LiDAR-GEiL: LiDAR GPU Exploitation in Lightsimulations

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Abstract: We propose a novel Light Detection And Ranging (LiDAR) simulation method using Unreal Engine's Niagara particle system. Instead of performing the ray traces sequentially on the CPU or transforming depth images into point clouds, our method performs this particle-based approach using GPU particles that execute one line trace each. Due to execution on the GPU, it is very fast-performing. In order to classify the results, the new implementation is compared to existing ray-tracing and camera-based LiDAR. In addition to that we implemented and compared common LiDAR approaches using ray-tracing as well as depth images using cameras. A general architecture for easy exchange between simulated sensors and their communication is given using the adapter pattern. As a benchmark, we evaluated real sensor data with a ray tracing-based virtual sensor.

1 INTRODUCTION

Using a simulation before testing in the real world is quite common in the field of robotics. By doing so, one conducts tests quickly, without the need to travel to the testing area and set up the scenarios. This avoids the necessity to have the robot together with its sensors close by enabling the possibility for parallel and distributed collaboration over long distances. Furthermore, the total control of the environment and everything within guarantees scenarios that are not possible or too dangerous in field tests. It is, for example, easy to change the time of day as well as weather conditions like rain and snow within seconds. Regarding safety issues, testing scenarios like crashes or incidents involving pedestrians are simulated in a controlled environment without damaging individuals or equipment. Another application is the generation of training data for neural networks(Vierling et al., 2019). Changes in lighting, viewing angles, and automatically created annotations are used to create data sets of realistic-looking images.

Since simulations are working with models of objects, there are differences from reality. They are simplified illustrations compared to the represented objects (Stachowiak, 1973). Considering only the important properties, it facilitates the complexity and the chaotic nature of the real environment. No simulation mimics the complete state of the environment with all its dynamic aspects and physical occurrences that can be observed in the real world. In the case of an ideally modeled LiDAR sensor, the simulation needs a physically correct representation of light photons. Taking into account absorption, and reflection in every frame for every sensor. Such accurate simulations are beyond the scope of standard hardware and require several additional information about the environment.

In terms of computer simulation, there is a tradeoff between the complexity of the simulation and the needed computing power and time. The optimal way to utilize the advantages of a simulated environment is to keep the complexity as low as needed for the application.

The used Unreal Engine (UE)[1] is a game engine developed by Epic Games[2]. It features real-time as well as physical-based rendering. Providing a physics engine, a large community, and a marketplace with monthly free content makes it a viable simulation software.

In this paper, UE is used for simulation of robots, their sensors and the environments they operate in. The implementation of the simulated sensors follows the physical principle of the real sensors. The implemented robots are digital copies of the vehicles based

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[1] https://www.unrealengine.com/en-US/
[2] https://epicgames.com/

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Table 1: Comparison of different LiDAR systems.

	CPU Ray Tracing LiDAR	Depth Camera LiDAR	Particle LiDAR (ours)
Collision accuracy	Collision Mesh	Visual Depth	Global Distance Fields
Performance	No GPU acceleration	GPU acceleration, but overhead from oversampling	GPU acceleration
Intensity simulation	Hard (extra cameras needed)	Easy	Hard (extra cameras needed)
Label generation	Easy	Hard (needs stencil buffer)	Very Hard
Simulation of rotating LiDAR	Hard	Very hard	Easy
Noise simulation	CPU bound	In parallel as post-processing of the image	in parallel on the GPU
Modification to Environment	Avoid Foliage	None	Avoid thin or very small objects/object parts
Other Problems	None	Accuracy depends on bit depth of Depth Buffer	Resolution dependent on distance to viewer.

on Computer-Aided Design (CAD) data.

