Development of a Virtual Environment using 3D Gaussian Splatting for Learning Robot Perception at Higher Education

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***Abstract*— Educational Robotics (ER) focuses on developing tools to enhance learning experiences. Simulators are recurrent in ER due to their convenience as substitutes for physical setups, providing assistance when teaching real robotics applications. However, one limitation is often the achievable level of realism. At Tecnologico de Monterrey, students majoring in robotics learn about autonomous robots through integration projects during their junior and senior years. To expand the availability of the required test courses, we propose a scene generation pipeline to create affordable simulated environments. We developed two versions of a simulator featuring a photorealistic 3DGS environment, LiDAR signals, and a ROS2 interface. We validated our proposal through trial runs with both real and simulated robots, as well as an assessment of image quality.**

I. INTRODUCTION

Robotics not only drives significant technological advancements, but also serves as an invaluable educational tool, facilitating learning by fostering STEAM (Science, Technology, Engineering, Art, and Mathematics) [1]. Educational Robotics (ER) emerges as a field focusing on the development of pedagogical tools and methodologies to enhance students' learning experiences in technology. ER helps develop creativity, critical thinking, and problem-solving skills in students. At the same time, it promotes collaboration and engagement in the performed activities, making learning more interactive and effective [2].

Virtual environments implemented as simulators [3] and virtual reality (VR) tools [4] are utilized for learning and developing robotics, where students can access tools that closely replicate properties of the real world, and often can do so in a remote location from their educational facilities [5]. Studies indicate that these facilitate the understanding of abstract concepts, maintain student motivation, and enhance the overall learning experience [6] [7]. Therefore, we believe that simulations and VR tools can assist in teaching advanced real-life 4D (dangerous, difficult, dirty & dull) applications requiring a certain degree of Robot Perception (RP) (e.g. infrastructure inspection [8] [9], search and rescue [10], etc).

To achieve affordable, portable and scalable photorealistic virtual environments for ER, we propose a scene generation pipeline leveraging on a modern 3D reconstruction technique along with a popular robotics simulator (Fig. 1). As educational innovation, we use our proposed pipeline for creating a tool to generate a virtual environment for teaching RP at an undergraduate level, while emulating a learning experience that is typically obtained only through a real physical environment.

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II. STATE OF THE ART

In recent literature one can find approaches that integrate classical [3] and modern [11] [12] robotics simulators, frameworks such as ROS, and graphics engines to create testbeds for developing Robot Perception (RP) algorithms (including Robot Vision) [13]. When using virtual environments for developing RP, an often-encountered challenge is the achievable level of realism [14]. Some approaches apply photogrammetry methods that leverage neural networks and optimization techniques to generate photorealistic 3D digital twins [15] [16].

3D Gaussian Splatting (3DGS) [17] is one of such optimization techniques, used in 3D reconstruction and rendering. Its characteristics include real-time performance, photorealistic quality [18], availability of optimized model variants [19] and integration in modern 3D engines [20] [21]. This puts 3DGS at an advantage with respect to classical photogrammetry [22] [23] [24] and other modern approaches such as NeRF [25] and Plenoxels [26], causing the exponential growth of its popularity after its initial release. Later contributions expanding the use of 3DGS included SLAM [27], [28], 3D meshing [29], and physics integration [30].

Another approach to create realistic virtual environments that we consider intriguing and worth mentioning is the use of Generative Artificial Intelligence (GenAI), such as the recently released Cosmos World Foundation Model (WFM) Platform [31]. This WFM uses datasets from real and synthetic sources to train itself and later creates a wide variety of virtual scenarios tailored for robotics development. GenAI has great potential once integrated into the currently available tools for robotics development [32].

