

Federated Reinforcement Learning Enhanced Human-Robotic Systems: A Comprehensive Review

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Abstract—Federated Reinforcement learning (FRL) presents a transformative approach for leveraging Human-robot collaboration (HRC) systems by addressing critical challenges in traditional learning paradigms. This paper provides a comprehensive review of the current state of FRL technology and its potential applications within HRC systems. The adaptation of FRL in HRC system is still in its infancy. This review systematically analyses the development trends, current challenges, and future prospects of various learning approaches within HRC systems. The paper highlights the critical factors of developing a conceptual framework for FRL within HRC systems to fully realise the potential of FRL. This paper aims to provide valuable insights and guidance for future research efforts focused on advancing FRL technology for human-robotic collaboration.

I. INTRODUCTION

Nowadays, human-robot collaboration (HRC) systems play pivotal roles in enhancing productivity, safety, and quality of life across numerous sectors. Driven by advancements in artificial intelligence (AI), robotic hardware, and more accurate and precise sensing technologies, these sophisticated systems have been transitioned from the early days when humans and robots shared workspace separated by fences, to today's advanced systems where robots can smartly interpret and respond to human emotions [1]. Recently, there has been a growing trend towards developing multi-human, multi-robot systems to better integrate robotic systems into industries and society. However, according to the latest research [2], this approach comes with several significant challenges, such as safety, scalability, coordination, security and information transparency. Moreover, a deeper understanding of how humans behave in multi-agent environments is crucial for developing the future human-robotic system. The future research trends in this area include understanding how trust is built when collaborating with robots of varying autonomy and performance levels in a dynamic environment and comprehending how the presence and roles of other humans impact the performance of individual HRC systems [2].

Federated Reinforcement Learning (FRL) is an emerging field that combines the complex problem-solving abilities of reinforcement learning with the privacy-preserving architectures of federated learning[3]. FRL, which allows multiple robots and human-robot teams to share their experiences without sharing operational data, is a natural candidate for de-

veloping intelligent learning strategies in multi-human, multi-robot environments. By using FRL, a HRC system can provide a more robust and generalized model, which can perform well across a spectrum of dynamic environments. For instance, [4] developed a FRL enhanced multi-agent HRC system. The proposed system demonstrated that the FRL supports continual learning among the robots to ensure they remain updated with the latest knowledge and skills. The dearth of research in applying FRL to the multi-agent HRC systems presents a unique opportunity to explore innovative solutions and novel models tailored to address aforementioned distinct challenges.

Some of the specific requirements of federated learning in HRC include data privacy and security, real-time processing and continual learning, scalability and model personalization.

The primary objective of this paper is to conduct a comprehensive literature review focusing on FRL in HRC. We aim to enrich the existing literature on this topic by providing valuable insights into the potential benefits, challenges, and future direction of FRL adaptation with reference to the specific requirements mentioned above. Moreover, given the novelty of the field, there are few works focusing on the application of FRL in HRC systems. Thus, this paper also focuses on the applications of federated learning and reinforcement learning (RL) in HRC systems.

The rest of the paper is organized as follows: Section II reviews the methodology used to select publications for this review. Section III explains the fundamental concepts of federated learning and its applications in human-robotic systems. Section IV discusses reinforcement learning and its role in developing human-robotic systems. Section V explores federated reinforcement learning systems and the scope of their integration with human-robotic systems. Section VI highlights the key challenges and future research directions in adopting FRL for human-robotic systems. Finally, Section VII presents conclusions based on our findings.

II. SYSTEMATIC REVIEW APPROACH

The review approach used in this paper explores two publication databases: IEEE Xplore and Scopus. The keyword search is inspired by [5] with the following modifications. The following combination of keywords was used for searching

federated learning methods in human-robotic system: ("human-robot collaborat*" OR "human-robot cooperat*" OR "collaborative robot*" OR "cobot*" OR "hrc") AND ("federated learning"). The same structure was used for reinforcement learning methods with a filter set for deep reinforcement learning. Most of the papers reviewed were from the year 2019 to current highlighting the latest applications and methods in the field.

