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Numerical Optimization of Multi-Sensor Estimation under Uncertain Measurement Constraints

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Abstract
Multi-sensor state estimation becomes challenging when sensor measurements and physical constraints are affected by possibly incorrect information. This paper proposes a quantum-information-robust optimisation framework for constrained multi-sensor estimation under measurement uncertainty.The key novelty lies in the integration of the Bures uncertainty set over the density operator directly into the worst-case estimation formulation. This approach goes beyond simply using quantum information measures for sensor weighting or feature extraction.Each sensor is represented by a density operator along with an admissible quantum uncertainty region. This allows deviations in measurement information to be characterized geometrically.A variational quantum parameterisation is then used to represent the system state. Uncertain physical constraints are incorporated through a worst-case violation term.The resulting formulation jointly addresses estimation accuracy, quantum-information uncertainty and constraint robustness—all within an optimization framework.The analytical properties of the proposed estimator are investigated. This includes the existence of a solution, the convergenceof the optimization procedure and the sensitivity of the estimated state to changes in the uncertainty radius.Numerical experiments with nonlinear sensors compare the proposed method with conventional weighted least-squares, robust classicaloptimization and variational quantum estimation.The results show that the proposed framework has the potential to maintain estimation accuracy and constraint feasibility when measurement uncertainty increases.

Keywords: Multi-Sensor Estimation; Quantum Information Geometry; Robust Optimization; Bures Distance; Uncertain Measurements; Constrained Optimization; Variational Quantum Estimation; Sensor Fusion.

1. Introduction

Multi-sensor state estimation is fundamental for systems, navigation, robotics and network sensing. Because sensors are heterogeneous, they provide imperfect information about the unknown system state.Classical multi-sensor fusion methods combine measurements using estimation, Kalman filtering, distributed filtering or consensus mechanisms.Established approaches include nonlinear Kalman-type estimators such as the Kalman filter (Arasaratnam &Haykin 2009), unscented filtering (Julier & Uhlmann 1997) and distributed fusion and consensus filtering (Gao & Harris 2002; Li et al., 2015; Sun et al., 2017).A comprehensive review shows that sensor fusion performance depends strongly on measurement uncertainty, sensor correlation, model mismatch and the reliability of sensing sources (Khaleghi et al. 2013).

Major difficulty occurs when the assumed measurement model or noise distribution does not accurately represent the operating environment.Conventional estimators usually rely on a probability model, so their performance becomes sensitive to outliers, distribution mismatch and uncertain sensor characteristics.Robust optimization

addresses this issue by optimizing against admissible realisations of uncertain parameters (Ben-Tal et al., 2009).Robust optimization it extends this principle by considering an ambiguity set of probability distributions, not just a single assumed distribution.In particular, Wasserstein-based DRO providessample guarantees and a tractable reformulation for optimization, under distributional uncertainty (Esfahani & Kuhn 2018).These developments motivate an estimation formulation where uncertainty is incorporated directly into the optimization objective not just handled through fixed sensor weights.

Quantum information theory provides a mathematical framework for representing uncertain information. A quantum state is represented by a density operator, and geometry provides measures of distinguishability and statistical distance (Uhlmann, 1976; Braunstein & Caves 1994).Quantum estimation theory develops an approach for extracting information about an unknown parameter from a quantum state (Helstrom, 1976; Paris, 2009). A broader treatment establishes the foundation of quantum states, channels, and information (Holevo, 2013; Nielsen & Chuang, 2010).These concepts make information geometry attractive for representing uncertainty in heterogeneous measurements.In parallel, quantum machine learning and variational methods establish the quantum circuit as a flexible computational representation for optimization and learning problems (Schuld & Killoran 2019; Cerezo et al. 2021).

Variational quantum estimation is especially relevant for parameter state reconstruction.Meyer et al. (2021) show a toolbox for quantum multi-parameter estimation, which includes gradient-based optimization techniques suitable for parameterized quantum circuits.This approach provides a way to represent unknown states using variational parameters while still maintaining compatibility with hybrid quantum-classical optimization methods.However, relying on variational quantum representation does not account for uncertainty in the sensor measurements, and it does not ensure robustness under physical constraints.

