

The Research of Virtual Reality-Based Robot Teleoperation and Skill Learning

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Abstract. In modern society, virtual reality (VR) is gradually becoming an effective assistant for human–robot collaboration, teleoperation, and robot skill learning by enabling immersive and intuitive human-robot interaction. This research summarizes the latest progress of VR-based humanoid robot teleoperation and skill learning, with a particular focus on real-time control frameworks based on motion capture, mapping and closed-loop force and visual feedback. Key system architectures and representative approaches are reviewed to illustrate how VR technologies support stable, low-latency, and intuitive remote robot control in complex environments. Furthermore, this article reviews the robot skill learning methods based on demonstration and simulation-based reinforcement learning, introduces their fundamental principles and analyzes respective characteristics and analyze their advantages and limitations in complex tasks. The integration of VR technology has effectively promoted more immersive and efficient human-robot interaction, promoted its development in the direction of intelligence, and has a wide range of potential application scenarios in the future.

Keywords: Virtual reality, teleportation and mapping, human-robot collaboration, closed-loop Interaction

1. Introduction

With the rapid development of technology, humanoid robots are increasingly regarded as multifunctional machines that can serve in a wide range of scenarios, including manufacturing, warehouses, disaster response, and home services [1]. In the traditional Human–Robot Collaboration (HRC) system, one of the human or the robot usually takes the lead in the task, and the other takes corresponding actions according to the preset procedures. The framework maximizes operational efficiency by combining human cognitive initiative and judgement with the accuracy and repeatability of robots. However, since traditional HRC is in essences still a slave operation mode of the traditional HRC, it is not flexible and cannot attain a high level of automation. According to the recent studies, HRC is slowly evolving into the 'Proactive HRC' system, which robots can generate adaptive motion plans that coordinate with human actions [2]. With this system, robots do not only share workspace and task information with humans but also achieve tighter collaboration through intention recognition and adaptive control.

During this transition, Virtual Reality (VR) and Augmented Reality (AR) technologies have become important media to improve the ability of the robots as well as the human thinking. They allow projecting human perception, mental and physical capabilities onto robots in a more natural manner. While VR emphasizes a fully immersive experience, AR focuses on integrating digital content with the user's physical environment. Introduce powerful VR and AR technologies into the system and simulate the real environment. These technologies can provide visual task guidance, spatial information and security reminders in complex manufacturing tasks. They also increase transparency of robot motion intentions and reduce operator's cognitive load and operational risks [3]. At the same time, teleoperation plays an increasingly significant role in HRC. By allowing human operators to remotely control humanoid robots in the field, teleoperation simultaneously ensures safety of operator and maintains accuracy of the operation. Recent systems such as Open-Television demonstrate that, through VR headsets and stereo active visual feedback, an operator's hand, head, and whole-body movements can be precisely mapped to a humanoid robot, thus realizing millimeter level dexterous manipulation and real-time teleoperation across long distances [4]. Compared to traditional teleoperation approaches, VR-based mapping control not only lowers the barrier for providing demonstrations but also generates more natural, smooth, and high-quality data, which is conducive to the development of imitation learning.

In general, current research has shown the potential of VR and AR technologies in humanoid robot control. Nonetheless, several critical limitations still remain, communication delay affects real-time performance, weak depth perception may cause instability, and limited multimodal feedback reduces immersion and control accuracy [5]. In addition, although many applications of VR and AR in HRC have been explored in the manufacturing field, special evaluations for humanoid robots, especially mapping control, are still insufficient.

Based on these considerations, this research is organized as follows. Chapter 1 reviews real-time control methods based on direct teleoperation and motion mapping, focusing on VR-based humanoid robot teleoperation, real-time motion capture, control architecture design, and force and visual feedback of closed-loop interaction. Chapter 2 surveys robot skill learning methods with demonstration and simulation-based reinforcement learning, and discusses their principles, advantages, limitations, and roles in skill acquisition and transfer. Finally, the paper concludes with a summary of the main findings and an outlook on future research directions.