2 RELATED WORK

The most common approach to simulate a LiDAR in the UE is *CARLA*(Dosovitskiy et al., 2017). This plugin provides the simulation of a LiDAR based on CPU raytracing. In addition, *CARLA* provides other sensors, such as a depth camera. Therefore, it is used for autonomous driving simulations. To include motion effects, *LiDARsim*(Manivasagam et al., 2020) intends to build a simulation based on the real world. It simulates a LiDAR sensor including motion effects by dividing each scan into 360 parts and simulating one degree of the rotating LiDAR scanner in each time step. (Hossny et al., 2020) outperformed the LiDAR simulations by using 6 depth cameras and projecting the images onto a sphere, where LiDAR points are sampled. In addition to the performance improvements caused by the omission of CPU ray traces, the authors add noise textures to the depth images to efficiently simulate LiDAR measurement noise. (Hurl et al., 2019) implemented a depth camera-based LiDAR sensor to generate a LiDAR dataset in the simulated world of the game *GTA V*. Another depth camera-based approach was utilized in (Fang et al., 2018), which also provided formulas to estimate the intensity of the LiDAR.

2.1 Contribution

To our knowledge, we are the first paper to exploit GPU particles for LiDAR simulations. Additionally, we compared the performance to different common implementations. To quantify the virtual results, we compared them to real sensor recordings. For better exchangeability, we provided a general sensor architecture using the adapter pattern.

3 SENSORS

(Wolf et al., 2020) gives an overview of the already implemented sensors in UE used by the Robotics Research Lab, RPTU Kaiserslautern. New approaches to the implementation of the sensors are described and compared in section 3.

3.1 Structure

This subsection describes the general architecture of our virtual sensors in the Unreal Engine. The basic design idea is that new concepts like sensors and communication principles can be integrated easily into the existing environment without having to take care of the basic functions. To achieve this, the adapter design pattern was used. It provides the portability needed for different applications. Figure 1 shows a simplified UML diagram of the sensor design. Note that parameters and methods have been omitted for the sake of readability. A complete diagram can be found on our GitHub organization[3]. Additionally, UE-specific naming conventions were ignored for the same reason. The detailed diagrams in figure 2 show the parameters and methods as an example. The class **SensorParent** is the base class for every sensor and contains parameters and functionality like the name of the sensor (*SensorName*), its representation as a 3D model(*SensorMesh*) and other values like its frequency (*TickIntervall*). For an unambiguous definition of sensor parameters and the output data, all sensors use structures defined in the specific class (*Parameters* for *RayTracingLiDARActor*) as input parameters and globally defined output structures in the *Utility* class. This assures that each LiDAR sensor type has the same structure of its output. That fact is used in the *AdapterComponent*, which

[3]https://github.com/RRLAB-KL/Sensors

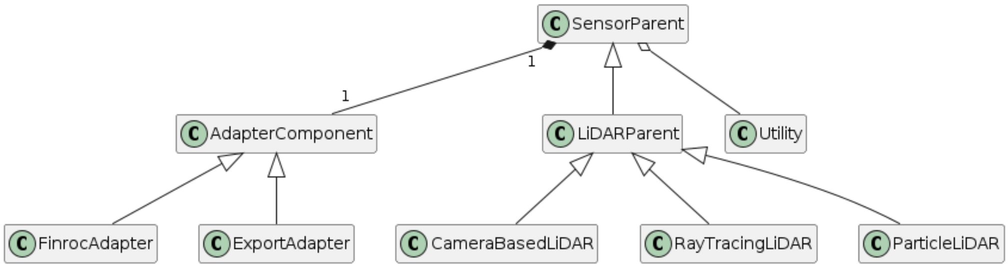
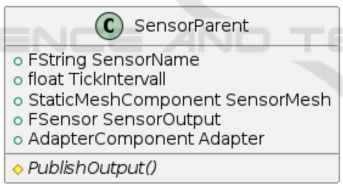
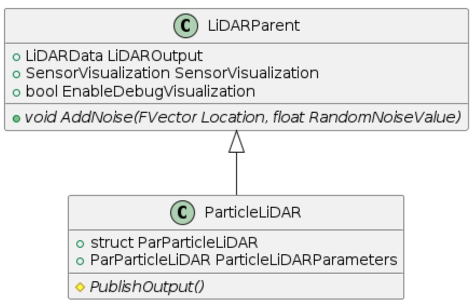


