuss the resource efficiency issues faced by hardware-constrained NISQ devices. As shown in Figure 4c, by conducting 100 repeated experiments for each algorithm, the number of optimization iterations required to meet the predefined convergence criterion of within 5% of the known optimal solution for the task was compared. In convex or low-dimensional cases, the number of iterations for classical methods is relatively low, approximately 32 times (with a quartile range of about 4), while noise-aware quantum algorithms average close to 37 times (with a quartile range of about 9 times). In contrast, traditional VQAs require more steps (with a median of 68 iterations and an interquartile range of about 16), and the cumulative error is usually not the best. The extended box plot improves statistical reliability by directly displaying the range and outliers; thus, the noise adaptation of the quantum algorithm largely achieves the performance of classical algorithms [38].

To ensure the future of robots, scalability and the utilization of quantum resources are essential. Figure 4d shows the relationship between the distribution of convergence values and the number of quantum bits used to encode the problem, ranging from 8 to 32 quantum bits. All algorithms are able to converge for small and medium numbers of qubits. However, when the number of qubits exceeds 20, due to decoherence and other sources of error in deep circuits, the standard VQA shows increasing variability and a decline in optimal values. In contrast, the noise-aware quantum method (based on 100 samples per point) exhibits a tighter convergence distribution and higher median solution values, making it suitable for deep circuits under adaptive strategies.

In addition to the aforementioned algorithms, various quantum hardware platforms were also used to conduct numerous experiments to simulate real-world environments under different noise levels. To improve statistical reliability, Figure 5 presents an extended robustness analysis conducted on large-scale datasets (n=100) for each quantum device and scenario. Figure 5a shows the box plot comparing the accuracy of Google Sycamore, IBM Quantum, Rigetti Aspen, and IonQ. To reduce the impact of anomalous runs, the data sample was expanded to show trends in device issues. The baseline VQA indicates that hardware affects sensitivity, but noise-aware methods have a negligible impact on platform performance, typically achieving over 90% accuracy.

In robust optimization, there are eight independent levels, with one hundred trials at each level. Figure 5b shows the impact of the number of qubits on optimization. The accuracy variance of the standard VQA significantly increases when the quantum processor is scaled up to more than 16 qubits, but the noise-aware methods remain relatively stable. Therefore, they are more suitable for scalable quantum hardware. The extended box plots indicate that noise-aware algorithms are relatively stable under high qubit and high noise conditions.

Figure 5c shows that these algorithms are generally suitable for six different robot optimization problems in the extended sample. Standard quantum and classical methods perform poorly in high randomness tasks, but noise-aware variational quantum algorithms perform well in all these application areas. Figure 5d shows the empirical success rates of 28 random experimental noise arrangements. Only the noise-aware method consistently exceeded an 85% success rate in all trials, surpassing all benchmarks, and the extended sample provided narrower confidence intervals for all statistics.