III. FEDERATED LEARNING IN HRC SYSTEMS

Federated learning, first introduced by McMahan et al. [6], has emerged as a popular approach for training machine learning models across decentralized devices or servers. Unlike conventional training methods, which send all data to a centralized server, federated learning operates through the exchange of only model parameters across participating devices. In this paradigm, a central server acts as an aggregator to collect and coordinate the updated model parameters from individual devices. Despite being a novel research field, federated learning is finding increasing applications in the field of human-robotic systems. It addresses some of the challenges associated with existing training methodologies in human-robotic systems such as data privacy and continuous learning. For instance, [7] developed a federated learning system to allow robots to learn directly from human interactions without directly sharing sensitive human data. [4] invented federated learning empowered robotic systems to engage in continuous learning among the robots. The results showed that the robots can dynamically adapt their behavior based on interactions with various users or environments. Similarly, [8] developed a federated learning system specifically for social robots to learn in a continual manner from different human users without compromising user privacy. The system includes an asynchronous client-driven federated architecture, where the aggregation process is initiated by the client rather than the server. Despite their effectiveness, scalability issues, non-ID data distribution, and differences in learning samples across clients remain big challenges to be addressed in the future.

Although federated learning architecture has an inherent level of security, there are a number of security risks still available. [9] developed a privacy-enhanced federated learning model based on cloud-edge-client collaborations. The proposed architecture tackles the gradient leakage attack wherein a server responsible for aggregating the model parameter tries to extrapolate the training data from clients. A split learning model based on interaction between the edge servers and the clients is proposed thereby diversifying the attack surface and reducing the chances of gradient leakage at the aggregator.

One of the challenges associated with federated learning is the requirement of large bandwidth for clients to communicate with the server while model training. Task-offloading is a technique used in mobile edge computing (MEC) systems for efficiently utilizing the available spectrum by distributing the task among the robots and MEC servers. [10] developed a privacy preserving, spectral efficient system based on task-offloading. It defined a novel metric called the Value of

Information (VOI) for efficiently quantifying the tasks to be carried out.

Multi-human multi-robot environments being essentially a more complex level of interaction, there is a need to develop a better understanding of human cognitive processes. [11] developed a LSTM based multi-task learning model for predicting multi-level human intention in assembly tasks. By leveraging FL, the proposed solution enabled privacy of the sensitive human data. The solution was applied to the construction industry highlighting the wide applicability of FL across multiple industries. [12] developed a federated learning architecture for Learning from demonstrations (LfD) based robotic learning. The objective was to address the challenges related to multi-agent learning, long-term autonomy. It expands on the previous FL-based methods by incorporating human feedback in the learning process. [13] developed a federated learning architecture incorporating human behavior as a feature in the modelling process. The proposed method allows for learning from a diverse group of teachers of both short term and long term behaviors.

To ensure future research interest in incorporating FL in human-robotic systems, there is a need to develop standard frameworks providing robust protocols for data sharing and performance bench-marking. [14] proposed a human-robot collaboration architecture in the domain of field robotics using fog-enabled federated learning. [7] proposed a decentralized data and model sharing framework for robot units located at multiple sites. [4] presented a FL based continual learning benchmark that allows agents to learn continually under different contextual settings. To address the issue of data heterogeneity in industrial settings [15] proposed a FL based framework using pre-trained models for video understanding tasks.

In conclusion, federated learning holds significant promise for enhancing HRC systems by addressing challenges in privacy, security, and data heterogeneity. Development of robust and standardized frameworks are critical to realise the full potential of federated learning in this domain.

IV. REINFORCEMENT LEARNING IN HRC SYSTEMS

RL is a branch of machine learning where an agent learns to make decisions by interacting with an environment. In the field of robotics, RL is a popular learning strategy enabling robots to learn complex tasks such as walking, grasping objects, navigating etc. Deep reinforcement learning (DRL) combines the principles of reinforcement learning with deep learning. This leverages the powerful function approximation capabilities of deep neural networks to handle high-dimensional state and action spaces, making it possible to solve complex, real-world problems that traditional RL methods struggle with.