Figure 1: Simplified UML diagram of the components of the sensors as well as the adapters. A more detailed version can be found on GitHub.

has a specific implementation in each sensor (*Adapter* of the *SensorParent*). Independent from the specific sensor, the method *PublishLiDARData* receives a LiDAR structure (defined in *Utility*) as an input. The specific behavior is implemented in the corresponding adapter child class. The *ExportAdapter* takes the structure and writes the points of the point cloud into a CSV file for later processing. The *FinrocAdapter* converts the unreal data to custom data types used by our robotic framework Finroc[4]. The parent class for every LiDAR-based sensor is the class **LiDARParent**. Here, the output structure *LiDAROutput* is stored which contains the output data like an array of 3-dimensional points, the field of view, the number of scan lines, and additional data. The method *AddNoise* uses a simplified noise model provided by the **Utility** class and is overwritable.



(a) Class diagram of the SensorParent class which is the parent class of all sensors.



(b) Class diagram of the LiDARParent and its child, the ParticleLiDAR.

Figure 2: More detailed class diagrams of the SensorParent and the ParticleLiDAR sensor with its direct parent.

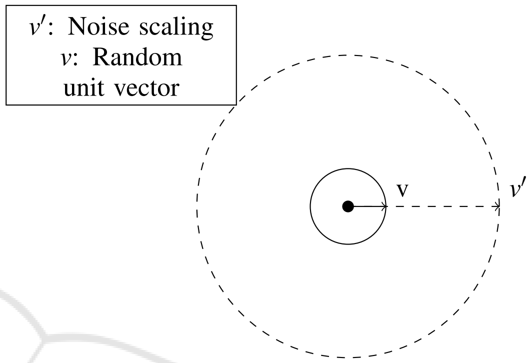


Figure 3: Visualization of our simple sensor model. The input value is represented by the black dot in the center. The vector v is the random unit vector which is multiplied by a scaling value resulting in the vector v' which is the original vector with additional noise.

Figure 3 shows a visualization of the sensor model. For simplicity, only the case for 2D is considered. The raw input value is represented by the black dot in the center. First, a random unit vector (v) is generated which is multiplied by a noise scaling value defined by the user. The resulting vector v' represents the original value with additional noise. The class **ParticleLiDAR** shows the minimalistic setup necessary for the integration in the system. They define their specific parameters in a structure and override the *PublishOutput* method based on how the point cloud is generated. The use of the adapter pattern in this approach has two big advantages. First, every new LiDAR sensor is integrable into the existing system also using every adapter as long as it stores its values in the struct *LiDAROutput* and implements the method *PublishOutput*. Second, if an additional adapter is implemented, all the existing sensors are usable. For this, the conversion of unreal data to the new data types is defined in the method *PublishLiDARData*.

[4]https://www.finroc.org/

3.2 LiDAR

Different LiDAR technologies have evolved over time (see Figure 4). The practically most used technology is mechanically rotating LiDARs. Therefore, the simulation of LiDAR sensors focuses on these systems. This enables the virtual testing of algorithms in a simulated environment and the gathering of synthetic data. Table 1 compares the state-of-the-art algorithms with our proposed method.

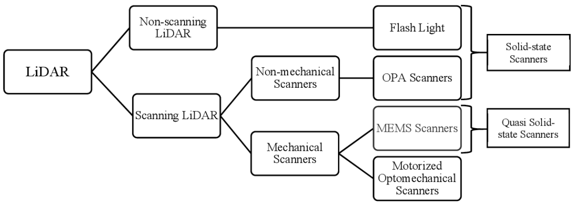


Figure 4: Classification of LiDAR systems (Wang et al., 2020).

