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Author’s Note on Proposal

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Distributed Quantum Multi-Agent Deep Reinforcement Learning for 6G Wireless Systems

Background The sixth-generation (6G) wireless systems will be an *artificial intelligence (AI)-native network*, as envisioned by industry, academia, and standardization bodies [1]. Deep reinforcement learning (DRL) with decentralized architecture has been proposed to address various 6G problems ranging from transceiver design to radio resource management and intelligent spectrum access. Inter alia, distributed multi-agent DRL (MADRL) [2] has been envisaged as an indispensable part of AI-native 6G networks because: 1) MADRL enables implementing distributed wireless protocols at the edge; 2) MADRL agents can share experiences so that less-trained agents can learn from their better-skilled partners; and 3) MADRL can accommodate heterogeneous agents with various learning goals and device capabilities. However, existing MADRL frameworks are limited in many ways: 1) *non-stationarity*: state transition and each agent's reward function are affected by joint actions so that non-stationarity holds; 2) *instability and scalability*: as the number of agents increases (e.g., systems with thousands of wireless devices), the complexity and action spaces increase exponentially; 3) *partial observability*: full observability of states from the environment does not hold in sophisticated multi-agent cases; and 4) *high training burden*: the need for updating large number of deep neural network (DNN) parameters makes MADRL computation-hungry and time-inefficient.

Motivation To overcome these limitations, we propose a *novel framework of quantum MADRL (QMADRL)* that combines the benefits of quantum mechanics with those of distributed MADRL, and that will be *designed and deployed to address major 6G wireless challenges*. Recent works on quantum machine learning (QML) showed that quantum mechanics are beneficial for improving efficiency [3] and enhancing generalization [4] for machine learning systems. Moreover, several works illustrated that quantum mechanics can enhance learning efficiency and robustness for DRL. For example, comparable or better learning performance with much lighter parameter updating of quantum DRL algorithm has been reported in [5], compared to conventional DNN-based DRL. *A fundamental question* here is whether one can build a novel QMADRL framework that can be used to design AI-native 6G wireless systems, with low latency and high reliability. Although there exist some recent works on quantum DRL, e.g., [5-7], they cannot be used to address 6G wireless problems because they mostly rely on a single agent or they make impractical assumptions for 6G systems, e.g., quantum errors were not considered and full observability of environment was naively adopted.

Aim and Methodology The *aim of this project* is thus to lay the theoretical foundations of *distributed* QMADRL for the design, analysis, and optimization of AI-native 6G wireless systems and protocols. 1) A first key goal is to develop new distributed QMADRL algorithms tailored towards solving optimization problems in 6G networks with distributed wireless data, in terms of radio resource coordination, e.g., beamforming design, spectrum access, resource (power, bandwidth) allocation, and energy efficiency. Decentralized actors will be redesigned with variational quantum circuit (VQC) including state encoding as well as parametric quantum circuit (PQC) and quantum measurements, while VQC-based critic would remain centralized for dealing with non-stationarity. Here, we will investigate the impact of various existing PQC ansatzes, and then design novel ansatzes that can better adapt to 6G transmission scenarios. 2) For QMADRL, we will investigate the signalling overhead and information sharing among distributed agents, and we will theoretically and empirically show how and when quantum designs can reduce such overhead, while identifying its impact on the learning in impactful use cases within 6G networks. Our designs will incorporate practical considerations on partial observability of complex 6G wireless environments. The application of VQC-aided training architecture for QMADRL can significantly reduce the number of training parameters, which thus can potentially help overcome the scalability and latency challenges of conventional DNN-based MADRL frameworks. Next, we will leverage promising techniques such as space compression, meta-learning and transfer learning to enhance the robustness and scalability of the proposed QMADRL for large-scale and heterogeneous 6G networks. 3) In the current noise intermediate-scale quantum (NISQ) era, quantum errors caused by quantum decoherence and imprecision of quantum gates will inevitably jeopardize the learning performance of VQC-based schemes. Hence, we will explicitly investigate the *fundamental effects of quantum noise on our QMADRL* solutions, and we will propose efficient strategies to counter this shortcoming, including hybrid optimization, ensemble learning, and use of kernel matrices.