III. METHODOLOGY

At Tecnologico de Monterrey, undergraduate students majoring in robotics learn about dynamic systems, control

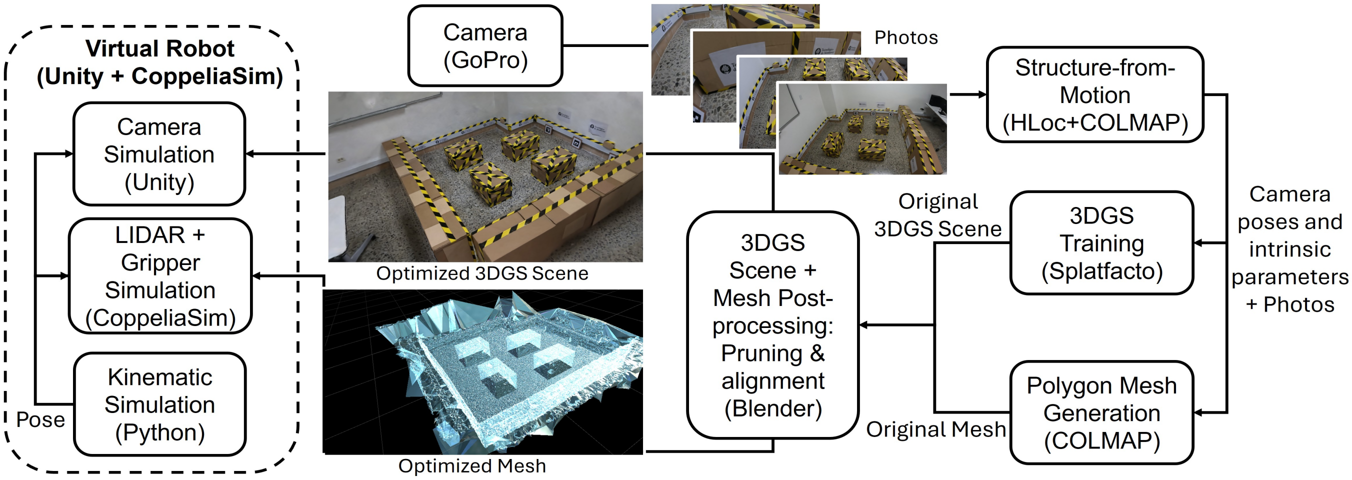

Fig. 1. Overview of the Scene Generation Pipeline

engineering, computer vision (CV), neural networks, as well as localization and mapping through an integrative project spanning their junior and senior years. The goal of the junior-year students is to make a Puzzlebot® [33] navigate within a physical circuit by following a line and enabling it to make steering decisions based on traffic signs without human intervention [34]. By their senior year, the students program the robot to simultaneously locate itself and map (SLAM) a previously unknown environment, while completing a parcel delivery task. The deliverable is a software project that allows the robot to complete the intended mission (Fig. 2).

In the quest to expand the availability of our testing environments while keeping similar learning experiences, we proposed a scene generation pipeline (an overview in Fig. 1), and implemented two proofs-of-concept (PoC) of a simulator. The simulator consists mainly of an integration work among ROS2, Unity 3D Engine [35] and CoppeliaSim [36], along the resulting 3D scan of a place of interest as a 3DGS scene and as a polygon mesh. The first PoC includes a 3DGS scene for junior students, consisting of a test circuit with traffic signs to try-out autonomous driving for the Puzzlebot®. The second PoC includes a 3DGS scene for senior students, consisting of an obstacle course with "parcel delivery" ports. Both cases implemented a ROS2 communication interface (Fig. 2). The junior scene was developed first and focused mostly on simulating the images coming from the camera (Fig. 3). The senior scene was developed later with an improved kinematics model of the robot, an added LiDAR simulation through the generation of a polygon mesh using photogrammetry, and a mock-up subscriber for the gripper control signal, as its physical simulation was not implemented (Fig. 4).

The dataset used to create the 3DGS scenes included at least 1000 images from Standard 1080p videos taken by a GoPro HERO 10 Black at an illuminance range of 400 to 1500 lux. The Structure-from-Motion (SfM) approach for feature extraction, matching and spatial reconstruction (including the polygon mesh) included the use of HLoc [37] and COLMAP [23] [24]. The 3DGS scenes were generated using the NeRF Studio gsplat library [38] and the default Splatfacto model with the suggested "Quality and Regularization" settings [19]. Post-processing was then done using Blender 4.0 [20] to prune floating outliers and align the 3DGS scene (imported into Unity) with the reconstructed polygon mesh (imported into CoppeliaSim).