3.2.1 CPU Ray Tracing

The most widespread method of LiDAR simulation is sending a specified number of traces in several directions and returning to the hit location. It is determined by the intersection of one ray with an object in the environment. Unreal Engine provides a CPU-executed function dedicated to this purpose called *LineTraceSingleByChannel*. The advantages of this method include the high precision of the collision point with the environment, and no communication between GPU and CPU is needed. Additionally, the actors at the collision point can be retrieved directly, which allows better possibilities for recording LiDAR datasets. Since Unreal Engine executes each line trace sequentially on the CPU, this method results in non-optimal performance. The second-biggest disadvantage of this method is that the CPU traces collision meshes rather than the actual visual scene. Even if the full-scale object is used as the collision mesh, displacement effects such as bump maps or tessellation alter the scene without modifying the collision mesh. Retrieving material properties such as roughness from a Line Trace is not directly possible in Unreal Engine.Therefore, additional methods have to be used to acquire the intensity values of the point cloud. For example, different depth cameras are used to measure the surface properties or the amount of surface reflected light. This is implemented by simulating a light source at the position of the LiDAR. Then the amount of reflected light towards it is measured (although NIR light must be approximated by red light since UE lacks NIR light simulations).

3.2.2 Depth Camera Based Techniques

A common approach to increase performance is to eliminate the ray traces on the CPU using depth images. In depth-camera-based approaches, multiple-depth images of the scene are rendered. The Depth Buffer of each image is used to acquire the depth channel of the image. Then, the RGBD image is transformed into a 3D point cloud using the following formulas from *PseudoLidar* (Wang et al., 2019):

$$
\begin{aligned}
z &= Depth, \\
x &= \frac{(UV[0]-0.5)\cdot z}{tan(FOV[0])\cdot 0.5}, \\
y &= \frac{(UV[1]-0.5)\cdot z}{tan(FOV[1])\cdot 0.5}
\end{aligned}
\tag{1}
$$

where UV$\in[0,1]$ is the pixel location and FOV is the field-of-view in the horizontal and vertical direction.
Different pixels in one row of the image correspond to different vertical angles of the LiDAR, since the projection of vertically equal polar angles into the image causes hyperbolic lines in the image plane (see Figure 5). Various methods have emerged to counter the unrealistic distribution of rays that would result from a trivial approach to map one pixel-row to a LiDAR scan line directly. These methods include hyperbolic approximations (Wolf et al., 2020), projections of unit points into the images (Hurl et al., 2019), and spherical image wrapping (Hossny et al., 2020).

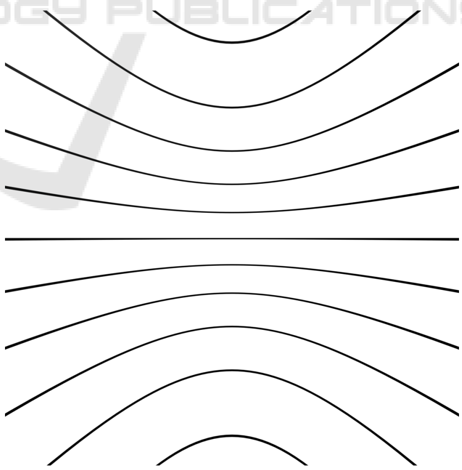


Figure 5: Visualization of LiDAR scan lines with 11.25° spacing in an image with 120° FOV.

In the following section, only the projections of unit points are considered for comparison.
Depth-Camera-based LiDAR sensors have the advantage of using visual depth. This is the most accurate representation of the scene in game engines since displacement effects are also taken into account. The

disadvantages are the lower precision of the depth at higher distances, as well as the resulting delay in transferring images from GPU to CPU.

3.2.3 Particle LiDAR

Game engines use particles for visual effects that require a higher number of operations, but lower interaction between particles. The simulation of sparks in flames is one such example. The resources of the GPU are sufficient to simulate these particles entirely and the export to the CPU takes place when the data is needed.

