MIDGARD: A Simulation Platform for Autonomous Navigation in Unstructured Environments

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Abstract—We present MIDGARD, an open source simulation platform for autonomous robot navigation in unstructured outdoor environments. We specifically design MIDGARD to enable training of autonomous agents (e.g., unmanned ground vehicles) in photorealistic 3D environments, and to support the generalization skills of learning-based agents by means of diverse and variable training scenarios. MIDGARD differs from other major simulation platforms in that it proposes a highly configurable procedural landscape generation pipeline, which enables autonomous agents to be trained in diverse scenarios while reducing the efforts and costs needed to create digital content from scratch.

I. INTRODUCTION

Autonomous ground robot navigation is still a major challenge in machine learning and robotics. The complexity of the task is exacerbated when dealing with unstructured and extreme outdoor environments, as in the case of planetary exploration\textsuperscript{[1]}, forest inventory\textsuperscript{[2]}, search and rescue tasks\textsuperscript{[3]} or precision agriculture\textsuperscript{[4]}. Learning-based control models have been successfully applied to tackle navigation tasks\textsuperscript{[5], [6], [7]} in structured environments; however, learning-based sensorimotor control in unknown, variable, and highly cluttered real-world scenes is much more complex than indoor or controlled settings, and it is still an open research area\textsuperscript{[8]}. To generalize well to real-world applications, these approaches require a significant amount of training data, covering a multitude of variable conditions and scenes. This makes real-world training and validation infeasible, due to the high costs, risks of vehicle damage, large training times, and limited scene variability, thus highlighting the necessity of simulation environments. Simulation strategies have been adopted since the early days of research on autonomous navigation\textsuperscript{[9]}. However, while many simulators exist for indoor navigation, e.g., HABITAT\textsuperscript{[10]}, AI2-THOR\textsuperscript{[11]}, and House3D\textsuperscript{[12]}, there is a general lack of simulators for outdoor unstructured environments. Research on outdoor navigation has mostly focused on structured settings, by means of simulation platforms such as CARLA\textsuperscript{[13]}. The CARLA simulator is able to model the complexity of urban scenes with a high-degree of realism, introducing a versatile tool for autonomous driving research. However, besides focusing on urban environments, CARLA does not support scene customization, as these are hand-crafted by digital artists, thus hindering the possibility to train and validate learning models in variable settings.

Motivated by the lack of available simulation platforms for navigation in unstructured environments, in this work we introduce MIDGARD\textsuperscript{[1]} a simulation platform specifically designed for outdoor navigation in highly cluttered and unstructured environments. MIDGARD comes with four different natural environments, i.e., Meadow, Forest, Volcanic, and Glacier, and supports procedural generation of navigation scenes. A demonstration of the variable scene generation capabilities of MIDGARD is presented in Fig.\textsuperscript{[1]}Compared to navigation in urban environments, where scene variability is somewhat limited and mostly given by the dynamics of pedestrians and other vehicles, variability in unstructured environments is given by the scene itself. This makes the procedural generation of scenes a key element in the tackled task to encourage the agent to generalize over changing settings. Additionally, MIDGARD is based on Unreal Engine (UE)\textsuperscript{[14]} and takes advantage of state-of-the-art technologies in rendering and simulation to provide a realistic navigation platform, which is a key element for transferring knowledge from the virtual environment to the real world. Finally, the 3D environment is paired with an OpenAI Gym\textsuperscript{[15]} compatible python interface, which supports fast and reliable communication between agents and environment.

In summary, the contributions of this paper are:

- We introduce MIDGARD, a flexible photorealistic simulation environment designed to support research on autonomous navigation in outdoor and extreme environments.
- We propose a novel procedural level generation workflow to synthesize arbitrary 3D scenes, thus reducing the efforts necessary to render new scenarios. The resulting variability of the scenes allows the development of generalizable learning-based autonomous agents.