To validate the use of the simulator as a learning tool for the aforementioned robotics techniques, software projects from 3 teams of students (2 for the junior course, 1 for the senior course) were used to control the robot in the simulator, and the performance was compared against real tests on the physical course. The software development tools used, and the program logic implemented by the teams were not altered when running tests on the virtual circuit to ensure a fair comparison against the performance on the physical course. Finally, we assessed the quality of the simulated images.

IV. EXPERIMENTS AND RESULTS

For the case of the junior course, the validation test consisted of three trials (Fig. 5): first, a comparison of CV performance when detecting the track line to be followed and the pertinent traffic signs; second, a test to confirm the ability of the robot to complete a full lap of the given circuit (while being driven by a PID controller aiming at the track line); and third, a quick assessment of the quality of the simulated images through the overlap of HSV histograms.

Whilst parameters such as PID gains, image filter thresholds and ROIs needed to be adjusted due to the simplistic kinematic and camera model at this point, we obtained promising results: Both junior teams detected the track line and traffic signs at all times; one team ran a full lap without human intervention, while the other team required limited assistance to complete a lap; also we obtained an average of 50% overlap between HSV histograms from the real and simulated images despite the unaligned camera poses and background differences, suggesting that the simulated images are in the range of photorealism.

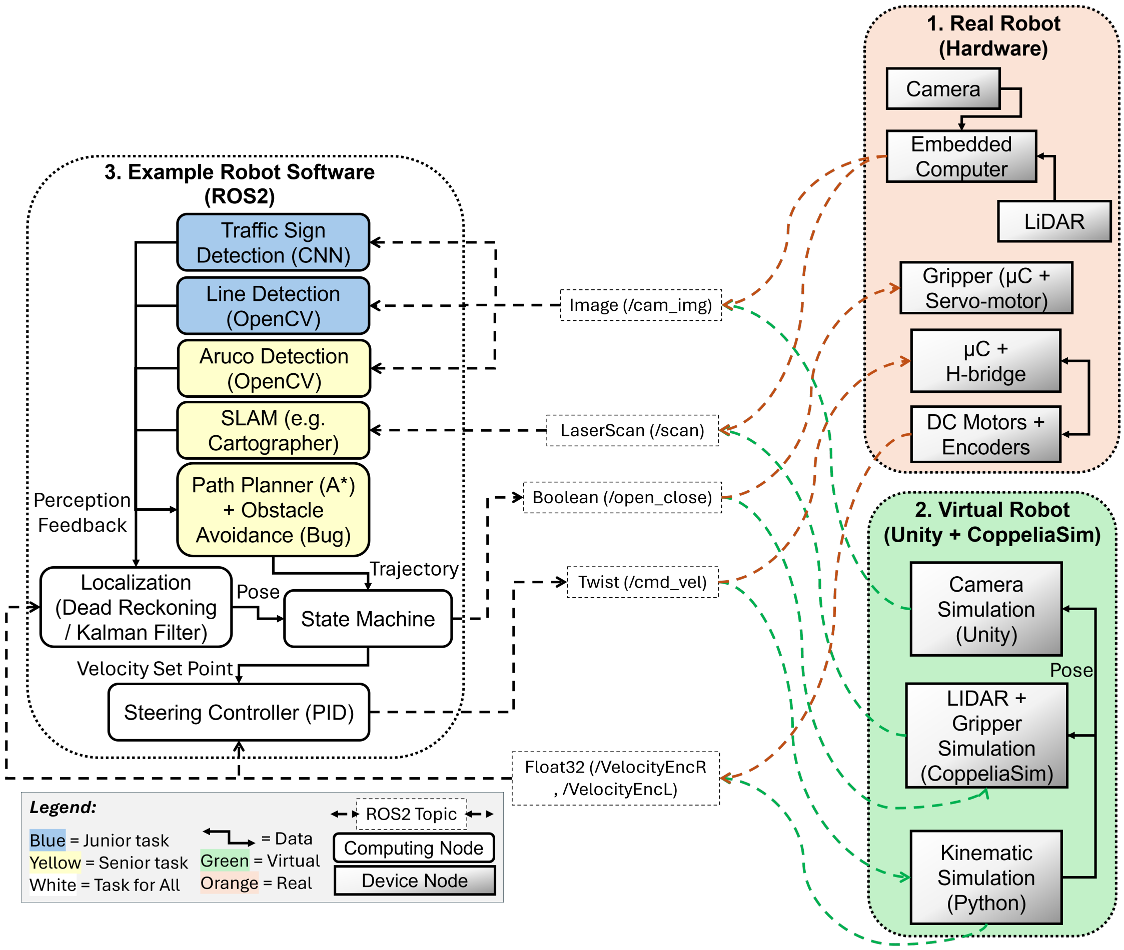

Fig. 2. Schematic of integration project: Either a Real Robot (1) or our Virtual Robot (2) can be used to develop the Example Robot Software (3)

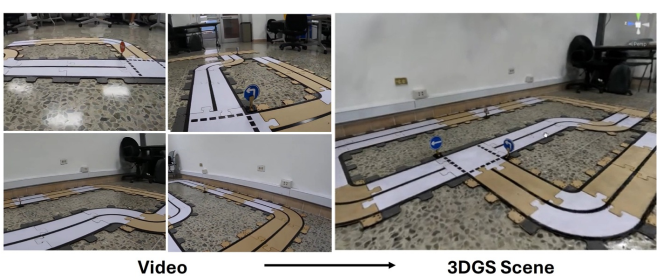

Fig. 3. Scene for Junior Circuit Course

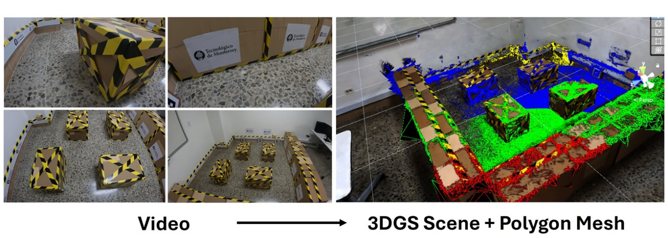

Fig. 4. Scene for Senior Obstacle Course

With the experience acquired creating the junior scene, we then proceeded to create the senior scene utilizing CoppeliaSim for the LiDAR simulation in addition to the previously mentioned tools. In this case, the validation test consisted of four trials (Figs. 6, 7, 8 and 9): the first to confirm the CV performance by detecting the ArUco markers; the second to assess the quality of the simulated images through the use of a set of quality metrics (PSNR, SSIM, cosine distance of VGG16 features, and normalized histogram overlap of HSV, LAB and RGB channels) using 15 pairs of 1280x720-pixel 1-to-1 real (taken with an RPi-Cam, and not part of the 3DGS training set) and simulated images (Table 1); the third to verify the ability of the robot to navigate the obstacle course autonomously by reading the LiDAR scan and implementing a bug algorithm as a simple, yet effective method for obstacle avoidance; and the fourth to try exploring an outdoor scene by driving the virtual robot manually while running a SLAM algorithm (i.e. Cartographer [39]) to verify the portability of our pipeline.

Despite the need to modify some parameters like obstacle avoidance tolerance, image processing thresholds and ROIs due to complexity of the task, we obtained promising results: The senior students were able to effectively detect the ArUco markers; the robot could navigate at least once without hu-