Recent studies begin to connect quantum information processing with multisensor fusion. I notice that Zhang et al. (2026) develop a quantum–information–basedmultisensor fusion approach for autonomous underwater vehicle trajectory tracking using density-operator representation and quantum information measure. I also see that Guo et al. (2026) investigate quantum multi-sensor data fusion inside a self-supervised learning framework for industrial IoT anomaly detection. These studies show a growing relevance of quantum information methods to multi-sensor problems. They mainly emphasize adaptive fusion, feature extraction or learning-based architecture.

This observation motivates the work. The proposed framework represents each sensor by a density operator and an admissible Bures-metric uncertainty region. The resulting uncertainty is incorporated directly into the estimation objective while uncertain physical constraints are handled through a worst-case violation term. The unknown system state is represented variationally so the formulation can connect quantum information geometry with quantum-classical optimization.

The main contribution is not just the use of quantum information measures for sensor weighting. Is it a claim of quantum computational speedup.Instead, the contribution lies in a quantum-information-geometric robust optimization formulation. In this framework, measurement uncertainty, sensor information geometry, variational state estimation and uncertain constraints are all handled within an optimization structure.Theoretical conditions for existence, convergence and sensitivity are developed. Then numerical experiments are conducted to compare the proposed method with variational baselines.

The remainder of the paper develops the formulation, theoretical properties, optimization procedure and numerical evaluation of the proposed framework.

2. Problem Formulation

Consider a system with an unknown state $x \in \mathbb{R}^n$observed by Nheterogeneous sensors. The measurement generated by sensor $i$consists of a nonlinear transformation of the system state together with an uncertain measurement error. The general observation model is

$$z_i = h_i(x) + \varepsilon_i,\ i = 1, \dots, N. \qquad (1)$$

Here, $z_i$denotes the measurement, $h_i(\cdot)$ represents the sensor-specific observation function, and $\varepsilon_i$accounts for measurement uncertainty. The sensors may have different observation dimensions, noise characteristics, and reliability levels.

Unlike estimation methods that assume a known error distribution or accurate estimated covariance matrix, this study considers the case where measurement uncertainty is only partially known.Such uncertainty may arise

from sensor degradation, calibration error, environmental disturbance, incomplete historical data or model misspecification.Consequently, the estimator should remain reliable even when actual measurement behaviour is different from the description.

To represent this uncertainty, each sensor is associated with a nominal information state, denoted by ρ_i^0. In the proposed framework, this information state is represented as a density operator, allowing the uncertainty associated with sensor information to be described using quantum-information geometry. The admissible deviation from the nominal state is controlled by an uncertainty radius. The estimation problem is also subject to operational restrictions.These may include limits on state variables, conservation relationships, or other application-specific requirements.Because of these constraints, they can also contain parameter satisfy them only under nominal condition it may not guarantee feasibility under actual operating conditions.

The proposed approach therefore considers three related aspects: sensor measurement, uncertainty in information representation and uncertain physical constraints.Objective it is to obtain an estimate that balances measurement agreement with robustness and constraint feasibility.The state is unknown. It is parameterized using a quantum representation, in the following formulation.The variational quantum representation provides a search space. It also allows quantum-information representation of sensor uncertainty to be incorporated directly into the optimization process.The resulting framework is designed to avoid relying on nominal sensor statistics. Instead, it seeks an estimator that remains stable when the level of measurement uncertainty increases.

3. Proposed Quantum-Information-Geometric Robust Optimization Framework

The proposed method integrates quantum-information geometry with constrained optimization to produce a reliable state estimate from heterogeneous sensors. The framework differs from quantum sensor-fusion methods. Because a quantum representation is used, the framework defines an uncertainty set and, over this uncertainty set, the framework optimizes estimation loss.