II. RELATED WORK

Simulation platforms have been proposed as a suitable alternative to training in the physical world for many tasks that require direct interaction with the environment\textsuperscript{[16], [17], [18], [19], [20], [21]}. In recent years, high-quality simulation engines have been proposed: some of them focus on structured environments setups\textsuperscript{[10], [13], [22]}, while others address unstructured environments\textsuperscript{[23]}. Among the existing

\textsuperscript{1}In Norse mythology, Midgard is one of the nine realms and the name literally means “kingdom of men”, i.e., Earth. Since this work proposes a simulation platform for “terrestrial” environments, it seems to be an appropriate name.
simulators, the one closer to MIDGARD is CARLA [13], a simulation engine for open urban driving based on Unreal Engine [14]. However, CARLA employs pre-built urban environments (two towns with six weather conditions each) requiring manual crafting of new 3D scenes. This limits the possibility to train and validate learning models over multiple scenarios, hindering the generalization skills that these models may gain. This especially holds for deep reinforcement learning models that, as known, require large training data.

The HABITAT [10] platform makes a significant step forward to support “training on simulation” of AI agents by adding flexibility to agent configuration, scene rendering and control of the environment state. HABITAT focuses on embodied AI training in indoor, small-sized scenes and is thus unsuitable to outdoor navigation. Additionally, HABITAT lacks some features such as lighting control, which can be useful to extend scene variability. Recently, Müller et al. introduced OAISYS [24], a photorealistic terrain simulation pipeline for unstructured outdoor environments, built on-top of Blender [25]. Like MIDGARD, OAISYS targets unstructured environments, but lacks real-time agent interaction, precluding the possibility to use it as a training framework for autonomous agent.

III. MIDGARD SIMULATOR

We envision MIDGARD as a simulation platform primarily focused on autonomous navigation in outdoor unstructured environments. It is designed as a flexible open source simulator built using Unreal Engine (UE). The design choices made in the development of MIDGARD focus on providing the required tools to train autonomous agents to navigate highly-cluttered, unstructured natural environments. The simulator core relies on the engine’s ability to support large landscapes and dynamic asset placement for procedural scene generation. This is one of the main features and contributions of MIDGARD, designed to provide scene variability and control over the navigation difficulty of the landscape. These design choices are translated into an extensive set of APIs that give great control over the simulator configuration and agent interaction. At the same time, the whole simulator is highly modular and customizable, and new APIs and functionalities can be added on top of the existing simulator core. Additionally, the simulator allows human experts to control agents directly, supporting synthetic dataset creation and the development of imitation learning approaches [26], [27].

These objectives are obtained through the following implementation choices:

- **OpenAI Gym-compliant Python frontend**: the simulator supports agent interaction through a standard OpenAI Gym environment [15], commonly used to train reinforcement learning (RL) methods in Python.
- **Blueprint extensible**: Although the core of the simulator is written in C++ for high efficiency and resource management, the higher levels of the software stack are coded in Blueprint, which is particularly suitable for fast prototyping without any required knowledge of C++ programming.
- **Synchronous or asynchronous**: The platform allows the AI agent to run both synchronously and asynchronously with respect to simulation time.
- **Configurable simulation speed**: Simulation speed is configurable and adjustable to requirements, allowing for faster training and predictable frame rate.
- **Agent API**: Provides flexible and customizable agent interaction, supporting the definition of user-defined control actions inside the simulation environment.
- **Scene API**: Provides control for scene selection, such as map size, obstacle spawning, time-of-day changes, and additional scene-related parameters.
- **Sensors API**: Allows to define the set of sensors available to the agent (e.g., RGB camera, depth, semantic segmentation, instance segmentation, GPS-like location) and acquire observations and measurements.

A. **MIDGARD components**

The three main MIDGARD components, implementing the core functionalities of the simulation platform, are: 1) communication protocol, 2) procedural landscape generation, 3) virtual agent. Simulator APIs are implemented through a robust, yet flexible, communication protocol based on HTTP that supports easy data transfer between the 3D simulator and the OpenAI Gym front-end. The procedural scene generation relies on a customizable system of scene descriptors, which contains all the parameters used to place the scene assets, and provides the agent with great scene variability. Lastly, the virtual agent control interface and simulated sensor data provide the required tools and information for the navigation task. In the following, we provide a detailed description of each of these components.