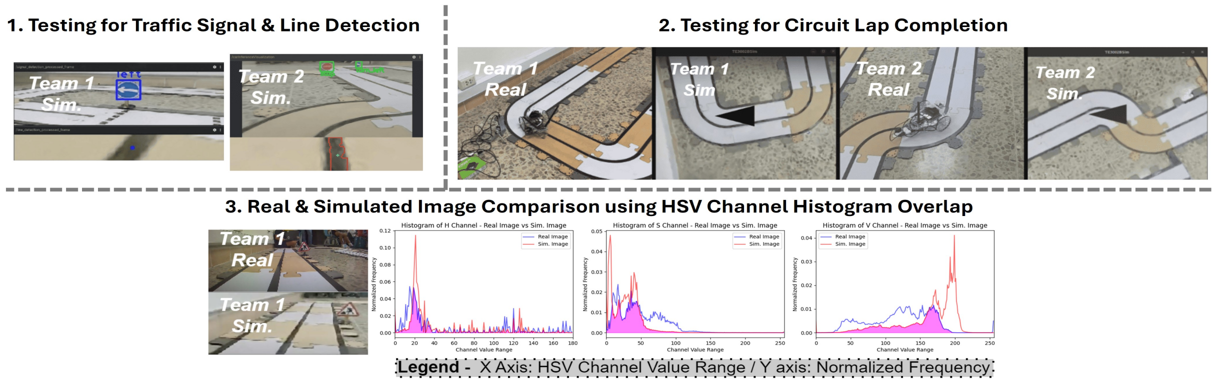

Fig. 5. Trial tests for Junior project

Fig. 6. Image assessment tests for Senior project: ArUco Detection (1) and Image Quality (2)

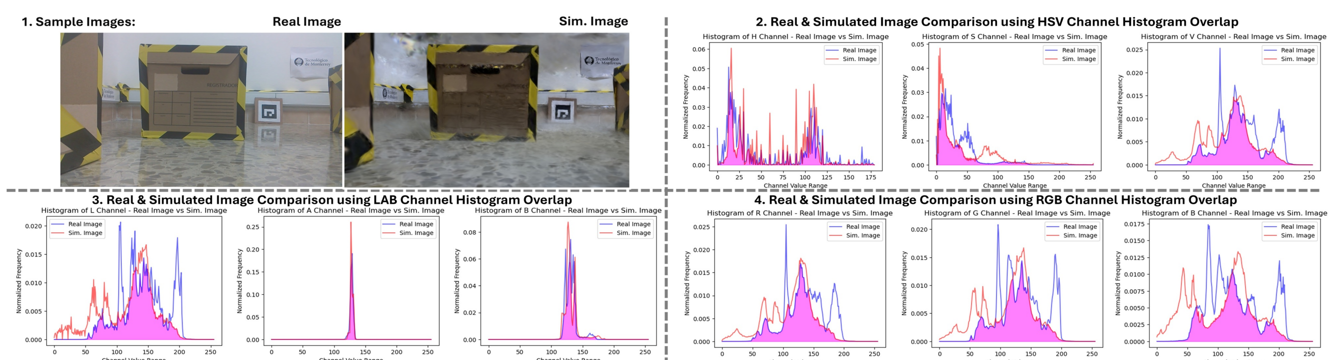

Fig. 7. Histogram Overlap tests for Senior Project

man intervention; the image quality, had a tendency towards the range of similarity (Luma PSNR average was above 28 dB, while the rest of the metrics had normalized averages above 0.52); and the SLAM algorithm was able to create a map of its virtual surroundings on an outdoor scene.

It should be noted that the image comparison made was influenced by the use of a different type of camera for scanning the scene (GoPro) and for taking the real sample images for comparison (RPi-Cam), as well as the variable lighting conditions during image collection. We also tried doubling the number of images to train the 3DGS model to increase the quality of the resulting scene (1282 vs. 2564). However, the change in the average value and standard deviation of the metrics did not appear to be significant despite the change in the amount of images.

Like in the junior course, issues were encountered such as variable illumination and light reflections in certain zones of the scene at certain camera poses. In the case of the junior scene, the challenge was to assure the correct detection of the track line, as well as dealing with the natural imperfections of the track and traffic signs. In the case of the senior scene, it was dealing with the imperfections of the LiDAR signals and the ArUco markers that needed to be detected at different sections of the scene. Finally, student feedback suggests that in overall, the developed simulator accurately emulates the learning experience of the real environment.