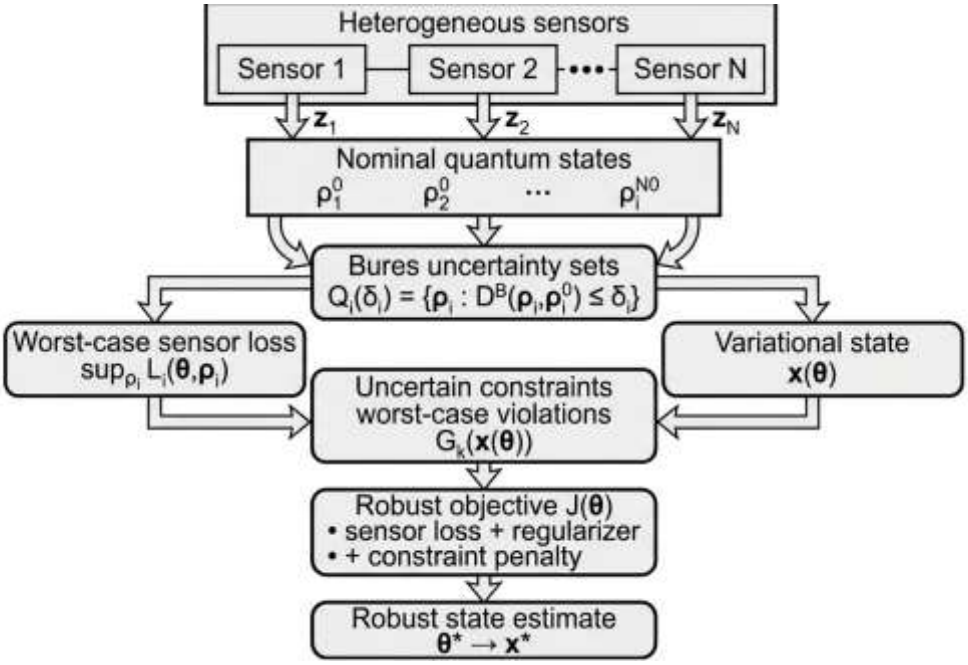


Figure 1. Quantum-information-geometric robust optimization framework.

In the above Fig. 1, each heterogeneous sensor is represented by a nominal density operator $\rho_i^0$and a Bures-metric uncertainty set $\mathcal{Q}_i(\delta_i)$. The admissible quantum states are incorporated into a worst-case sensor-loss formulation, which is jointly optimized with a variational state representation and uncertain physical constraints to obtain the robust estimate $x^\star$.

3.1. Quantum-information-geometric uncertainty set

For each sensor i, let ρ_i^0 denote the nominal density operator obtained from its available measurement information. The admissible uncertainty in this representation is defined by a Bures neighbourhood,

$$\mathcal{Q}_i(\delta_i) = \{\rho_i, : , \rho_i \succeq 0 \ \mathrm{Tr}(\rho_i) = 1 \ D_B(\rho_i, \rho_i^0) \leq \delta_i\}. \qquad (2)$$

Here, $\delta_i$is the uncertainty radius associated with the sensor i. The set $\mathcal{Q}_i(\delta_i)$contains all information states considered plausible under the specified uncertainty level. Consequently, the optimization does not rely exclusively on the nominal state ρ_i^0. Instead, it seeks an estimate that remains reliable for every admissible state within the corresponding Bures neighbourhood.

The uncertainty radius may be determined from measurement error from validation data, from confidence information or from a prescribed robustness level.A sensor may have an uncertainty radius, so the framework can represent heterogeneous sensing reliability without imposing identical statistical assumptions.

3.2. Quantum parameterization and sensor loss

The unknown state is parameterized using a variational quantum circuit. Let $U(\theta)$denote a parameterized circuit, and let θbe its classical parameter vector. Measurements of selected observables produce the estimated state $x(\theta)$. This representation allows the estimation problem to be solved through a hybrid quantum-classical optimization procedure.

For each sensor, the difference between the observed information and the predicted measurement generated from $x(\theta)$ defines a residual. The residual is represented by a compatible Hermitian observable, denoted by $\hat{r}_i(\theta)$. The corresponding quantum-weighted loss is obtained from its expectation under the uncertain density operator. This construction allows the sensor loss to vary according to both the estimated state and the admissible quantum information state.