1) **Communication protocol**: To enable communication between external applications, like the Gym environment and the Unreal Engine, we design a data exchange protocol that enables easy interoperability, while at the same time being reliable, platform-independent, and simple to extend. To meet these requirements, we choose a client-server approach, which relies on HTTP to exchange messages. Messages are in the form of JSON documents for flexible communication supported by most programming languages. The HTTP server is natively implemented in Unreal Engine through the *Remote Control* plugin, which exposes Blueprint or C++ methods as HTTP endpoints.

2) **Procedural landscape generation**: Scene generation in MIDGARD represents the main advance w.r.t. existing simulators, as it is fully procedural and requires no human intervention, except for the setup stage.

Four different types of scenes can be generated:

- **Meadow**: Easy-medium difficulty navigation scene with obstacles like small or medium rocks and bushes. Slightly uneven surface covered in grass that reduces obstacle visibility. It also features a large, non-traversable lake.
- **Forest**: Medium-high difficulty scene with dense obstacles such as trees, rocks, broken branches, puddles, and bushes. The surface is slightly uneven and covered in grass, woody debris, and leaves.
- **Volcanic field**: Medium-high difficulty scene with dense obstacles — mostly rocks. It has an overall flat color, making obstacles hard to distinguish from traversable surfaces. The surface is highly uneven and rocky.
- **Arctic glacier**: Medium-high difficulty scene, similar to the volcanic scene, with sparse obstacles, such as snow-covered rocks and ice planes. The flat color of icy surfaces makes objects hard to distinguish.

For each scene type it is possible to generate an infinite amount of variation. The procedural generation is controlled by two main elements: 1) the *LevelManager*, an object responsible for setting the state of the environment and processing incoming requests (e.g., requests from the GYM front-end); 2) the *SceneDescriptor*, an object containing all the scene-specific attributes. The scene creation process mainly consists of placing assets and obstacles to fill the map: the assets are tagged with a traversability flag, which determines if the agent is able or not to traverse them. The set of obstacles available for each scene is defined in the *SceneDescriptor*, one for each scene type, which contains the list of placeable obstacle assets and instantiation parameters. All the placeable assets, 3D static meshes such as rocks and vegetation, used inside the simulator are part of the Quixel Megascans Library and share a consistent scale, resolution, and real-world PBR textures [28]. Procedural generation is performed partitioning the landscape into a number of cells controlled by the difficulty level $D$. Each cell contains a single obstacle, spawned at a random location inside the cell. The resulting number of cells thus controls the obstacles density (smaller cells result in cluttered scenes, whereas larger cells produce scattered obstacles). Cell size is controlled by the $C_{min}$ and $C_{max}$ parameters, provided in the *SceneDescriptor*: $C_{min}$ is the minimum cell size, while $C_{max}$ is the maximum cell size. The difficulty level, along with the minimum and maximum cell sizes, is used to compute the actual cell size $C_D$ as shown in Eq. (1)

$$C_D = C_{max} - D(C_{max} - C_{min})$$

(1)

The effect the difficulty level has on the environment can be seen in Fig. [Fig.]

3) **Virtual agent**: The virtual agent is an instance of an autonomous robot in the simulated scene. The virtual agent in MIDGARD consists of two modules: 1) the perception module, and 2) the control suite. The MIDGARD perception module provides a full set of sensors designed for navigation, as well as dataset collection. This module includes two types of sensors: 1) visual sensors in the form of on-board cameras; 2) low-level sensors that provide vector information of the agent state measurements.