Outcomes The proposed research will *contribute simultaneously to AI, machine learning, quantum computing, and 6G wireless systems* thus providing scientific foundations for pioneering the emerging yet promising interdisciplinary area of QMADRL applied to 6G wireless systems. Dr. Li plans to submit high-impact papers to leading communications (e.g., IEEE Transactions on Wireless Communications), AI (e.g., IEEE Transactions on Pattern Analysis and Machine Intelligence), and quantum (e.g., Quantum Information Processing) venues, while regularly publishing in top-tier international conferences, e.g., GLOBECOM, NeurIPS and ICML. Besides, this project's scientific outcomes can potentially contribute to the development of future 6G standards, by introducing quantum to aid the AI-native nature of 6G networks.

Difference from Previous Research Dr. Li's previous research experience includes proposing and analysing wireless protocols, and designing classical DRL or innovating quantum-inspired DRL algorithms for optimizing wireless communications, where 6G networks, distributed learning, signalling overhead among AI agents, robustness and scalability of decentralised learning algorithms, VQC-aided actor/critic, and quantum noise were not considered. This project will holistically and rigorously focus on initiating robust and scalable distributed multi-agent AI frameworks together with practical quantum aids to help design, analyze and optimize intelligent 6G wireless systems, and thus pioneering this first-of-its-kind interdisciplinary research area.

Research Reasons for Selected Institution [redacted] has posed priority on quantum and its applications, where several quantum initiatives have been launched to pioneer this highly promising technology, e.g., [redacted] and [redacted]. Dr. Li will work with colleagues in the [redacted], where the host mentor Prof [redacted]'s world-class expertise in AI-native wireless systems will provide an ideal platform for Dr. Li to pioneer this emerging research area of distributed QML for AI-native 6G networks, by tightly collaborating with [redacted]'s quantum initiatives.

Contribution to Fellow Career Goals Dr. Li's career goal is to become a world-leading researcher in the emerging area of distributed QML for 6G systems. This fellowship can provide an optimal path for boosting his chances of achieving his long-term aspiration, by offering him invaluable real-world expertise in leading research projects independently, and helping him expand his scholarship, track record and academic visibility.

References **[1]** Talwar, Shilpa, et al. "6G: Connectivity in the era of distributed intelligence." IEEE Communications Magazine 59.11 (2021): 45-50. **[2]** Zhang, Kaiqing, et al. "Multi-agent reinforcement learning: A selective overview of theories and algorithms." Handbook of Reinforcement Learning and Control (2021): 321-384. **[3]** Liu, Yunchao, et al. "A rigorous and robust quantum speed-up in supervised machine learning." Nature Physics 17.9 (2021): 1013-1017. **[4]** Caro, Matthias C., et al. "Generalization in quantum machine learning from few training data." Nature Communications 13.1 (2022): 1-11. **[5]** Chen, Samuel Yen-Chi, et al. "Variational quantum circuits for deep reinforcement learning." IEEE Access 8 (2020): 141007-141024. **[6]** Saggio, Valeria, et al. "Experimental quantum speed-up in reinforcement learning agents." Nature 591.7849 (2021): 229-233. **[7]** Li, Ji-An, et al. "Quantum reinforcement learning during human decision-making." Nature Human Behaviour 4.3 (2020): 294-307. **[8]** Li, Yuanjian, et al. "Path planning for cellular-connected UAV: A DRL solution with quantum-inspired experience replay." IEEE Transactions on Wireless Communications (2022).

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分布式量子多智能体深度强化学习在 6G 无线系统中的应用

背景 第六代（6G）无线系统将是一个人工智能（AI）原生网络，正如业界、学术界和标准化机构所设想的那样 [1]。为了应对从收发器设计到无线资源管理和智能频谱接入等 6G 问题，已经提出了具有分布式架构的深度强化学习（DRL）。其中，分布式多智能体 DRL（MADRL）[2] 被认为是原生 AI 6G 网络的不可或缺的一部分，原因有：1）MADRL 使得在边缘实现分布式无线协议成为可能；2）MADRL 智能体可以共享经验，以便训练较少的智能体能够从技能更强的伙伴那里学习；3）MADRL 能够适应具有不同学习目标和设备能力的异构智能体。然而，现有的 MADRL 框架在很多方面都存在局限性：1）非静态性：状态转移和每个智能体的奖励函数都受到联合动作的影响，因此非静态性成立；2）不稳定性和可扩展性：随着智能体数量的增加（例如，成千上万无线设备的系统），复杂度和动作空间呈指数级增长；3）部分可观测性：在复杂的多智能体情况下，无法获得环境状态的完全可观测性；4）高训练负担：更新大量深度神经网络（DNN）参数的需求使得 MADRL 计算量大且耗时。