Unreal Engine's particle Engine *Niagara* provides enough functionality to simulate a single laser beam on one particle. The underlying principle of particle-based LiDAR sensors is to first generate particles, each performing a line trace, calculated on GPU. Afterward, all collision points of the entire line traces are exported to the CPU. This results in a high-performance LiDAR model. It provides one of the most efficient ways of visualizing point clouds in simulation. Depending on the use case, different variations of this approach can be implemented, the basic one is:

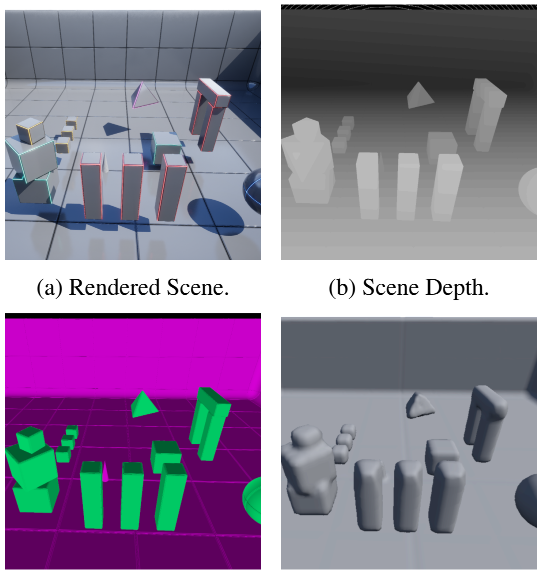
Algorithm 1: Basic Particle Lidar.

```
Input: SensorTransformation S
Initialization: Spawn particles
while sensor running do
    Place particles in a unit sphere around S
    for particle do
        // in parallel
        dir = particle.location expressed in S
        LineTrace(start:S.loc, direction: dir)
        particle.positon = LineTrace.result
    Export positions of all particles
```

Instead of Algorithm 1, one can use a time interval $[t_0, t_n]$, split into n timesteps, and in each time step t_i, $1/n$ of the traces are performed to simulate a rotating LiDAR.

Another variant of the algorithm is to destroy particles that do not collide, and hence have the location $(0,0,0)$. This step is executed simultaneously for all particles but requires the respawning of those in the next frame.

The collision position can also be directly expressed in relation to the sensor. Thus the execution of the transformation on the CPU is avoided. The drawback of this option is that the visualization of the particles does not align with the actual collision points anymore. For example, using this variant, the particle that collides with an object $1m$ in front of the sensor would be displayed at $p = (1,0,0)^T$ in the world coordinate system.



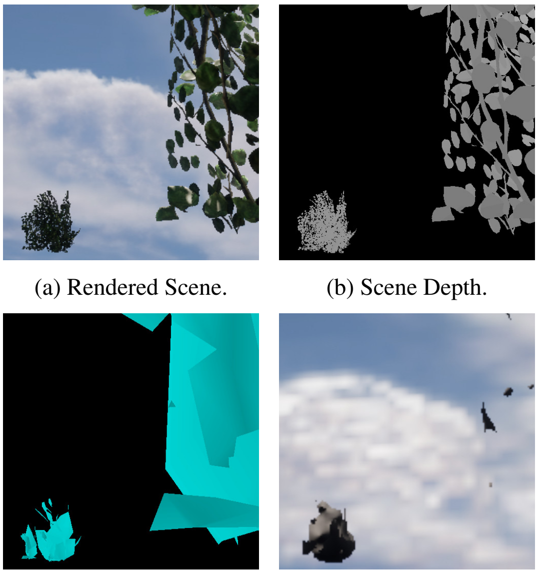
(a) Rendered Scene. (b) Scene Depth. (c) Collision Mesh. (d) Signed Global Distance Fields.

Figure 6: Visualization of different collision methods.

Particle Tracing. In UE, there are two types of traces that a particle can perform. One is a spherical trace for the distance fields, which is available in UE4 and UE5. It is compatible with every operating system and graphics card. Distance fields are seen as low-resolution copies of the environment. They are used by UE to efficiently simulate shadows and global illumination. Although the low resolution of these fields greatly accelerates line traces, the blurry geometry shapes lead to much smoother LiDAR point clouds compared to real ones. The alternative is the use of UE's Hardware Ray-Tracing for collision detection. It was added experimentally in the UE5 Update but is only available on Windows with NVIDIA RTX GPUs. This paper focuses on the former method, while the latter can be explored in the future.

