Telepresence Robot in IoT-Enabled Sustainable Healthcare Systems

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In the Internet of Things (IoT) era, telepresence robots (TRs) are increasingly a part of healthcare, academia, and industry due to their enormous benefits. IoT provides a sensor-based environment in which robots receive more precise information about their surroundings.

IoT healthcare environment remote management telepresence robot

1. Introduction

In the modern era, human–robot interaction is increasing in scope and demand in many application areas, including healthcare systems and military applications. This is due to the advancement and capability of robots to perform complex tasks in dangerous and/or prohibited environments. The evolution of the digital era and smart robotic designs continue to simplify daily routine tasks with fast response times and precision [1][2][3]. Researchers are working very hard to design such robots; nonetheless, they have many limitations in performing various functions. On the other hand, it has become necessary for humans to involve robots in tasks from remote locations or in harmful situations, e.g., COVID-19. Robots are controlled by human beings who execute scheduled tasks from remote locations [4][5][6]. These systems aim to capture the environment appropriately and to maneuver based on acquired knowledge [7][8][9][10][11].

2. Telepresence Robot in IoT-Enabled Sustainable Healthcare Systems

In the recent era, the social lives of human beings have depended on technology. Although technologies have greatly improved the lifestyle of human beings, including in the workplace and social gatherings, more investigation can be undertaken to achieve customer satisfaction and systematic analysis [12][13][14][15][16][17]. TRs and autonomous vehicles (AVs) might be attractive alternatives in the human social ecosystem. In [18], a remote manipulator, considered the pioneer robotic arm, was implemented. Implementing these TRs is useful in a COVID-19 or otherwise hazardous environment that is inaccessible to humans [19][20][21][22]. In [23], researchers developed TRs for offices, healthcare systems, and nursing homes. Another useful application is augmented virtual reality, which is useful to simulate the feeling of a human–robot interactive environment [24][25][26][27]. In [28], immersed virtual reality was developed to provide guidelines for user design. Many challenges remain, including the implementation of adjustable height [16], motion along the slope surface [29], system stability [30], and low-speed control [31][32][33][34][35].

The well-known application areas of mobile robots include ocean exploration, approaching the moon, implementation in nuclear plants [36][37][38][39], and, recently, COVID-19 [40][41][42][43][44]. It is often difficult to repair in such scenarios; therefore, the alternate approach of a mobile robot to accomplishing these tasks from a remote location is quite demanding. In addition, the negotiation with the end consumer is condensed to mission provisions, and then automating mobile robots' communications with experts minimize it. Total operational autonomy is also required, especially in perception, decision, and control. However, the specificity of the application domain generates particular constraints which may sometimes be antagonistic, according to the relevant scientific discipline [30][31]. The trajectory control in the software architecture of TRs is presented by [16][44][45][46][47][48] in a dynamic traffic environment. Telepresence robots are utilized in many applications, and have shown tremendous results in human–robot interactions [43][44].

A more general architecture of the telepresence robot is presented in [20][31]. A telepresence robot comprises both software and hardware architectures. It contains hardware components, e.g., biosensors, which obtain information from the patient and send it to the consultant at a remote location using the available communication technology [6][10][32]. It also contains components which can produce the control inputs necessary for the robot to move in a stable position using the actuator connected to it. These actuators control the hardware actions, e.g., motion, speed, and position [33][34][35]. The presented work focuses on the identification and stabilization of the TR and the development of micro-controller-based architecture. The core responsibility of the design is to control the driving behavior and to avoid obstacles in the TR's track The design also contains the module with the best driving path, called the decision-making module. The function of this module is to provide the best path and safe driving with obstacle avoidance control. The term "maneuver" is most likely utilized in the literature to describe path planning. Still, for clarity and consistency, the term "behavior" is employed to label the entire journey of the presented research article. According to the activities generated by the mini-computer in computing, this study also considered other independent attributes such as position, trajectory, orientation, and speed.

Much research has been conducted in the healthcare system using the methods outlined in [49][50][51][52]. The benefits of employing these approaches in the healthcare environment have been evident during the COVID-19 pandemic, when it was required that doctors keep physical distance from their patients to protect themselves. However, to further improve and diagnose the patient, doctors must interact with them; here, the demand for telepresence robots arises. To send robots to the patient ward, care must be taken to avoid collisions of the robots with various obstacles in the hospital environment. Researchers need to propose algorithms for the proper operation of telepresence robots. Each approach has its pros and cons, the proposed approach included, and the idea is to implant a telepresence robot into the hospital environment with fewer obstacles. Utilizing the proposed approach, the doctors help to obtain an initial interaction with the patient and the telepresence robot while maintaining a safe distance. The first try was conducted considering the parameters given in **Table 1**.

