Leveraging Simulation and Virtual Reality for a Long Term Care Facility Service Robot During COVID-19

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ABSTRACT

Providing care to seniors and adults with Developmental Disabilities (DD) presents challenges associated with care, companionship, medication intake, and fall monitoring among others. Currently, measures to prevent the spread of COVID-19 have seen restricted access to those living in long-term care facilities (LTCFs). While technologies such as robotics and virtual reality (VR) have seen advances in overcoming the aforementioned challenges, the restrictions have impacted research and development relying on human participants. Recently, the use of synthetic data for training motion detection algorithms and virtual worlds has been gaining momentum as an alternative continue for simulating robot and human interactions instead of relying on public databases and physical locations. Here, we propose the development of VR robot simulator for Aether™, a socially assistive mobile robot created to help seniors and people living with DD to achieve a higher degree of independence. For example, Aether™can assist caregivers by alleviating the burden of care by monitoring the LTCF for tripping hazards, open doors and cabinets. Our simulator allows configuring the virtual Aether™robot to navigate a virtual environment and detect upper limb gestures performed by a virtual avatar. Our preliminary results indicate that the virtual sensor has detection equivalent to the real sensor, thus ensuring that the simulated data is transferable for real-world testing.

CCS CONCEPTS

• **Human-centered computing → Interaction techniques**; **Gestural input**;

KEYWORDS

developmental disabilities, elderly care, robotics, simulation, virtual reality

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SVR'21, October 18–21, 2021, Virtual Event, Brazil

ACM ISBN 978-1-4503-9552-6/21/10…$15.00
https://doi.org/10.1145/3488162.3488185

ACM Reference Format:
Silas F. R. Alves, Alvaro Uribe-Quevedo, Delun Chen, Jon Morris, and Sina Radmard. 2021. Leveraging Simulation and Virtual Reality for a Long Term Care Facility Service Robot During COVID-19. In *Symposium on Virtual and Augmented Reality (SVR'21), October 18–21, 2021, Virtual Event, Brazil.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3488162.3488185

1 INTRODUCTION

Providing high-quality care to seniors and adults with Developmental Disabilities (DD) presents challenges associated with personalized care and interventions as a result of the high variability of conditions within the population, and the limited resources of healthcare systems [25]. Such challenges are being leveraged thanks to welfare and emerging technologies [25] including robotics, Virtual Reality (VR), and Artificial Intelligence (AI). In 2017, seniors (aged 65 and older) accounted for 16.9% of the Canadian population, and are expected to grow to 24% by 2036 [34]. According to the census data of 2016, about 7.6% of the Canadian seniors live in collective dwellings, such as residences for senior citizens or health care and related facilities [33]. With regards to individuals living with disabilities, it is estimated that 755,000 Canadians have some form of cognitive disability [18], while 3.9% of the population suffers from a learning disability, and 1.1% live with DD [27]. This latter portion of the population often suffers from social and cultural stereotypes that equate disability with unemployability [15]. For example, 75% of working-age adults with an intellectual disability are unemployed, while 70% live below the poverty line [18].

Prior to COVID-19, access to long-term care facilities (LTCFs) for conducting in-person testing for human-robot interactions and robot's navigation data with service robots was possible. Currently, access to LTCFs is limited and varies depending on public health measures. Usually, data sets for training service robots include public data bases and data sets created by the researchers from live data collection. However, these methods present limitations faced during COVID-19 where the public data sets may not provide sufficient information with respect to the conditions of interest when training the service robot. Although live data collection can provide adequate context, it is not possible during the pandemic due to lockdown and social isolation measures. Such challenges have sparked the interest of using synthetic data to continue advancing research [7, 37]. For example, synthetic data sets have been proposed to overcome the challenges of collecting data, and the privacy and ethical issues that can limit the sharing of data sets [37].