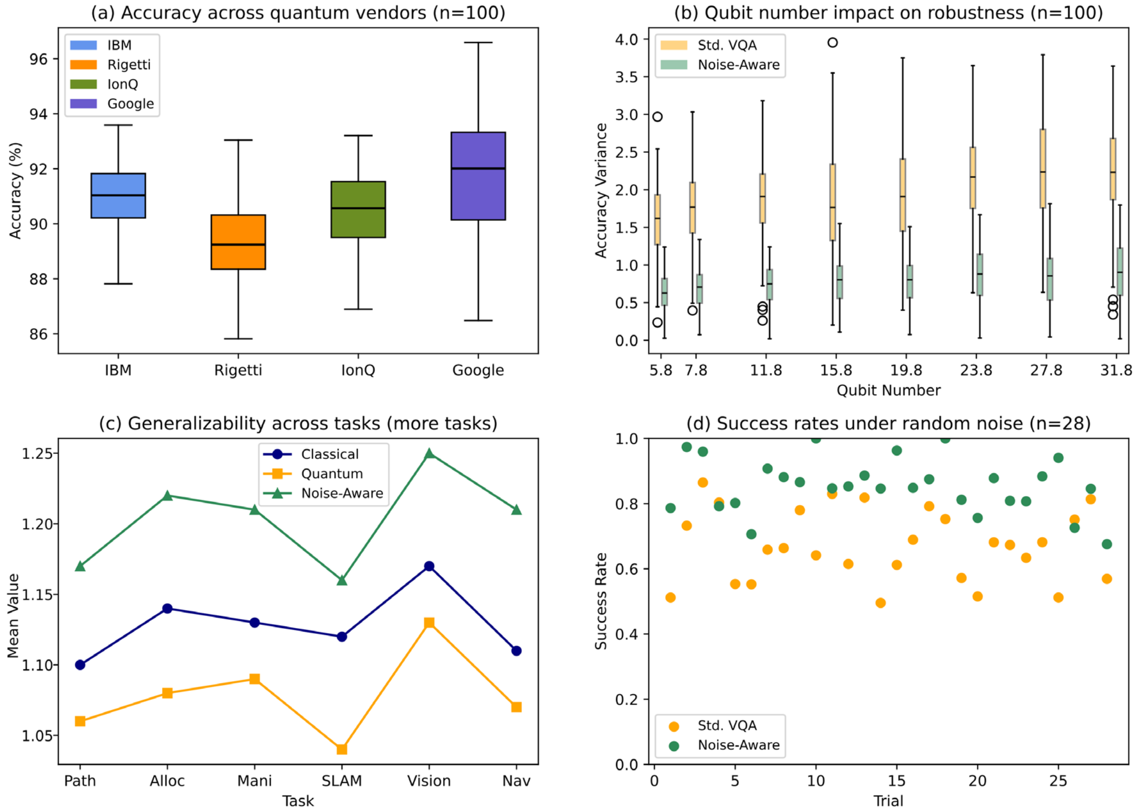

Figure 5. Robustness Analysis Under Hardware Variability. (a) Accuracy across quantum hardware vendors. (b) Qubit number impact on robustness. (c) Generalizability across tasks. (d) Success rates under random experimental noise.