3.2.4 Comparison

Tracing Collisions. Each method of LiDAR simulation uses a different method for the ray-environment collisions, see figures 6. CPU Ray Tracing uses the collision meshes of the object. It represents the mesh in a detailed, yet simplified way. Depth Camera based methods use the scene depth buffer. The particle-based method uses the global distance fields. The highest accuracy is performed by the depth buffer, since it takes also displacement effects into account.



(a) Rendered Scene. (b) Scene Depth.

(c) Collision Mesh. (d) Signed Global Distance Fields.

Figure 7: Collision visualization of foliage on two different scales. The bush consists geometrically of displaced planar faces, which leads to problems with the mesh reconstructions from a distance field.

This is not the case for collision meshes. In distance fields[5], the environment is split into voxels, where each voxel stores the distance to the nearest triangle. Distance fields are even less detailed than collision meshes. They are meant to be a low-resolution representation of the environment. It is used for Unreal's light engine *Lumen* and other parts that require a resolution/performance tradeoff. The resolution of these fields also varies based on the distance to the viewer, and problems occur when the mesh has non-volumetric parts, as in Figure 7.

Performance. Using the CPU for Line Tracing is the slowest method since the traces are performed sequentially in Unreal Engine. However, involving the GPU leads to communication delays because sending information from the GPU to the CPU takes a longer time. Depth Buffer methods have to capture and send more information to the CPU compared to Particle LiDAR methods. That makes Particle LiDAR systems the theoretically fastest method for simulation. This enables the simulation of the motion effects of LiDAR sensors.

Benchmarking Results (settings as in 4.1):
The time to create a point cloud is measured on an NVIDIA A10G with a simple scene. The export of the point cloud is not considered in the timing.
Ray Tracing: 165ms for 64 channels, 1040ms for 512 channels
Depth Camera: 70ms for 64 channels, 220ms for 512 channels
GPU Particles: 42ms for 64 channels, 50ms for 512 channels
This shows that GPU Particles are the fastest available method for generating point clouds, and that the number of points does not affect the performance as much as it does affect other methods. Visualizing the points takes an additional 120ms or $>$1000ms for 64 channels or 512 channels, respectively. Only the Particle LiDAR visualizes the point cloud without performance decreases. Hence, it is the only real-time capable method for capturing and visualizing large point clouds[6].

4 EXPERIMENTS

First, the simulated point clouds of the different LiDAR sensors are compared qualitatively. The second part of the experiments describes the comparison between real recordings and virtual point clouds. For this, simple objects are chosen and recreated in the simulation. During our experiments with the virtual sensor, it turned out that the objects we chose were too small for the particle LiDAR and our implementation of the camera-based LiDAR. Thus, we restricted our comparisons to the Ray Tracing sensor.

4.1 Point Cloud Difference

To measure the accuracy decrease of particle LiDARs, we calculated the mean distance between points in a point cloud from a Ray Tracing sensor and particle sensors. To put that value into context, we also provide the same measurements between Ray Tracing LiDARs and Depth-Camera LiDARs.

4.1.1 CPU Ray Tracing

The LiDAR to represent a CPU Ray Tracing sensor was based on *CARLA*'s LiDAR simulation, adapted for native UE and without noise simulation.

4.1.2 Depth Camera LiDAR

Instead of the standard six cameras needed to render the entire surrounding, only three with 120° FOV and

[5]https://docs.unrealengine.com/5.0/en-US/mesh-distance-fields-in-unreal-engine/

[6]The performance of GPU particle was measured with visualizing the particles

2048x2048 resolution were used to maximize performance.

A further improvement is the use of custom post-processing materials. It transforms each point into 3D local coordinates during the rendering of the image. This also takes the rotation of two of the cameras into account. The resulting image now has the XYZ coordinates of the surface point for each pixel in the RGB channels. Then the CPU reads the pixel values for specific pixels and adds an offset to the coordinates. The downside of this is that the 3D coordinates are getting quantized.