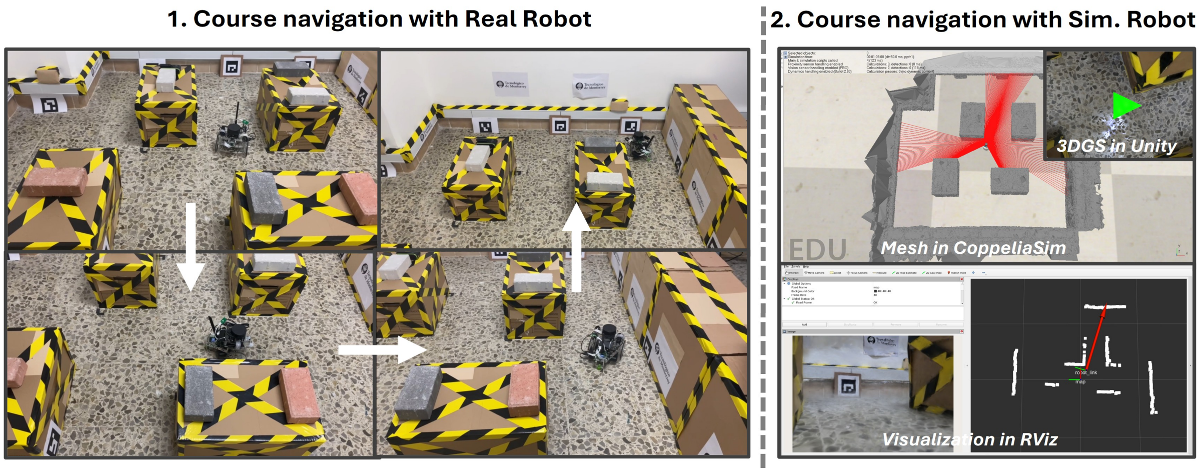

Fig. 8. Runtime tests for Senior project: Course navigation with Real (1) and Simulated (2) Robot

TABLE I
IMAGE METRICS FOR SIMILARITY ASSESSMENT IN SENIOR COURSE

Quality Metric (Real vs. Sim.)	Average	Std. Dev.
(YCrCb) Luma PSNR [dB]	28.33	0.86
(Grayscale) SSIM	0.68	0.07
(RGB) VGG16 Cosine dist.	0.52	0.09
(HSV) H Hist. Overlap	0.54	0.09
(HSV) S Hist. Overlap	0.63	0.08
(HSV) V Hist. Overlap	0.63	0.10
(LAB) L Hist. Overlap	0.63	0.07
(LAB) A Hist. Overlap	0.70	0.11
(LAB) B Hist. Overlap	0.65	0.06
(RGB) R Hist. Overlap	0.67	0.07
(RGB) G Hist. Overlap	0.64	0.07
(RGB) B Hist. Overlap	0.60	0.07

Fig. 9. RViz Visualization of SLAM test

V. CONCLUSIONS

In this document, we proposed a scene generation pipeline that leverages SfM algorithms, 3DGS and a robotics simulator to create an affordable virtual environment to teach and learn about Robot Perception (RP). The pipeline was implemented in 2 PoC robotics simulators. Based on this experience, we believe the current PoCs can serve as valuable tools for learning and practicing techniques related to RP at the undergraduate level, and potentially at graduate level.

In the past, 3D scans have already been used to create digital twins of objects for the development of robotic applications [15] [16] [40]. However, to our knowledge, the approach we took of using 3DGS to generate an entire virtual environment to create a robotics simulator is novel. Besides our educational application, we think that our approach could be replicated in applications for professional use. It may represent a feasible alternative particularly in situations where, due to complex reflection and refraction phenomena or harsh weather conditions [41] present in the environment, the visual aspects of the simulation require physics models that need heavy computations.

To address more complex challenges beyond RP tasks, we will continue refining the kinematic and dynamic models of the robot and the environment, incorporating system perturbations, and extending beyond the availability of test environments, to include more challenging scenarios. Moreover, we intend to make a port compatible with another popular simulator, Gazebo [3]. As well, we would like to integrate GenAI approaches to our solution to further enhance the learning experience. Finally, we also aim to study the simulator's impact on student engagement and learning outcomes when they are introduced to the techniques used in service robotics. We are looking to potentially apply gamification techniques and the theory of mental flow [42] to further enhance the educational experience.

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