To overcome the limitations imposed by COVID-19 and to further advance the development of service robots, in particular, Aether™. Here, we propose the use of robotics and virtual reality simulation to develop a simulated environment for testing and assessment of robot behavior when navigating a virtual environment, and detecting a virtual avatar. Such an approach will enable the use of synthetic data from virtual spaces and avatars. Aether™is designed to help seniors and people living with DD to achieve a higher degree of independence, as well as to assist caregivers by alleviating the burden of care. After evaluating the several venues where Aether™can help individuals with DD and their caregivers, together with our community partner, the Developmental Disabilities Association (DDA), we identified two main use-cases: *safety inspection*, where the robot wanders within a facility searching for safety hazards (e.g. objects blocking passage-ways, open doors, and tripping hazards) or fallen people; and *entertainment*, where the robot partake in cognitive stimulation activities, such as karaoke sessions, trivia games or bingo.

2 BACKGROUND

Over the past decade, the development of assistive technologies for people with DD, and in particular those with cognitive disabilities including the elderly, has drawn significant interest to develop solutions to improve the quality of life [17]. Some of these technologies include personal digital assistants [31], specialized computer training programs for [26], smart homes [36], and personal robots [10]. For example, a study with 109 participants (aged 35–89, $\mu = 50.52$, $\sigma = 12.49$) with DD suggests that assistive technologies are beneficial to everyday functional activities such as leisure, social connectedness, and community engagement [16]. Additionally, the entertainment value of digital interactions employing game-based interventions such as serious games, exergames, and gamification can provide additional therapeutic benefits for improving well-being [28]. A recent review on the usage of service robots to help elders without cognitive impairment and with dementia, reveals that interactions help the elders to achieve independence in basic daily activities and mobility by providing reassurance, and reducing stress [4].

2.1 Current Challenges

The use of social robots, in particular those that rely on computer vision for environmental navigation, fall detection, and human-robot interactions, require data sets with many hundreds to thousands of labeled examples to train high-capacity deep models in a supervised fashion [20]. Usually, data sets are created by capturing live data from the different locations where the robot will be deployed. This process ensures the machine learning models will be trained with data that is in a similar domain as the data captured "in the wild". However, the COVID-19 pandemic has limited access to the LTCFs, thus producing bottlenecks and reliability on publicly available data since capturing information from the location and the users are restricted. Furthermore, relying on public data sets has shown the lack of suitable content for proper training of the robot. For example, VPepper is a digital replica of the Pepper humanoid for elderly care that was developed for training caregivers and avoid excessive wear and tear [13]. The use of digital replicas in patient care can help reduce costs as driven AI solutions can help analyze data from the patients to help predict health-related conditions [14].

With respect to fall detection, training methods include videos, pictures, and motion data from inertial sensors [30]. In addition to the technology limitations involving the accuracy of the tracking, signal processing, skeleton extraction, and others [2], access to the target population remains the biggest challenge because of COVID-19. Digital replicas have been used in autonomous vehicle research [23], crisis management [24], assessment and treatment of post-traumatic stress disorder [9], and in education and training [8], among others. However, to the best of our knowledge, virtual avatars are not used to train fall detection.

2.2 Trends

The need for assistive technologies has been accentuated by the current COVID-19 pandemic, resulting in increased use of social robots in LTCFs to safely connect the elderly to the outside world, to help maintain their mental and physical health, in addition to assisting the care provide by caregivers [29]. For example, Belgium and the Netherlands have deployed robots to LTCFs to help seniors connect with family and friends while following social isolation [1, 12]. In addition to service robots, VR has been gaining momentum in the elderly care setting by providing immersive and engaging experiences that can be used for cognitive and physical training [6], for reducing the risk of falls [22], for reminiscence therapy [35], to reduce loneliness [5], and for leisure activities [21], among others.

3 METHODS

The development of the simulator required conducting an analysis of open source robot simulation tools that are typically used for live testing robotics sensors, algorithms, and overall robot performance. The analysis led us to select the 2021.1.2f1 version of Unity as it is compatible with Unity's Sensor SDK, which allow us to create laser-based sensors such as Time-of-Flight cameras and Lidars, and Unity's ROS TCP Connector that enables communication with ROS. This outcome was achieved by trying multiple combinations of ROS (Robot Operating System), Unity, and Unity's Sensor SDK due to incompatibility between various libraries due to still being in development.

3.1 Virtual Environment

A digital replica of our partner's LTCF was created using the real floor plans leveraging 3D models and photos for increased realism. Fig. 1 shows a top view of the digital replica used in our simulations. This process required a combination of authoring tools such as Blender for 3D modeling, Krita for texture editing, and the Unity game engine for programming the virtual interactions between the users and the robot.