The on-board camera system captures raw RGB pixel data, depth, and instance/semantic segmentation. In addition, cameras have a set of parameters to control the field of view, the relative pose with respect to the vehicle, and the capture

[2]https://quixel.com/megascans
resolution. The camera component runs asynchronously with the environment: it internally uses a frame buffer which provides access to the latest acquisition. The semantic segmentation sensor provides segmentation areas categorized as ground, grass, tree, rock, water, artificial. The low-level sensors utilized for measuring the agent state include: vehicle location and orientation in map-space coordinates, navigation target location and orientation, speed, and acceleration in body frame coordinates, and collision detection.

As for the control suite, MIDGARD includes two different types of vehicle models, which support different types of control actions: 1) Discrete: basic 4-wheel vehicle, controlled by a set of discrete actions that include brake, go forward, go backward, turn left, turn right. 2) Continuous: 4-wheel vehicle controlled through a continuous action set: brake, linear speed, and angular speed. Actions in the environment are performed until a new action is received. This approach allows to have asynchronicity between the agent and the environment, similar to what would happen in the real world.

IV. CONCLUSION

In this work, we presented MIDGARD, an open-source photorealistic simulation environment, based on Unreal Engine, for supporting research in autonomous navigation in outdoor unstructured environments. We paired our simulator with a Open AI Gym front-end, which provides an easy-to-use interface for training deep learning models and manages communication with the simulation engine under the hood. Furthermore, MIDGARD provides the user with a configurable procedural landscape generation mechanism, which supports the generation of infinite scene variations, thus improving the generalization capabilities of learning agents. MIDGARD can simulate a variety of sensors, such as RGB cameras, depth sensors, and GPS, which can be used to achieve rich representations of the state to solve the navigation problem, even under extreme landscape changes.

We envision MIDGARD as the future reference simulator for research on navigation in outdoor unstructured environments and we plan on continuing the development with the inclusion of more scenarios. Additionally, we also plan to evaluate on MIDGARD the performance and generalization capabilities of existing deep reinforcement learning methods for robot navigation, in order to both define baselines for future work and to investigate what is the best training regime for these methods for autonomous navigation.

REFERENCES

[1] M. Pfueger, A. Agha, and G. S. Sukhatme, “Rover-irl: Inverse reinforcement learning with soft value iteration networks for planetary rover path planning,” IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 1387–1394, 2019.
[2] J. Garforth and B. Webb, “Lost in the woods? place recognition for navigation in difficult forest environments,” Frontiers in Robotics and AI, vol. 7, 2020. [Online]. Available: https://www.frontiersin.org/article/10.3389/frobt.2020.541770
[3] J. Morales, R. Vázquez-Martín, A. Mandow, D. Morilla-Cabello, and A. García-Cerezo, “The uma-sar dataset: Multimodal data collection from a ground vehicle during outdoor disaster response training exercises,” The International Journal of Robotics Research, vol. 40, no. 6-7, pp. 835–847, 2021.
[4] A. S. Aguiair, F. N. dos Santos, J. B. Cunha, H. Sobreira, and A. J. Sousa, “Localization and mapping for robots in agriculture and forestry: A survey,” Robotics, vol. 9, no. 4, 2020.
[5] I. Carluchco, M. De Paula, S. Wang, B. V. Menna, Y. R. Petillot, and G. G. Acosta, “AUV position tracking control using end-to-end deep reinforcement learning,” in OCEANS 2018 MTS/IEEE Charleston, 2018, pp. 1–8.
[6] Y. Liu, K. Xie, and H. Huang, “Vgf-net: Visual-geometric fusion learning for simultaneous drone navigation and height mapping,” Graphical Models, vol. 116, p. 101108, 2021.
[7] Z. Liu, A. Amini, S. Zhu, S. Karaman, S. Han, and D. L. Rus, “Efficient and robust lidar-based end-to-end navigation,” in 2021 IEEE International Conference on Robotics and Automation (ICRA), 2021, pp. 13 247–13 254.
[8] D. C. Guastella and G. Muscato, “Learning-based methods of perception and navigation for ground vehicles in unstructured environments: A review,” Sensors, vol. 21, no. 1, 2021.