动机 为克服这些局限性，我们提出了一个结合量子力学与分布式 MADRL 优势的新框架，即量子 MADRL（QMADRL），并将其设计和部署以解决 6G 无线通信的主要挑战。最近关于量子机器学习（QML）的研究表明，量子力学有助于提高效率 [3] 并增强机器学习系统的泛化能力 [4]。此外，一些研究还表明，量子力学可以增强 DRL 的学习效率和鲁棒性。例如，量子 DRL 算法在参数更新量显著减少的情况下，能够获得可比或更好的学习性能 [5]，与传统的基于 DNN 的 DRL 算法相比。这里的一个基本问题是，能否构建一个新的 QMADRL 框架，用于设计原生 AI 6G 无线系统，具备低延迟和高可靠性。尽管最近关于量子 DRL 的研究工作存在 [5-7]，但它们大多依赖单一智能体或对 6G 系统做出不切实际的假设（例如，未考虑量子错误并天真地采用了环境的完全可观测性），因此无法解决 6G 无线通信问题。

目标与方法 因此，本项目的目标是为分布式 QMADRL 奠定理论基础，用于设计、分析和优化原生 AI 6G 无线系统及其协议。1）首要目标是开发新的分布式 QMADRL 算法，专门解决 6G 网络中分布式无线数据的优化问题，涉及无线资源协调，如波束成形设计、频谱接入、资源（功率、带宽）分配和能效优化。分布式智能体将通过变分量子电路（VQC）重新设计，包括状态编码以及参数量子电路（PQC）和量子测量，而基于 VQC 的批评者将保持集中式以处理非静态性。在此过程中，我们将研究现有 PQC 结构的影响，并设计更适应 6G 传输场景的新结构。2）对于 QMADRL，我们将研究分布式智能体之间的信令开销和信息共享，并在理论和实验上展示量子设计如何以及何时能够减少这些开销，同时识别其对 6G 网络中重要用例中的学习影响。我们的设计将结合 6G 复杂无线环境的部分可观测性问题。通过应用 VQC 辅助的训练架构，QMADRL 可以显著减少训练参数的数量，从而有望克服传统基于 DNN 的 MADRL 框架的可扩展性和延迟挑战。接下来，我们将利用空间压缩、元学习和迁移学习等有前景的技术，增强所提出的 QMADRL 在大规模和异构 6G 网络中的鲁棒性和可扩展性。3）在当前的噪声中间规模量子（NISQ）时代，量子退相干和量子门不精确引发的量子错误将不可避免地损害基于 VQC 方案的学习性能。因此，我们将明确研究量子噪声对我们 QMADRL 解决方案的基本影响，并提出有效的应对策略，包括混合优化、集成学习和使用核矩阵。

预期成果 该研究将同时为人工智能、机器学习、量子计算和 6G 无线系统做出贡献，从而为将 QMADRL 应用于 6G 无线系统这一新兴且前景广阔的跨学科领域奠定科学基础。李博士计划向领先的通信（如 IEEE Transactions on Wireless Communications）、AI（如 IEEE Transactions on Pattern Analysis and Machine Intelligence）和量子（如 Quantum Information Processing）期刊提交高影响力的论文，并定期在顶级国际会议上发表成果，如 GLOBECOM、NeurIPS 和 ICML。此外，本项目的科学成果有望通过引入量子技术以辅助 6G 网络的原生 AI 特性，为未来 6G 标准的发展做出贡献。

与以往研究的区别 李博士的以往研究经验包括提出和分析无线协议，设计经典 DRL 或创新量子启发的 DRL 算法来优化无线通信，其中未考虑 6G 网络、分布式学习、AI 智能体之间的信令开销、去中心化学习算法的鲁棒性和可扩展性、VQC 辅助的智能体/批评者、以及量子噪声。本项目将全面且严格地专注于启动具有实用量子辅助的鲁棒且可扩展的分布式多智能体 AI 框架，帮助设计、分析和优化智能 6G 无线系统，从而开创这一首创的跨学科研究领域。

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