3.2 Robot Simulation and ROS integration

We employed Unity's Sensor Software Development Kit (SDK) to simulate the Intel RealSense D455 RGBD camera [19] and the Slamtec RPLidar A2 [32], which Aether™uses for object detection and navigation. The Inertial Measurement Unit (IMU), locomotion

Figure 1: Top-view of a LTCF digital replica.

drive and odometer were simulated using Unity's default physics engine.

Aether™control software architecture was created using ROS, and integrated into the simulator employing the ROS TCP Connector package, also provided by Unity. To guarantee that the simulation does not interfere with the robot software, the simulator runs on a Lenovo 81SX000KUS laptop with Microsoft Windows 10, whereas ROS runs on an Intel NUC10i7FNH with Ubuntu 18.04. The communication between both machines is achieved through a direct IEEE 802.3ab (Gigabit Ethernet) connection.

3.3 Virtual Avatar

To create virtual senior avatars, we used MakeHuman, a 3D modeling software specialized in prototyping photo-realistic 3D human models that provides a high fidelity body mesh model, [11]. Makehuman allows the customization of the dimensions of body parts, as well as other features such as age and ethnicity. We employed Mixamo [3] to bind the skeleton to the 3D model, as well as to animate them with walking and fall patterns.

3.4 Avatar Control

The avatar movement is possible by employing pre-defined animations that cannot be customized, by manually animating the avatar employing a 3D animation software, or by employing a VR headset, in which case the body tracking is limited to the available sensors. For example, a VR headset and controllers allow controlling the avatar's head and arms. Although additional body tracking is possible employing motion capture suits and some mobile phones, within the scope of this project we focused on out-of-the-box functionality. The use of avatar movement increases the realism of the simulation as it allows validating how Aether™processes and responds to the environment. To control the avatar using a VR headset, we employed the OpenXR plugin integrated to an Oculus Quest 2 into the simulator. While using the Oculus Quest 2, the user can see the environment through the avatar's eyes, move the avatar's hands using the hand controllers, and move the avatar body around the scene using a joystick on the hand controller.

3.5 Detection Testing

Our preliminary testing will involve detection tests for the environment, virtual avatar and objects. With respect to the environment, a digital replica of a room within the DDA LTCF is used to compare how the virtual sensor data matches the real data sets from Aether™. The avatar and object detection test focuses on verifying the proper identification of human shapes when using virtual sensors.

4 PRELIMINARY RESULTS

To ensure that our simulator could achieve the expected goals, we created two scenarios for testing (i) the environment detection, (ii) and the avatar and object detection.

4.1 Environment Detection

As one of our goals is to fine tune the parameters of the robot navigation controller, we have to ensure that the virtual Lidar has comparable performance to the real Lidar. To evaluate their performance, we created a virtual replica of our test environment (i.e. JDQ office space), placed the real and virtual robot in an equivalent location, and recorded the output of their Lidars. As shown in Fig. 2, the data obtained from the real Lidar (red dots) is similar to that of the virtual Lidar (blue dots). Both sensors detected the walls at equivalent distances, but some objects placed within the environment were detected with different distances. The differences were due to the misplacement of furniture within the virtual replica.

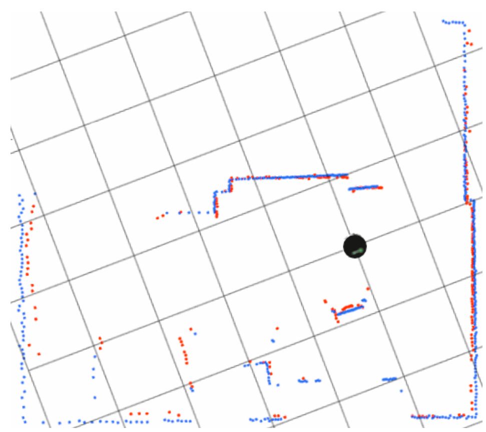


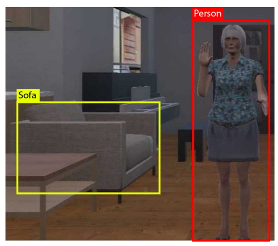
Figure 2: Data outputs of the real RPLidar (red dots) on the real environment, and the virtual Lidar (blue dots) on the virtual environment.