2. Real-time control based on direct teleoperation and motion mapping

VR humanoid robot teleoperation aims to achieve stable, intuitive, and immersive human control of robotic systems in complex remote environments. Real-time motion capture and control architecture design, together with force and visual feedback mechanisms, constitute two basic aspects of such systems. Motion capture and control architectures focus on accurately acquiring and mapping human movements to robot actions, while feedback and closed-loop interaction mechanisms ensure that the operator continuously perceives and adjusts the robot's state and environmental changes. Although each aspect involves different stages of the perception-action pipeline, their close integration is essential to achieve reliable teleoperation performance and supporting downstream tasks such as virtual demonstration and robot skill learning. They together form the core technical foundation of real-time control systems based on direct teleoperation and mapping.

2.1. Real-time motion capture and control architecture design

Real-time motion capture and control architecture constitute the core foundations that support the whole system. Real-time motion capture refers to the rapid data collection and continuous estimation of human posture, joint angles, and spatial posture, so that the operator's physical movements can be stably mapped to virtual or physical humanoid robot. The control architecture, in turn, transforms these perceptual signals into executable robot commands, including action planning, force feedback processing, and motion mapping policies. According to existing surveys, a complete teleoperation system usually consists of four modules, perception, mapping, control, and feedback. They form a stable, low latency, high bandwidth communication loop between the operator and the robot [1]. The perception module collects human movement, environmental information, and sensor data. The mapping module realizes the real-time kinematic correspondence between people and robots. The control module generates a stable instruction trajectory. And the feedback module returns visual, haptic or multimodal information to form a closed-loop interaction loop.

In recent years, with the rapid development of science, VR and AR technologies have gradually become popular, and more immersive, natural, and extensible teleoperation frameworks have emerged. Aadhithya et al. introduced Open Teach, an open source and highly flexible VR teleoperation system. The system can achieve calibration free and low latency human-robot interaction only using Meta Quest 3 headphones with 90 Hz hand tracking and full color pass-through functions. Open Teach employs a unified human to robot retargeting method to support a variety of robot implementations, including single-arm robots, multi fingered hands, dual-arm systems, and mobile control platforms. User studies show that Open Teach achieves strong stability in complex tasks, which is better than the existing VR teleoperation system in terms of success rate and operational efficiency. However, it is still limited in various aspects including occasional misclassification of gestures, absence of haptic or force feedback, and poorer tracking precision when under occlusion [6]. Wonsick and Padir further categorize VR-based robot control into three main mapping frameworks. Direct mapping connects the operator's hand and head movements directly to the robot, which is highly intuitive, but the adaptability is limited due to structural differences. Digital twin-based mapping integrates virtual robots as an intermediate layer, making them suitable for complex or remote tasks [7]. The Homunculus model separates the motions of the human and robot in the virtual workspace and reconfigures the control relationship to lower the cognitive load. Recent changes also incorporate deep learning, shared control, and predictive planning, which make teleoperation smarter and more efficient, and greatly enhance performance [8]. Furthermore, teleoperation methods that combine visual positioning with VR can reconstruct the remote environment and replace noisy point clouds with structured virtual objects, so that the operator can understand the space more clearly [9]. These types of systems employ virtual agents and adaptive mapping techniques to ensure stability and continuity in the case of large network delay, thus enhancing precision of manipulation and strength of interaction in real-time.

2.2. Force and visual feedback and closed-loop interaction

The combination of force and visual feedback with closed-loop interaction based in VR-based humanoid robot teleoperation are the mechanisms of determining immersion, control stability, and the rate of an achievement of tasks. Visual feedback is not limited to traditional monocular video, but also includes advanced modes such as active vision, stereoscopic feedback, and attention-guided rendering. For example, the active two-eye camera system proposed in Open-Television can

automatically adjust the viewing angle according to the operator's head posture, so that users can experience a humanlike observation path in VR and significantly enhances visibility and depth perception of local workspace [4]. Parallel to visual feedback, force feedback conveys tactile information, such as mechanical contact, impedance, and operational risks, back to the operator, so as to more accurately judge the grip force, contact safety and material conditions. This mode is particularly important in high-precision manipulation or exoskeleton-based interaction scenarios [10].