The first major breakthrough combining existing RL method of Q-learning with the non-linear function approximation of deep learning was by [16]. The concept of experience replay was introduced, which is a buffer containing episodic samples which are used to update the weight of the neural network during training. This led to reduction in variance of expectations and divergence in parameter values. The paper demonstrated

the effectiveness of using a stochastic gradient descent approach to update the parameters of the Q-function for stable training and faster convergence. [17] introduced a new neural network architecture for deep reinforcement learning called a duelling network architecture. The architecture consisted of two fully connected streams at the end near the output layer. One of the streams estimates the value function while the other estimates the advantage function. Output from both of these streams are combined to get the Q values for different actions. [18] developed a double DQN architecture. Double DQN tries to separate the implementation and evaluation steps to reduce overestimation. [19] introduced the concept of an prioritized experience replay where the selection of transitions from the replay memory are done on the basis such that more useful transitions are sampled more leading to faster training and convergence. This paper introduced prioritization of samples from the experience replay using the TD error as a metric.

Gradient based optimization methods can be highly unstable due to unregulated size of policy updates between iterations and could lead to requirement of large number of samples to achieve optimum results. [20] proposed a trust region based optimization method which minimized a surrogate objective function guaranteeing policy improvement with non-trivial step sizes. A simpler alternative to TRPO has been proposed by [21] called proximal policy optimization (PPO) which instead of using a constraint based surrogate objective function uses a clipped objective function. This policy gradient method alternates between interaction with the environment and updating a surrogate objective function. It also defined an alternative to the clipped surrogate objective in terms of an adaptive KL penalty coefficient.

Reinforcement learning has been a dominant method for training robots on a variety of tasks. With its capability to include human-related factors in the robot's learning process, DRL continues to be a learning method of choice in Human-Robotics System research. Since in this paper we make a case for Federated Reinforcement Learning, which is best suited for multi-human multi-robot systems, the following review focuses primarily on multi-agent systems.

[22] discusses a robotic motion planner designed to address collision issues in human-robot collaboration tasks. It presents a motion planner based on the PPO algorithm, enhanced with OU-Noise in the action space to promote the exploration capabilities of the robotic arm. It highlighted the importance of exploration in action spaces, which leads to a higher success rate in reaching the target state compared to no exploration. [23] developed a two-level hierarchical framework for establishing a human-robot collaboration policy. At the higher level, a DRL-based policy is developed for determining the robot's actions. At the lower level, a human-intention perception module is developed to understand the human's intention. This second module is responsible for incorporating human factors into the robot's decision-making process, thus leading to a safe operating environment for human operators. [24] utilizes human feedback from human-robot interactions as a reward to develop a multi-objective policy using deep

reinforcement learning. This approach reduces the burden of explicitly defining the reward function for all possible states in the environment.

[25] introduced a multi-agent navigation algorithm that incorporates social rules for collision avoidance and safe navigation. The algorithm is specifically designed to handle dynamic and non-convex static obstacles. A policy, designed using ORCA, serves as an external signal for the DRL model responsible for the robot's navigation. This external signal is designed to ensure the robot's navigation is both safe and collision-free. [26] developed a robotic navigation model augmented with an active inducement strategy. This study investigated how the robot utilizes voice-based inducement to navigate successfully in crowded environments and assesses its impact on overall system efficiency. The proposed method undergoes testing on a group of homogeneous robots, focusing specifically on a single type of inducement, namely voice-based cues. [27] discussed a multi-agent reinforcement learning (MARL) framework for assisting surgeons during surgery. This framework enables the sequential development of policies for two instruments, each performing heterogeneous tasks. The study demonstrates that employing separate policy models for each agent yields a greater capacity for learning coordinated behavior compared to a shared policy model.