Table 1. Telepresence robot parameters.

Parameters	Unit	Value
Obstacles	3 × 3 feet	9 (fixed)
Track	Coiled	1
Initial Point	-	Doctor's Office
Termination Point	-	Patient Ward
Total Distance	Meters	130

A review of the literature review found that most human–robot interactions were implemented efficiently, except for disconnection or delays [49]. The proposed approach is comparatively easy to implement, more flexible, and efficient. Further, various factors, e.g., design variations and human interaction deficiencies, were discussed in terms of the capability of object avoidance and new peripheral connection to exhibit better human-like behavior remotely.

The research gaps have been clearly mentioned and are now highlighted as:

- There is a dire demand for a telepresence robot to be designed that could be utilized in the pandemic situation. A safe physical distance between the target and the transmitter is usually required.
- The design of such a robot, capable of human–robot interaction, is a popular topic to explore, and is receiving much attention in academia, industry, and healthcare systems.

The telepresence robot is an extremely nonlinear system with a gearbox for power transmission, and its precise mathematical model is not simple to derive. Therefore, a system identification approach was implemented to find the approximate model of the system [53]. The root locus method was used to design a speed controller by introducing appropriate poles and zeros [53]. The results validated the identified model of the system. The results were also compared with the A* algorithm [54] to highlight the importance of the proposed work.

A more generalized diagram is shown in **Figure 1**, equipped with a telepresence robot (auto-MERLIN). The mobile robot aimed to equip auto-MERLIN to leave prescribed paths, navigate, detect obstacles, and avoid them. It required entirely new control electronics to be developed. The robot utilized the powerful direct current (DC) motor TruckPuller3 7.2 V for the drive and the powerful model-equipped servo motor HiTec HS-5745MG for steering [55]. The drive motor was equipped with an optical position encoder from the company M101B MEGATRON Elektronik AG & Co. [56], which the speed and direction can determine.