The worst-case loss of the sensor $i$is then obtained by maximising this quantity over $\mathcal{Q}_i(\delta_i)$. Thus, the estimator is explicitly protected against adverse information states rather than optimized only for the nominal sensor condition.

3.3. Robust constrained estimation

Let $G_k(x)$denote the worst-case violation associated with the k-th uncertain physical constraint. A regularisation term $R(x)$can additionally be included to control undesirable state behaviour or improve numerical stability. The proposed estimator is formulated as

$$\theta^\star = \arg\min_{\theta\in\Theta} \left\{ \sum_{i=1}^{N} w_i \sup_{\rho_i \in \mathcal{Q}_i(\delta_i)} L_i(\theta, \rho_i) + \lambda R\big(x(\theta)\big) + \beta \sum_{k=1}^{K} G_k\left(x(\theta)\right)^2 \right\}. \qquad (3)$$

In this formulation, $w_i$denotes the nominal contribution of sensor i, while $\lambda$and βcontrol regularisation and constraint robustness, respectively. The first term minimises the aggregate worst-case sensor loss, the second stabilises the estimation process, and the third penalises violations of uncertain physical constraints.

The central feature of Equation (3) is the interaction between the Bures uncertainty sets and the robust objective. Increasing $\delta_i$enlarges the admissible information region and consequently makes the estimator more conservative. When $\delta_i = 0$, the uncertainty set collapses to the nominal state, and the formulation approaches a nominal quantum-assisted estimator.

The framework therefore provides a transition between nominal estimation and robust estimation. Then, assign a quantum reliability score after estimation uncertainty geometry directly influences the feasible adversarial state considered during optimization.This constitutes a methodological distinction of the proposed approach.

The optimization problem can be solved using a hybrid procedure in which quantum circuits evaluate state-dependent quantities while a classical optimizer updatesθ.. The next section establishes the mathematical properties of this formulation, with particular emphasis on the existence of an optimal solution, convergence, and sensitivity to uncertainty.

4. Theoretical Analysis

This section establishes mathematical properties of the proposed quantum-information-geometric robust estimator.The analysis focuses on three aspects: the existence of a solution, the convergence of the optimization

procedure and the sensitivity to measurement uncertainty.These properties provide justification for using the quantum-information-geometric robust estimator under uncertain sensor information.

4.1. Existence of an optimal solution

The first result concerns the existence of a solution to the robust optimization problem. Assume that the parameter domain Θis compact, the state mapping $x(\theta)$is continuous, and the sensor loss and constraint-violation functions are continuous in their respective arguments. Since each Bures uncertainty set $\mathcal{Q}_i(\delta_i)$is closed and bounded in the finite-dimensional density-operator space, it is compact.

Under these assumptions, the worst-case sensor loss obtained by maximizing over $\mathcal{Q}_i(\delta_i)$is well defined. The resulting robust objective is therefore continuous over the compact parameter domain. By the Weierstrass extreme-value theorem, at least one minimizer exists.

Proposition 1. If Θis compact and the state, loss, and constraint functions are continuous, then the proposed robust estimation problem admits at least one optimal parameter vector $\theta^{\star} \in \Theta$.

This result is important because the worst-case optimization does not introduce an ill-posed estimation problem when the uncertainty sets are properly bounded.

4.2. Convergence of the optimization procedure

The optimization can be implemented using a hybrid quantum-classical procedure. The quantum circuit evaluates the state-dependent quantities, while a classical optimizer updates the circuit parameters. Suppose that the resulting robust objective $J(\theta)$is differentiable and has an L-Lipschitz continuous gradient. With a sufficiently small constant step size, or an appropriate diminishing step-size sequence, the gradient-based update satisfies the standard descent property

$$\boxed{J(\theta^{t+1}) \leq J(\theta^{t}) - c \parallel \nabla J(\theta^{t}) \parallel^{2},\ c > 0.} \qquad (4)$$

Therefore, the objective is non-increasing along the optimization sequence, and the gradient norm approaches zero under the boundedness assumption. The algorithm consequently converges to a point of the robust objective. If the objective is also convex in the optimization parameter, then the stationary point is globally optimal.For implementation, the gradient can be obtained using parameter-shift evaluation for a suitable variational quantum circuit.However, the theoretical convergence result does not depend on any quantum-gradient technique. Convergence follows from the regularity of the resulting function.