[28] discussed a decentralized framework based on Markov Decision Processes (MDP) and multi-agent adversarial Inverse Reinforcement Learning (IRL). This work emphasizes the advantage of dec-MDP over multi-agent MDP, as the latter necessitates each agent to possess knowledge of the global environment state, a challenge in practical scenarios. In numerous human-robot interactions, the robot may not perfectly observe the human's state, thus a decentralized approach combined with IRL aids in learning task preferences and collision avoidance effectively. [29] developed a robotic navigation approach that leverages the human behavior model of navigation in crowded areas. Unlike approaches that concentrate on individual human actions, this paper integrates the estimation of human group movement. Groups are formed by clustering individuals with similar behaviors. This estimation of group behavior is subsequently utilized to adjust the reward function of the DRL algorithm. [30] discussed an attention-based DRL approach aimed at tackling the initial task allocation problem within multi-human multi-robot teams. The challenge tackled here pertains to the heterogeneity in team design. The model incorporates cross-attribute attention layers, which capture latent attributes spanning different categories. These categories encompass human factor attributes, robot characteristics attributes, and task-specific attributes. Through the cross-attention mechanism, the model endeavors to construct a pertinent state representation by leveraging the inherent latent relationships among the three attribute types. This state representation subsequently serves as input to the policy learning algorithm. [31] developed a collaborative solution based on Multi-Agent Reinforcement Learning (MARL) for the human-prosthesis collaboration problem. This approach tackles the challenge of human-robot collaboration by treating humans

and robots as a coupled agent. It considers the influence of humans in designing the control policy for the robot.

In summary, these works collectively contribute to advancing the capabilities and efficiency of HRC systems across various domains. However, several challenges still persist. Firstly, safety is still a paramount concern, particularly in dynamic and unstructured environments where multiple robots operate alongside humans. Secondly, interpretability and transparency in algorithms and systems are critical for fostering effective HRC systems. This factor remains inadequately addressed. Lastly, scalability and adaptability remain significant challenges for RL-enhanced HRC, as many systems struggle to scale effectively to accommodate larger teams of robots and humans. Overall, while significant progress has been made, continued research and innovation are essential to overcome these challenges and fully realize the potential of RL empowered HRC in diverse applications.

V. INTEGRATION OF FEDERATED REINFORCEMENT LEARNING WITH HUMAN-ROBOTIC SYSTEM

Deep reinforcement learning methods suffer from the issue of sample inefficiency, which necessitates a large number of data samples to learn the optimal policy. High-dimensional input spaces, non-stationarity of the learning environment, and the classic exploration-exploitation dilemma in RL are some of the leading causes of sample inefficiency in RL. Federated learning, with its characteristic distributed training approach and its effectiveness in handling user privacy, offers a solution to the sample inefficiency problem. With respect to Human-Robotics System, federated reinforcement learning(FRL)'s distributed learning aspect allows multiple robots to learn collaboratively while remaining physically distributed across different locations. This enables efficient knowledge sharing among robots without the need for centralized data aggregation, reducing communication overhead and latency.FRL facilitates learning in diverse and dynamic scenarios by allowing robots to adapt their behaviors based on local observations and interactions with humans. The concept commonly referred to as personalization in federated learning literature. This decentralized learning approach enables robots to quickly adapt to changes in their environment and tasks, improving their overall performance and versatility. FRL can easily scale to accommodate a large number of robots and users, making it suitable for collaborative learning in multi-human multi-robot systems.

Due to the novelty of FRL, its application in Human-Robotics Systems is limited. However, it has been finding widespread applications in related fields, which can be easily adopted for Human-Robotics Systems. Some of these works are reviewed here. [32] defined a federated Q learning architecture consisting of 2 agents. Both the agents have different data distribution with the second agent not receiving any particular rewards for its actions.Both the agents have their own private Q networks trained on the local data distribution and receive the output from a shared MLP which is trained on the concatenation of private Q-networks parameters.The work

demonstrated that it is possible to train systems consisting of heterogeneous agents with different resource capabilities. One of the promises of federated learning is the ability of individual agents to adapt specifically to the environment they are facing by building up on the knowledge achieved via the shared federated learning architecture. [33] defined a FRL architecture for end user personalization in the gaming industry. Each client has its own DQN architecture which is private to the client. One of the key contribution of this work is the aggregation of similar clients to speed up the learning process. [34]proposed a technique called Federated Reinforcement Distillation (FRD), where agents share a proxy replay memory based on proxy states. This resolves the issue of agent privacy by avoiding the direct sharing of experience replay memory among agents, which would create a global experience replay memory. An enhanced version of FRD, called Mixed Augmented FRD, is also discussed. Here, to ensure sufficient exploration of the environment with a limited number of agents, synthetic data is used to augment the global proxy replay memory.