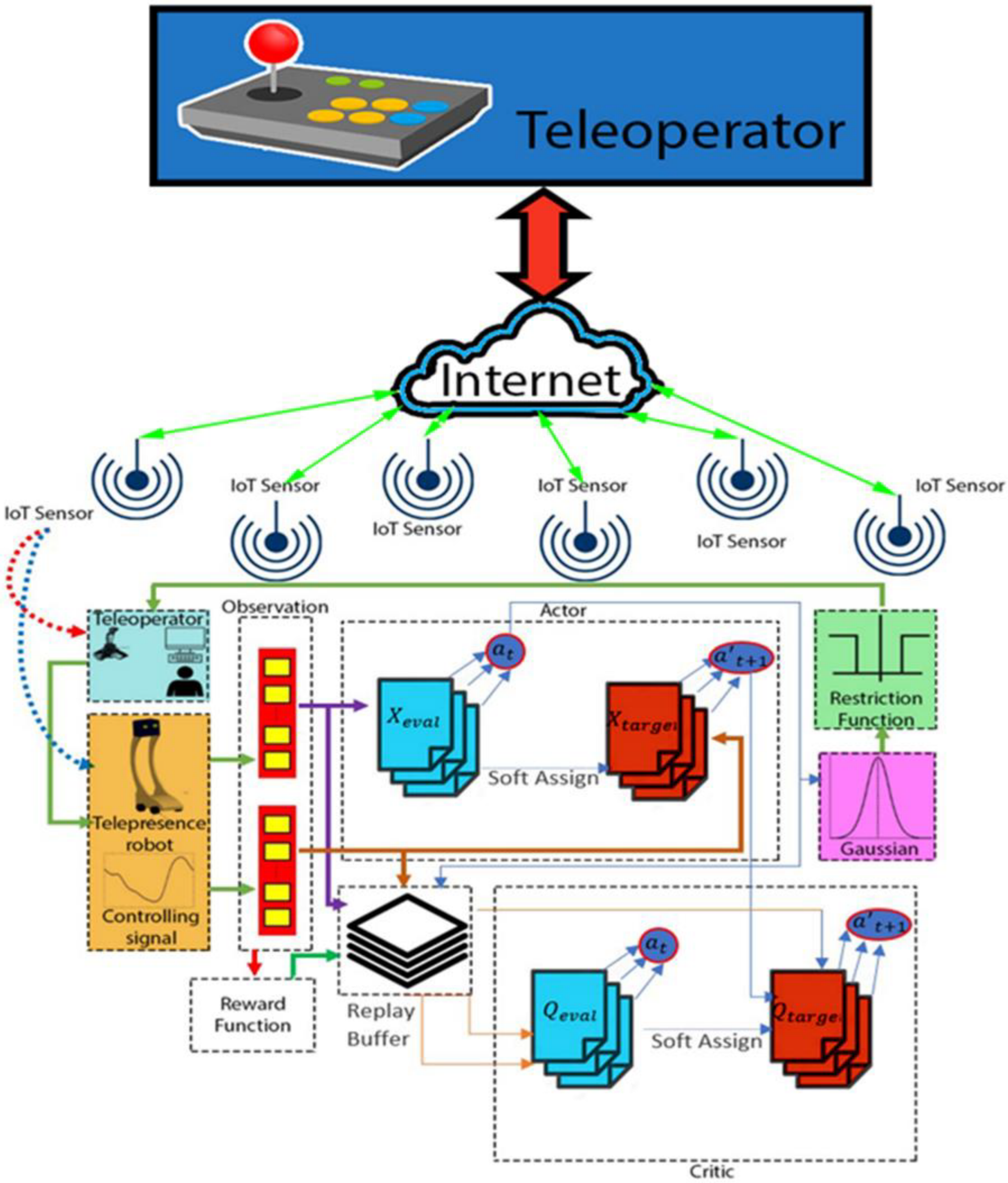

Figure 1. A generalized block diagram with telepresence robot attachment [53].

The TR is designed to maneuver around in dynamic environments (i.e., offices), encountering fixes and moving obstacles. It is worth underscoring the challenges for the telepresence robot while maneuvering in a distant place, controlled by a commanding user. There are various approaches which are worth mentioning. The background section can be further enhanced by adding the following approaches, with each approach's limitation given in **Table 2**.

Table 2. Different approaches with limitations.

Authors	Approaches	Limitations
T. M. Howard [57]	This approach creates sensitive search spaces which showadditional benefits over existing approaches when steering in diverse paths. It digitizess the stroke and state space, and	Utilizing this approach, it is easy to satisfy the environmental constraints when the planned trajectories are expressed in state space, but their dynamic probability cannot

Authors	Approaches	Limitations
	transforms the original control problem into a graph search problem, which permits the use of pre-computed motion.	be easily guaranteed. It also requires a high amount of computational power.
S Wang [58]	This approach utilizes the state lattice for the trajectories and chooses the optimum constraint based on the cost criteria. In this approach, it is simpler producing reasonable paths using the motion planner.	This approach increases the chances of unnecessary shorts in a spatial horizon. For optimum work, it is recommended that a non-uniform sampling of the spatial horizon should be used to construct the state lattice.
M. Likhachev [59]	Authors in this approach present an algorithm which solves the constrained sub-optimality.	It requires superior a priori modelling of the environment. If the models are not precise, the algorithms give inaccurare results, which is also not recommended in a dynamic environment.
M. Brezak [60]	This approach interpolates lines and circles, and conducts the path investigation over the continuous trajectory planning.	The obtained results are not optimal, and the trajectories are not smooth.
W. Lim [61]	These approaches implement numerical optimization, which is an extension of sampling and interpolation.	Due to the additional optimization step, thecomplexity increases, and this approach not recommended for real-time applications in this case.
David Silver [62]	Authors demonstrate a deterministic policy gradient algorithm with continuous actions.	The implementation of this approach can result in rough-moving behavior. The cost function derivation becomes complex. It is also not recommended in an environment of moving obstacles.
F Naseer [63]	The deep reinforcement learning (DRL)-based deep deterministic policy gradient (DDPG) enhances control over the TR in case of connectivity issues. It also suggests a proper approach to maneuver the TR in unknown scenarios.	This method needs further enhancement in case of dynamic obstacles and further improvement for multi-robotic tasks. Its performance is worse in cases of moving obstacles and disconnectivity.

None of the previous studies considered a non-technologically-oriented controller to operate telepresence robots remotely. It is not possible for a telepresence robot to be used as a simple on–off to cover all behaviors displayed by remote telepresence robots. Despite a simple user controller technique, it appears that previous telepresence robot controllers had no control over expressive material, nor what we consider to be the need to rationalize the design to control telepresence robots.

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