4.3. Sensitivity to measurement uncertainty

Robustness should also be evaluated in terms of how the optimal estimate changes when the uncertainty level changes. Let δrepresent the collection of sensor uncertainty radii, and denote the corresponding optimizer by $\theta^{\star}(\delta)$. If the robust objective is sufficiently regular and strongly convex in a neighborhood of the optimum, perturbations in the uncertainty radius produce bounded changes in the optimal parameters.

Under a strong-convexity condition with modulus $m > 0$, and assuming that the objective has bounded sensitivity C_{δ} with respect to the uncertainty radius, the optimal parameters satisfy

$$\boxed{\parallel \theta^{\star}(\delta_1) - \theta^{\star}(\delta_2) \parallel \leq \frac{C_{\delta}}{m} \parallel \delta_1 - \delta_2 \parallel.} \qquad (5)$$

This result establishes a Lipschitz-type stability property.In terms of a moderate change in assumed measurement uncertainty should not cause an arbitrarily large change in the estimated solution.Result it also provides a basis for studying the robustness curve in numerical experiments.

4.4. Robustness of constraint satisfaction

The proposed formulation punishes worst-case constraint violation.Consequently, when the uncertainty radius grows, the increase in uncertainty radius not only changes the measurement-fitting term but also raises the level of caution needed to keep the system physically feasible.If the uncertainty set stays compact and the constraint function stays continuous, then worst-case constraint violation remains finite.

The framework therefore provides two forms of robustness.First, it concerns estimation stability, characterized by the sensitivity of parameters to uncertainty.Second, it concerns feasibility achieved by incorporating worst-case constraint violation directly into the objective.These results establish that the proposed framework is well-posed under standard regularity conditions.Analysis also clarifies a limitation: convergence guarantee they usually concern stationary solutions of variational optimisation problems, and in the nonconvex case they do not imply a globally optimal quantum solution. In the numerical experiment, in Section 6, they therefore evaluate both estimation performance and optimizationbehaviour.

5. Quantum Optimization Algorithm

The optimization problem described in Section 3 consists of two linked parts: the estimation of an unknown state using a variational quantum representation; second, the assessment of the worst-case sensor loss over a quantum-information-geometric uncertainty set. The proposed solution therefore follows a quantum-classical optimization strategy.The measurement data from each sensor has been converted into its corresponding nominal quantum representation. The uncertainty radius is then specified from the available measurement variability or a prescribed robustness level. A parameterized quantum circuit is initialized with a parameter vector $\theta^{(0)}$. The circuit produces the current state estimate $x(\theta)$, which is used to calculate the predicted sensor measurements and corresponding residuals.

For each sensor, there is a maximization step. It evaluates the largest possible loss over the Bures uncertainty set.This step represents the worst-case information condition that the robust estimator takes into account.The resulting sensor loss is combined with regularization and a constraint-violation term. This combination helps to create an objective.

The outer optimization updates the variational parameters using the objective gradient. In its basic form, the update is

$$\boxed{\theta^{(t+1)} = \theta^{(t)} - \eta_t \nabla_\theta J\left(\theta^{(t)}\right),} \qquad (6)$$

where $J(\theta)$is the robust objective and $\eta_t$is the optimization step size. The gradient may be evaluated using parameter-shift rules for compatible quantum circuits or by another suitable gradient-estimation procedure.

The computational procedure repeats until the predefined convergence criterion is satisfied, such as when the change in the objective or parameter vector becomes sufficiently small and quite crucial. The final circuit parameter is used to obtain the estimated state. This final value is key to the overall accuracy.

The complete workflow consists of five stages: sensor-data encoding, quantum-state representation, worst-case uncertainty evaluation, robust parameter optimization and constraint verification and how each stage builds on the previous one.This structure allows the quantum component to act both as a state parameterization mechanism and as part of the uncertainty- optimization framework and clear advantage in this dual role.

The proposed algorithm does not assume that a quantum computer provides speedup over classical optimization and I believe this realistic view sets a solid foundation.