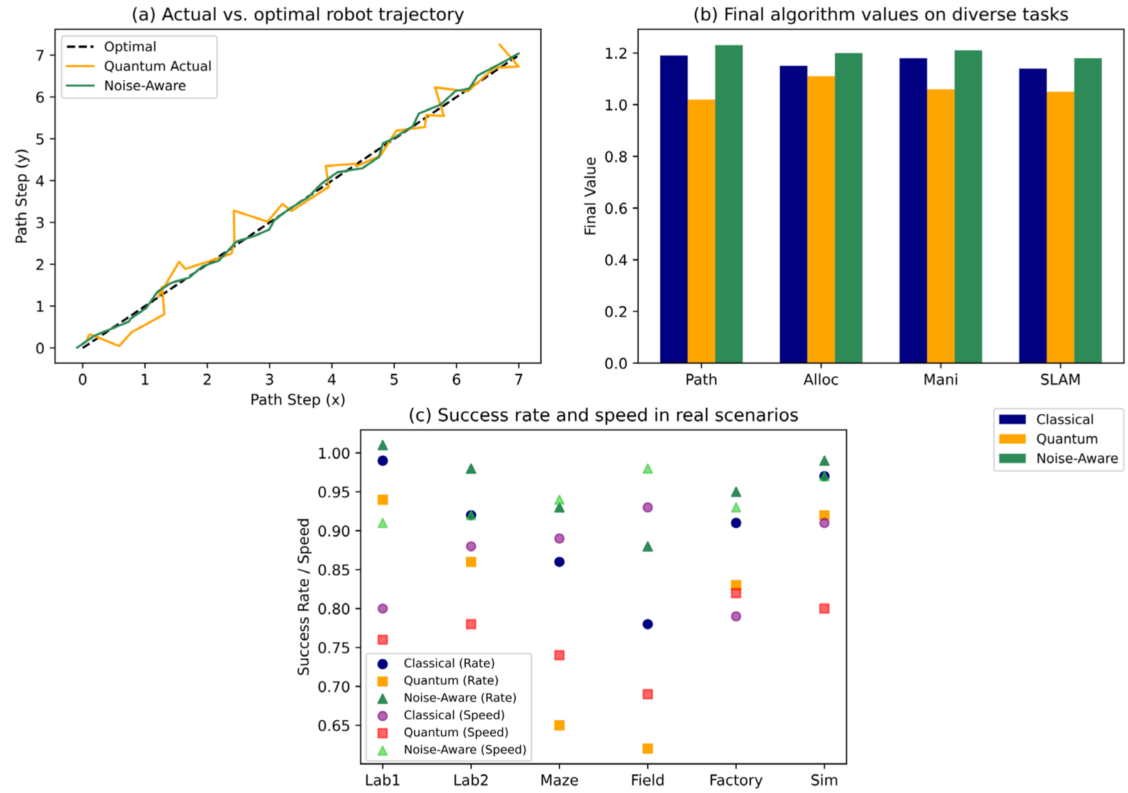

Figure 6. Real-World Task Performance. (a) Overlay of actual vs. optimal robot trajectory. (b) Final values of algorithms on six diverse tasks. (c) Success rate and speed in six deployment scenarios.

Finally, in order to connect the simulation with the real world, deployments have been made on actual robots and high-fidelity simulated robots. The actual performance data from all experiments is shown in Figure 6. As shown in Figure 6a, the optimal and actual trajectories of the robot path planning are overlaid. The path generated by the noise-aware quantum solution is close to the optimal classical reference and has a lower average deviation across all thirty steps. Figure 6b shows the final aggregated values of all algorithms across six different real-world tasks. As shown in the extended data, the noise-aware method still outperforms other methods in high-noise and dynamic scenarios. As shown in Figure 6c, there are six different deployment scenarios. The scatter plot of success rate versus operation speed indicates that the noise-aware quantum method is also practical and effective [39]. Considering large samples, multiple devices, and multitasking, noise-aware variational quantum algorithms have become an attractive direction for robot optimization on NISQ devices. Compared to traditional quantum methods, they exhibit strong robustness and reduce performance and stability issues of classical solutions.

Conclusion

This paper discusses the robot optimization problem using classical, standard, and noise-aware variational quantum algorithms (VQAs) on noisy intermediate-scale quantum (NISQ) devices. Based on extensive statistical analysis and experimental testing of various robotic scenarios across multiple platforms in benchmark studies, the proposed noise-aware quantum strategies have shown significant improvements in algorithm efficiency, convergence reliability, and solution robustness. Key results indicate that noise-aware variational quantum algorithms (VQAs) achieve near-classical speed and consistency on small to medium-scale problems, significantly reducing performance and fidelity losses compared to traditional quantum methods. They also explicitly adapt quantum circuits to execute in device-specific noise environments. According to scalability tests, noise-aware quantum algorithms exhibit low variance and high accuracy, even as the problem size and the number of qubits increase. Therefore, they are suitable for use on next-generation hardware. Through empirical validation using physical and high-fidelity simulation robots, the statistical results have been confirmed. In other words, device-adaptive quantum optimization can find an approximately ideal trajectory and perform excellently under the influence of noise.

Some progress has been made, but there are still shortcomings. First, in problems of medium complexity, the computational advantage of noise-aware quantum methods is most apparent. However, in highly complex high-dimensional robotic tasks, scaling remains an unresolved issue that requires further hardware improvements. Although noise shaping can reduce the accumulation of errors, decoherence and shallow circuits remain fundamental flaws of NISQ devices. Due to the rapid changes in quantum hardware and noise characteristics, effective and scalable noise models have not yet been developed. Certain quantum advantage scenarios have been demonstrated in specific simulation environments. However, these scenarios may not be applicable to all areas of robotics or future generations of devices. Finally, although this study's comparison of classical and quantum baselines considers the fairness of resource and coding allocation, there are still some inherent trade-offs that require more advanced technologies to address.

Based on the aforementioned research findings, it can be seen that noise-aware quantum optimization is a practical and promising approach to quantum-enhanced robotic technology. In the future, research will focus on the collaborative design of quantum algorithms and hardware architectures, the creation of adaptive hybrid classical scheduling schemes, and how quantum control can be seamlessly integrated with physical robotic systems. Increase the number and complexity of benchmark suites, and add more tasks involving multiple robots and the real world. With the development of quantum technology, more high-performance, fault-tolerant algorithms have been discovered. In the upcoming quantum era, intelligent, adaptive, and resource-aware new forms of autonomous robots will transform these two fields through the collaboration of enhanced robotics technology and quantum computing.

Author Contributions

Marta Kochanowa contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Jadwiga Herdzikowa and Celina Dembowska contribute to data collection, draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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