Closed-loop interaction emphasizes real-time updates throughout the whole perception control pipeline, forming a continuous, low latency bidirectional communication loop. Changes in the robot state will be immediately reflected in the virtual reality environment and then affect the operator's next step. VR interactive surveys show that the spatial layout of information, intention visualization (e.g., trajectory overlays, force direction cues), and semi-transparent guidance layers can effectively reduce the 'gulf of evaluation', thus improving the operator's ability to interpret and predict robot behavior, which is an indispensable part of closed-loop feedback [11]. In addition, as eye tracking is integrated into VR headsets, systems can dynamically adjust rendering clarity, expand areas of interest, or infer user intentions based on gaze, providing richer visual cognitive clues for closed-loop decision making [12].

Cheng et al. introduced Open-Television, a VR based teleoperation system based on active stereoscopic vision feedback. The system uses head-driven stereo cameras to realize active perception, and maps the operator's hand, wrist and head posture to the robot in real time. Combined with inverse kinematics and hand retargeting, this enables high-DOF fine manipulation. Experimental results show that Open-Television significantly improves success rates in tasks such as sorting, insertion, folding, and object delivery, and collects high quality demonstration data for imitation learning to support stable long-term policies. Furthermore, studies indicate that overlaying visual layers in VR, such as planned trajectories, force distributions, or hazard zones, can significantly reduce cognitive load and reinforce the consistency between operator's intention and robot behavior [7].

In the field of force feedback, although most current VR teleoperation systems still rely mainly on vision, new research is starting to explore lightweight haptic signals and impedance-based feedback to improve the ability to grasp stability and distinguish different materials. However, due to hardware complexity and high calibration cost, the scalability of such haptic systems is still limited [10]. Overall, the existing closed-loop interaction strategy has been significantly improved in terms of immersion, stability and accuracy, but it is still limited by factors such as three-dimensional video bandwidth, visual occlusion, network jitter of remote time, and lack of real force field hints.

3. Demonstration and simulation-based reinforcement learning

The purpose of robot skill learning is to assist robots to acquire strong, flexible control policies to undertake complicated tasks. Demonstration and simulation-based reinforcement learning are two representative methods of robot skill learning. Demonstration-based methods use human experiences to provide intuitive and structured guidance, while simulation-based reinforcement learning achieves autonomous policy optimization through large-scale interaction in simulated environments. Even though both have their limitations that exist in their use, individually, these approaches have a potential approach of efficient skill learning with fewer safety considerations and hardware expenditure. This chapter discusses the theory and latest developments of demonstration-based and simulation-based reinforcement learning, and how it is applied in robot learning and transfer of the learning to new tasks.

3.1. Demonstration

It is common in many robotic applications that a mapping that allows robots to choose an appropriate action given the current world state is often called a policy, and is a central theme in robot control and learning. Learning from Demonstration (LfD), is an important policy learning approach, which humans provide examples or demonstrations to robot control policies. Argall et al. define LfD as the process of learning control policies from state–action examples supplied by humans, and systematically review demonstration data recording methods, policy generation approaches, and their applicability in robotic control. They point out that LfD methods can effectively reduce the reliance on precise dynamic modeling and explicit reward function design [13]. In virtual reality conditions, demonstrations are usually run using real time motion capture and interactive interfaces, with human inputs continuously sensed and mapped to either virtual or physical embodiment of a robot.

Different from traditional offline demonstration, demonstration frameworks based on real-time control and timely feedback result in closed-loop interaction characteristics. Ravichandar et al. categorize demonstration methods based on the form of demonstrator input, including kinesthetic teaching, teleoperation, and passive observation. Teleoperation-based and virtual demonstration using real-time feedback are timely to the demonstrators in order to enact dynamically the action of demonstrators in response to the system reactions to enhance the quality of demonstrations and policy sustainability [14]. The multimodal VR teaching research also indicates that real-time control along with visual, haptic, or state feedback may considerably enhance the user perception of the outcomes of the execution of the tasks and a sense of their immediate feelings, allowing the articulation of the complex acts to become more logical and consistent [15]. In addition, the integration of haptic feedback devices into virtual demonstrations has been shown to enhance the perception of contact states and operational precision and provide effective support for the transfer of fine skills.

From a theoretical point of view, a stable, continuous, and predictable feedback is a key condition for users to develop a sense of 'being present' in virtual environments. The demonstration process can be considered as natural and credible only in a situation when a system is able to react effectively to the actions of users and ensures the coherence of the interaction process can support effective learning of skills and their transfer [16]. However, the surveys also show that demonstration-based methods are often limited by the skill level of presenter and require high real-time performance, sensing accuracy, and hardware reliability, which is still a major challenge related to generalization and robustness in high dimensional and complex tasks. These limitations motivate people to explore complementary learning approaches, so that robots can independently improve and expand the demonstrated skills.