The purpose of the work is to investigate whether a quantum-information-geometric representation can provide a mathematical framework for robust multi-sensor estimation and the results.Computational complexity and practical implementation remain considerations, and they are examined through a numerical study in the next section.

6. Numerical Experiments and Results

The experiment considered a three-dimensional state observed through five heterogeneous nonlinear sensors.A numerical study was done to check how well the new quantum-information-geometric estimation method works when there is uncertainty in the measurements.The experiment looked at a three-state system that was measured using five different nonlinear sensors that are not the same. For each uncertainty radius, 50 independent Monte Carlo trials were generated, with measurement noise increased as the uncertainty radius increased and occasional measurement contamination introduced to represent non-ideal sensing conditions. The tested uncertainty radii were $\delta = 0.01,0.05,0.10,0.20,$and 0.30. The proposed method was compared with weighted least squares (WLS), a classical robust estimator, and a variational quantum estimator (VQE). Performance was evaluated using RMSE, MAE, maximum constraint violation, and mean optimization iterations.

The results show a clear robustness advantage over conventional WLS as measurement uncertainty increases. At the smallest uncertainty radius, $\delta = 0.01$, WLS produced an RMSE of 0.1306, whereas the proposed QIG method achieved 0.1101. This corresponds to an RMSE reduction of approximately 15.7%. As illustrated in Figure 4, the advantage becomes particularly relevant in the higher-uncertainty regime. At $\delta = 0.30$,, the RMSE of WLS increased to 0.1924, while the QIG estimator produced an RMSE of 0.1580, corresponding to a reduction of approximately 17.9%. The QIG estimator therefore exhibited a slower degradation in estimation accuracy as the measurement uncertainty increased. This behaviour is consistent with the motivation for explicitly incorporating uncertainty into variational estimation rather than relying solely on nominal sensor information (Meyer et al., 2021).

At moderate uncertainty, the proposed formulation was also competitive with the classical robust estimator and the VQE baseline. At $\delta = 0.10$, QIG achieved the lowest RMSE among the four methods, with an RMSE of 0.1093 compared with 0.1099 for the classical robust estimator and 0.1100 for VQE. At $\delta = 0.20$, the corresponding RMSE values were 0.1425, 0.1403, and 0.1404, respectively. These results indicate that the principal benefit of the proposed formulation is not a universal reduction in nominal estimation error, but improved resistance to uncertainty while simultaneously enforcing the estimation constraints.

Constraint feasibility provides a stronger distinction between WLS and the robust formulations. At $\delta = 0.30$, WLS reached a maximum constraint violation of 0.4921 and a mean violation of 0.0568. In contrast, the QIG estimator reduced these quantities to 0.0024 and 0.0003, respectively. Thus, the maximum violation was reduced by approximately 99.5%. Similar behaviour was observed at lower uncertainty levels: at $\delta = 0.05$, the maximum WLS violation was 0.2608 compared with only 0.0006 for QIG. Figure 4 should therefore be interpreted together with the constraint-violation statistics, since accuracy alone does not capture the principal objective of the proposed constrained robust formulation.

The optimization behavior was also stable across the uncertainty range. The average number of iterations required by QIG increased from 12.56 at $\delta = 0.01$to 18.92 at $\delta = 0.30$, reflecting the additional optimization difficulty introduced by larger uncertainty regions. As shown in Figure 5, this increase remained gradual rather than exhibiting unstable growth. The classical robust estimator required between 10.56 and 12.68 iterations over the same range, while WLS required approximately 7–8 iterations. The additional iterations required by QIG are therefore the computational cost associated with explicitly accounting for measurement uncertainty and constraint robustness.

Overall, the numerical results support three observations.First, when measurement uncertainty increases, the performance of every estimator degrades. However, the degradation is less severe for the formulation showing the importance of robustness.Second, explicitly treating the constraint reduces infeasibility much more than nominal WLS estimation, highlighting the value of robustness in constraint handling.Third, the proposed QIG formulation remains numerically stable across the tested uncertainty range. This robustness, however, requires optimization iterations.These findings are consistent with the use of variational optimization for noisy multi-parameter estimation (Meyer et al., 2021) and with recent demonstrations of quantum-information-geometric mechanisms for heterogeneous multi-sensor fusion (Zhang et al. 2026).Importantly, the present results do not imply a quantum speedup. They evaluate the robustness properties of the proposed information-geometric optimization formulation.