We were not able to make the virtual Lidar fully compatible with the real one due to the limitations of Unity's Sensor SDK. We successfully set the measurement error (1%) and update rate (10 Hz) to be the same, but we could not modify the sensor's resolution. Therefore, while the real sensor provided 360 measurements, the virtual sensor provided 500 measurements. This behavior was expected, given that the Sensor SDK is still under development, and we are using it under a preview license.

4.2 Avatar and Object Detection

For our preliminary tests, we created two older-adults avatars – one male and one female – to be controlled using Oculus Quest 2. Fig. 3a shows a first-person view of the environment through the avatar's eyes. The hand raised in front of the Aether™robot was controlled by the user raising the VR controller. The hand movements of the avatar are detected by the robot through its RGBD camera and Lidar. The detection data is converted and published to a ROS topic to be displayed with RViz, a ROS application used to visualize different sensor data as seen by the robot point-of-view. Fig 3c shows the color image, depth image, point cloud, and Lidar data received from the robot. The color images were also fed to a ROS node implementing the YOLO object detection in order to verify its capability of detecting the virtual avatar. Fig. 3b shows that YOLO was able to detect the avatar and the sofa on the scene.

(a) First person point of view of Aether™



(b) YOLO's object and avatar detection

(c) Simulated depth sensor data using RViz

Figure 3: Robot and virtual avatar detection.

5 DISCUSSION

The integration of ROS with the Unity game engine, in addition to the Sensor SDK allowed us to capture depth maps that are suitable for simulating the robot's navigation and detecting surroundings, objects, and avatars in the LTCF. We successfully integrated all components after several trials and errors between all the pieces of software. The process required constant communication with Unity's Sensor SDK developer team for communicating problems and requesting clarifications. During the development, the most worrisome compatibility limitation was the lack of support for VR rendering using DirectX. Unity's default XR (extended reality) framework supports only DirectX 11, whereas the Sensor SDK requires the ray-tracing capabilities of DirectX 12 to simulate laser-based sensors. To overcome this limitation, we used OpenXR, which supports DirectX 12. After incorporating the VR rendering, then we had to improve the communication between the output of the sensors from the GPU into ROS. This process required us to create shaders that converted the sensor outputs to a ROS-compatible format before downloading them asynchronously to the CPU.

A byproduct of creating the digital replica of the LTCF consists of a series of 3D assets that were transferred into virtual gathering spaces such as AltspaceVR or Hubs by Mozilla. Using virtual gathering environments during the COVID-19 pandemic has allowed us to connect with various stakeholders to discuss various aspects of the project without requiring them to be co-located. Additionally, the crossplatform support of these virtual gathering tools allows users to join using their mobile devices, computers, and VR headsets. Fig. 4 shows a collaborative team meeting to discuss the realism of the virtual room and robot replica.

Figure 4: Team meeting in AltSpace VR with members joining using VR headsets and the Desktop application.

6 CONCLUSION

This paper presents a virtual simulator that leverages robotics and VR for virtual navigation and human-robot interactions simulation. Our preliminary results indicate that the virtual sensors are able to detect the environment and elderly avatar. Additionally, the data is suitable for virtually training Aether™. While larger work remains to be done, our initial findings suggest that the use of VR and robotics in a virtual environment for elderly care is promising when designing and testing features when physical access to LTCF is restricted, as it enables remote collaborations where all stakeholders can participate in iterative design and decision-making processes.

Future work will focus on evaluating our current person detection and fall detection modules. We will also use it to generate synthetic data to train the machine learning models that implement our detection modules. To that end, we will create more avatars to reflect the DDA based on aggregated anonymous data collected on their LTCFs. Additionally, we will implement consumer-level body tracking to record animations for the virtual avatar. We will also make use of the avatars to have them wandering around the virtual LTCF to test the robot navigation stack in a human-centered environment. We expect to use these simulations to fine-tune the parameters of the navigation controllers.

ACKNOWLEDGMENTS

We acknowledge the financial support of Mitacs, AGE-WELL, JDQ Systems Inc. and Developmental Disabilities Association (DDA).

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