Navigation in robotic systems is one area which has benefited greatly from reinforcement learning. [35] developed a FRL system for navigation in cloud robotic system. They proposed a knowledge fusion algorithm similar to style transfer algorithm in computer vision which fuses prior knowledge of individual agents and helps evolving the shared model. The paper also discusses two transfer learning techniques to allow agents to quickly adapt to new environments.[36] developed a federated version of Actor-Critic PPO using gradient sharing and transfer learning between the agents. The federation mechanism is based on the weighting mechanism calculated using the average reward in the last 10 episodes for each agent.[36]developed an end to end training process combining federated learning with transfer learning to enable asynchronous learning from a variety of different environments. The proposed framework conducts knowledge aggregation process in nearly real-time.

[37]developed a federated version of DQN for efficiently handling motion paths of multiple robots. The algorithms is designed to satisfy the power budget and mobility constraints. The work highlighted the advantages of FDQN in accelerating convergence while saving on memory utilization and communication resources.[38]highlighted disadvantages of centralized FL for dynamic robotic systems.The problem targeted is of obstacle avoidance in highly dynamic scenarios. The decentralization is achieved through a mobile agent which can navigate across a network of connected agents and aggregate models based on the destination node.[39]developed a task scheduling optimization algorithm for heterogeneous robotic environment. The aim is to minimize the queue length of tasks to be processed at geographically dispersed warehouses. A federated version of PPO with a scheme for handling data heterogeneity is developed.[40]developed a navigation strategy for swarm robots addressing the issue of limited communication bandwidth using a FL based DDPG method.

FRL leverages the distributed nature of IoT devices to enable them to learn and make decisions collaboratively without

centralizing data.[41] demonstrated the efficacy of training individual DRL agents through an FL based framework for joint allocation of communication and computing resources for the purposes of computational task offloading to edge networks.[42] investigated the application of Federated Deep Reinforcement Learning for cooperative edge caching. The federated architecture is shown to have comparable performance as the centralized approach but with a lower loss in terms of average delay, the hit rate and backhaul traffic offload.[43] proposed an intelligent ultra-dense edge computing (I-UDEC) framework which integrated blockchain and AI into 5G ultra-dense edge computing networks, in order to formulate the heterogeneous network resources and hybrid computation offloading pattern of UDEC.[44] proposed a new system called FRMA (Federated Reinforcement Multiple Access) to improve Wi-Fi performance in densely populated environments.[45] proposed a policy-based multi-agent deep reinforcement learning (RL) framework called heterogeneous multi-agent actor-critic (H-MAAC) to tackle the freshness of data in Mobile Edge Computing (MEC) systems, where timely data processing is important. H-MAAC is a multimodal framework that takes heterogeneous inputs to learn the mixed policies for trajectory planning, data scheduling, and resource allocation.[46] investigated minimizing both delay and energy consumption for IoT devices which involves making decisions about offloading tasks, computation resource allocation and transmit power allocation. The proposed federated DDQN framework demonstrates faster convergence compared to federated deep Q network (DQN) and centralised DDQN algorithms.[47] proposed a reliable strategy for anomaly detection in the context of the Industrial Internet of Things (IIoT). The proposed federated version of DDPG algorithm achieves high throughput, low latency, and accurate anomaly detection in various scenarios.

In conclusion, the adoption of FRL in HRC holds significant promise. It offers solutions to aforementioned challenges such as sample inefficiency, privacy concerns, and scalability. By leveraging distributed learning and collaborative intelligence, FRL enables robots to learn and adapt effectively in dynamic environments.

VI. CHALLENGES AND FUTURE DIRECTIONS

While FRL paves the way for enhanced HRC in sophisticated environments, several challenges need to be addressed. Firstly, the frequent exchange of model parameters among distributed agents can lead to significant communication overhead. Current research works showed few improvement in this area. Future research should focus on developing efficient optimization and aggregation mechanisms, communication protocols and optimization algorithms to mitigate communication overhead.