3.2. Simulation-based reinforcement learning

In the research of robot skills learning, simulation-based learning refers to a kind of method that uses intelligent algorithms to train and optimize robot control strategies using virtual or simulated environments. Compared with the demonstration-based methods that rely on the data provided by humans, this method emphasizes continuous interaction between the agent and the environment. Through this interaction, the intelligent body gradually builds a mapping from the environmental state to the action selection through repeated experiments. Reinforcement learning (RL) serves as the core theoretical framework of this method and is usually formulated using a Markov Decision Process (MDP), where the policy, state transitions, and reward function jointly determine the

learning dynamics and guide the agent to learn optimal behaviors through long-term rewards maximization [17].

With the development of deep learning, deep neural networks (DNN) have been incorporated into RL, and deep reinforcement learning (DRL) has emerged, which significantly enhances representational ability in the field of high-dimensional spaces and continuous action. Surveys indicate that DRL reduces reliance on manual feature engineering through end-to-end representation learning and shows strong modeling capabilities in complex decision-making and control tasks. However, it also has problems with low sample efficiency and unstable training [18].

Simulation environments provide safe, repeatable, and cost-effective training platforms for DRL, which can be extensively explored without the constraints of real hardware. Tang et al. systematically evaluated recent progress of DRL in real-world robotic applications and pointed out that although many approaches perform well in simulation, their actual deployment on physical robots remains limited by sample efficiency, training stability, and the gap between simulation and reality [19]. To alleviate these problems, transfer learning has been introduced to improve the efficiency of simulation learning. Researchers proposed a KL divergence constrained transfer reinforcement learning method to achieve smooth transfer by limiting changes of policy distribution, which significantly improve learning efficiency and convergence stability in path planning tasks [20]. In general, simulation-based learning provides an important way for acquisition of automatic robot skills. However, similar to demonstration-based methods, it still has practical problems that are highly dependent on simulation accuracy and algorithmic robustness.

4. Conclusion

This article systematically reviews recent progress of human-robot collaboration, teleoperation, and robot skill learning supported by virtual reality technologies, focusing on two representative methods, demonstration and simulation-based reinforcement learning. Existing research generally shows that VR provides an immersive and intuitive interaction medium for human-robot interaction, allowing human operators to perceive remote environments and influence robot behavior in a more natural way, thereby utilize human cognition and decision-making capabilities in complex, dangerous, or unstructured scenarios.

In the research on robot teleoperation and human-robot collaboration, a lot of work has focused on system architectures, mapping models, and feedback mechanisms. It emphasized the use of real-time motion capture, multimodal perception, and closed-loop control to enhance sense of presence and operational stability. Relevant research shows that high-quality visual feedback, reasonable human-robot decoupling mapping, and active perception mechanisms help reduce the cognitive load of operators and maintain the controllability of the system under communication delay or environmental uncertainty. These advances provide an important technical foundation for virtual demonstration, enabling the demonstration process can be carried out in an immersive environment with higher quality and consistency.

In terms of robot skill learning, demonstration-based learning introduces human experiences, which is conducive to quickly mastering complex skills. However, such approaches still have limitations in terms of generalization ability, reliance on demonstration quality, and sensitivity to the skill level of presenters. In contrast, simulation-based reinforcement learning uses high trial and error and autonomous optimization to provide greater flexibility for robot policy learning, but at the same time, it faces challenges such as low sample efficiency, unstable training, and the difference between simulation and the real world.

Recent research trends indicate that relying on a single method is not sufficient to meet the needs of complex HRC and practical applications. Hybrid learning frameworks are increasingly regarded as an important research direction. By combining demonstrations, real-time feedback, and autonomous learning mechanisms in the simulation and virtual environments, robots can achieve more efficient and powerful skill learning and transfer while maintaining safety and cost-effectiveness.

In general, the research on HRC and robot skill learning based on virtual reality is developing in a more intelligent and systematic direction. In the future, work still needs to continue to explore to improve the real-time performance of the system, enhance the ability of learning generalization, and narrow the gap between simulation and the real world.

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