7. Discussion

The numerical results indicate that the principal benefit of the proposed quantum-information-geometric (QIG) formulation is its ability to maintain estimation quality while explicitly accounting for measurement uncertainty and uncertain constraints. As the uncertainty radius increased from $\delta = 0.01$to $\delta = 0.30$, the RMSE of WLS increased from 0.1306 to 0.1924, whereas the corresponding QIG values remained within 0.1093–0.1580. The improvement is particularly evident in the high-uncertainty regime, where QIG reduced RMSE by approximately 17.9% relative to WLS. More importantly, the maximum constraint violation remained close to zero for the robust methods, while WLS reached 0.4921,$\delta = 0.30$. These observations support the use of explicit uncertainty sets and worst-case constraint terms when nominal sensor models may be unreliable.

Comparison with VQE is also informative, and VQE produce estimation error at several uncertainty levels, but the formulations have different objectives.VQE mainly provides a representation and optimization mechanism. The proposed QIG framework it incorporate measurement uncertainty into a robust objective.Consequently, the contribution does not claim to be an improvement over variational quantum estimation in nominal accuracy.Instead, the evidence it suggest information-geometric uncertainty formulation provides an additional mechanism for controlling sensitivity to uncertain measurements and maintaining constraint feasibility.This

distinction is important because recent research already demonstrates quantum approaches to sensor fusion and quantum-assisted multi-sensor learning (Zhang et al. 2026; Guo et al., 2026).

The results also reveal a computational trade-off. QIG required approximately 12.56 iterations at the smallest uncertainty radius and 18.92 iterations at $\delta = 0.30$, compared with approximately 7–8 iterations for WLS. This additional optimization effort aligns with a conservative objective. It evaluates sensor information within an uncertainty region instead of relying only on nominal measurements.Therefore, the proposed method should be viewed as a robustness-oriented estimator. It is not intended as a cheaper replacement for classical fusion.

Limitations they should acknowledge.First, the experiment they are simulation based on a finite-dimensional emulator, and they do not establish performance on physical quantum hardware.Second, the tested state dimension, sensor model and uncertainty radius are limited; a heterogeneous sensor network may introduce additional optimization and encoding challenges. In the current formulation, it uses Bures-metric uncertainty set and its interpretation as fully distributionally robust optimization it requires explicit mapping between classical measurement distribution and quantum density operator.Finally, the variational optimization problem it nonconvex, so theoretical convergence result they should not be interpreted as guaranteeing a globally optimal solution for arbitrary circuit architectures.

Despite these limitations, the results support the methodological argument of this work: quantum information geometry. Quantum information geometry can be used not as a sensor-weighting or fusion mechanism but also as a geometric description of measurement uncertainty inside a constrained robust optimization problem.This provides a direction from the recent quantum multi-sensor fusion approach, which mainly emphasises adaptive fusion, feature extraction or learning architecture (Zhang et al. 2026; Guo et al. 2026).

8. Conclusion

This paper proposes a quantum-information-robust optimisation framework for multi-sensor estimation under uncertain measurements and physical constraints.The main contribution of this paper is the integration of the Bures uncertainty set directly into the worst-case constrained estimation formulation. This integration extends the use of information geometry beyond conventional sensor weighting and fusion within the quantum-information-geometric robust optimization framework.

The numerical study showed that the proposed QIG estimator maintained competitive accuracy as measurement uncertainty increased and substantially reduced constraint violations compared with WLS. At $\delta = 0.30$, QIG reduced RMSE by approximately 17.9% relative to WLS while reducing the maximum constraint violation from 0.4921 to 0.0024.

The results of this paper are based on emulation, not on physical quantum hardware. Therefore, this paper does not establish quantum advantage.Future work proposed in this paper will focus on a sensor network exact Bures-ball optimization and experimental validation on a quantum platform.

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