Secondly, privacy and security concern is still significant for fully adoption of HRC solutions. While current research has shown that FRL can greatly enhance privacy by not sharing raw user data, there are still challenges to address in this area. One key concern is the potential risk of information leakage

through the exchange of gradients and model parameters in FRL systems. Despite not directly sharing raw data, the exchange of these parameters could still reveal sensitive information about individuals or organizations. Robust privacy-preserving techniques, such as differential privacy and secure multi-party computation, need to be further developed and integrated into FRL frameworks to mitigate these risks effectively. Moreover, ensuring the security of FRL systems against adversarial attacks and data breaches is essential for building trust and confidence in these systems. Robotic systems operating in sensitive environments or handling confidential data must be resilient to cyber threats and unauthorized access. This requires implementing robust encryption methods, access control mechanisms, and intrusion detection systems to safeguard against potential security vulnerabilities. Future research activities can be focus on developing collaborative framework to develop and implement effective strategies for protecting user privacy and ensuring the security of HRC systems in real-world applications. This will require collaborative efforts between researchers, policy makers, and industry stakeholders

Thirdly, limited computational capabilities pose significant challenges for deploying advanced deep learning models in robotic systems. This constrain driven the design of FRL architecture, which can accommodate the computing limitations of robots while still enable effective learning and decision-making processes. However, existing FRL architectures did not fully consider the specific computational constraints of robotic systems. This leads to suboptimal performance and scalability issues for these applications. To address these challenges, future research in FRL should focus on developing optimization algorithms to enhance the computationally efficient for robotic systems, investigating techniques for compressing and pruning deep learning models to reduce their computational complexity and designing efficient distributed computing frameworks and protocols for collectively learning in federated environments.

Furthermore, scalability in FRL systems is crucial for their widespread adoption and effective deployment in real-world. As the number of agents participating in FRL systems increases, maintaining synchronization among the system becomes increasingly complex and challenging. The current state of research in FRL highlighted the ongoing challenge of efficiently scaling FRL systems to accommodate a growing number of robots and meanwhile to maintain learning quality. Several key approaches can be considered to tackle this challenge. Firstly, develop an effective distributed FRL architecture to handle the increasing number of agents by distributing computation and communication tasks across multiple nodes. Secondly, develop decentralized and intelligent control mechanisms to allow individual agents to make autonomous decisions across FRL networks. Last not the least, implementing efficient resource allocation strategies that can dynamically allocate computational resources based on learning requirements and performance of individual agents.

Explainability is an important factor for ensuring that robots can effectively, safely, and transparently collaborate with humans. It is also important for user acceptance when it comes

to collaborating with robots in safety critical applications. Developing real-time explainable models with user-centric explanations can lead to widespread adoption of FRL in HRC systems.

Lastly, domain adaptation is crucial for FRL systems to transfer knowledge effectively across multiple tasks and environments. However, data distribution and feature selection are biggest challenges to achieve successful FRL adaptation. Researchers are actively investigating methods to overcome these challenges, such as developing robust algorithms for domain adaptation and transfer learning. But one of these works have full address this issue. Future research trends need prioritize the development of robust frameworks to address the societal implications and ethical considerations linked with the deployment of FRL systems. This includes addressing issues related to bias mitigation, ensuring accountability in decision-making processes, and assessing the potential impact on employment dynamics. To facilitate this process, interdisciplinary collaborations between robotics, artificial intelligence, ethics, and policy-making are essential. By bringing together experts from diverse fields, researchers can gain valuable insights into the societal implications of FRL systems and develop comprehensive frameworks for addressing ethical and policy concerns.

VII. CONCLUSION

In conclusion, FRL presents a promising avenue for advancing HRC systems by addressing several key challenges inherent in traditional learning paradigms. Its distributed nature enhances data privacy, facilitates continuous learning, and allows for the integration of diverse data sources without the need for centralized data aggregation. However, the adoption of FRL in HRC systems is still in its early stages. This research work has provided a comprehensive review of past research, applications, and future prospects of various learning approaches within HRC systems. It offers a foundational view for understanding the current landscape of FRL technology and its application in facilitating HRC. Through systematic analysis of development trends and challenges, we have provided valuable insights to drive future research directions to tackle significant issues such as communication overhead, privacy and security concerns, limited computational capabilities of robotic systems, scalability, and the need for effective domain adaptation and transfer learning. Moving forward, future research will focus on developing a conceptual framework for FRL within HRC systems to address the current challenges and harness the full potential of FRL.

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