 Simulator and documentation will be publicly released.

Fig. 2. Comparison of the effects of the difficulty level on the obstacles density in the Forest scene (top) and Volcanic scene (bottom).
[9] D. Pomerleau, “An autonomous land vehicle in a neural network,” Advances in Neural Information Processing Systems, vol. 1, 1998.

[10] M. Savva, A. Kadian, O. Maksymets, Y. Zhao, E. Wijmans, B. Jain, J. Straub, J. Liu, V. Kolotun, J. Malik, et al., “Habitat: A platform for embodied ai research,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 9339–9347.

[11] E. Kolwe, R. Mottaghi, W. Han, E. VanderBilt, L. Weihs, A. Herrasti, D. Gordon, Y. Zhu, A. Gupta, and A. Farhadi, “Ai2-thor: An interactive 3d environment for visual ai,” arXiv preprint arXiv:1712.05474, 2017.

[12] Y. Wu, Y. Wu, G. Gkioxari, and Y. Tian, “Building generalizable agents with a realistic and rich 3d environment,” arXiv preprint arXiv:1801.02209, 2018.

[13] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Kolotun, “CARLA: An open urban driving simulator,” in Conference on robot learning. PMLR, 2017, pp. 1–16.

[14] Epic Games, “Unreal engine.” [Online]. Available: https://www.unrealengine.com

[15] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba, “OpenAI gym,” 2016.

[16] A. Gaidon, Q. Wang, Y. Cabon, and E. Vig, “Virtual worlds as proxy for multi-object tracking analysis,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 4340–4349.

[17] V. Haltakov, C. Unger, and S. Ilic, “Framework for generation of synthetic ground truth data for driver assistance applications,” in German conference on pattern recognition. Springer, 2013, pp. 323–332.

[18] S. R. Richter, Z. Hayder, and V. Kolotun, “Playing for benchmarks,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 2213–2222.

[19] S. R. Richter, V. Vineet, S. Roth, and V. Kolotun, “Playing for data: Ground truth from computer games,” in European conference on computer vision. Springer, 2016, pp. 102–118.

[20] J. Skinner, S. Garg, N. Sunderhauf, P. Corke, B. Upcroft, and M. Milford, “High-fidelity simulation for evaluating robotic vision performance,” in 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2016, pp. 2737–2744.

[21] F. Xia, A. R. Zamir, Z. He, A. Sax, J. Malik, and S. Savarese, “Gibson env: Real-world perception for embodied agents,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 9068–9079.

[22] S. Shah, D. Dey, C. Lovett, and A. Kapoor, “Airsim: High-fidelity visual and physical simulation for autonomous vehicles,” in Field and service robotics. Springer, 2018, pp. 621–635.

[23] Y. Song, S. Naji, E. Kaufmann, A. Loquercio, and D. Scaramuzza, “Flightmare: A flexible quadrotor simulator,” arXiv preprint arXiv:2009.00563, 2020.

[24] M. G. Müller, M. Durner, A. Gawel, W. Stürzl, R. Triebel, and R. Siegwart, “A photorealistic terrain simulation pipeline for unstructured outdoor environments,” in 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2021, pp. 9765–9772.

[25] B. O. Community, Blender - a 3D modelling and rendering package, Blender Foundation. Stichting Blender Foundation, Amsterdam, 2018. [Online]. Available: [http://www.blender.org]

[26] A. Loquercio, E. Kaufmann, R. Ranftl, M. Müller, V. Kolotun, and D. Scaramuzza, “Learning high-speed flight in the wild,” Science Robotics, vol. 6, no. 59, p. eabg5810, 2021.

[27] H. Karnan, G. Warnell, X. Xiao, and P. Stone, “Voila: Visual-observation-only imitation learning for autonomous navigation,” arXiv preprint arXiv:2105.00371, 2021.

[28] B. Burley and W. D. A. Studios, “Physically-based shading at disney,” in ACM SIGGRAPH, vol. 2012. vol. 2012, 2012, pp. 1–7.