To find out which pixels are relevant, the horizontal and vertical angles of the LiDAR scan points are calculated. Unit vectors made of these angles are projected into the camera image. Through this, pixels corresponding to particular LiDAR points are found.

4.1.3 Particle LiDAR

To enable meaningful benchmark, no motion effects were simulated and algorithm 1 was used.

4.1.4 Measurement Method

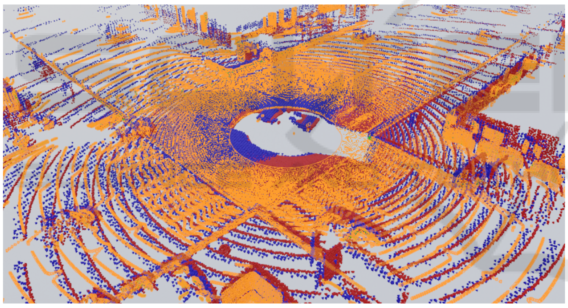


Figure 8: Visualization of a point from different simulation methods. Red: Ray tracing (used as a reference). Blue: Depth camera approach. Orange: Particle LiDAR.

For every point in the ray tracing point cloud, we calculated the Euclidean distance to the nearest point in the depth camera point cloud as well as to the nearest particle LiDAR point cloud. The distances were then averaged. Figure 8 shows the different point clouds. For the depth-camera based approach, the points are forming a grid, caused by the quantization of the XYZ values, and in the distance, each ring is made up of straight lines due to the quantization of the depth buffer.

Results:

Mean distance Ray Tracing LiDAR and Particle LiDAR:

$0.936\,m$

Mean distance Ray Tracing LiDAR and Depth Camera LiDAR:

$0.447\,m$

The results from the Particle LiDAR, when assuming the ray tracing as a reference, are worse than those from depth camera LiDAR, but it shows, that the data follows the same structure. However, the results depend strongly on the used scene, making a standalone statement nearly impossible.

4.2 Comparison with Real Sensors

To evaluate the different simulated sensors (see subsection 3.2), they are compared with a real one. A problem is the meaningful comparison of the two sources. It requires an accurately measured environment that is replicated in the simulation and a detailed sensor model considering its noise. Since our noise model is very basic, simple-shaped objects are chosen as benchmarks. We measured them at different distances from the sensor. In the real environment, we used the Ouster OS1[7] laser scanner with a vertical resolution of 128, a horizontal resolution of 1024 and 360° field of view. For recording, we chose three different objects: two cardboard boxes with the dimensions of 237x114x179 and 322x215x295 both in *mm*, as well as a bin with a diameter of 270 *mm* and a height of 300 *mm*. For a qualitative comparison, we recorded the objects, both in simulation and reality. We alter the distances between one and six meters with an increment of one meter. For a more robust comparison, we recorded around five seconds of data for every object and distance. This takes into account noise and outliers and results in 36 recordings. The setup is shown in figure 9.

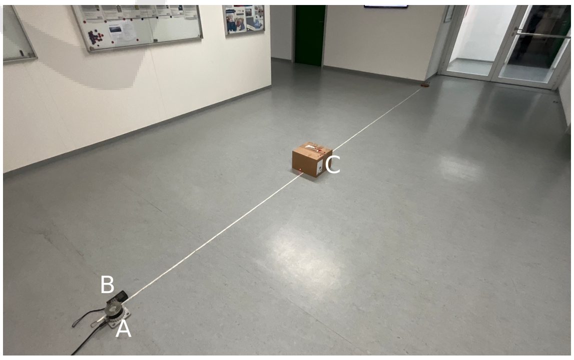


Figure 9: Setup of our recordings. The object in the middle (C) is the large box. The laser measure (B) is next to the laser scanner (A) in the lower left corner.

[7] https://data.ouster.io/downloads/datasheets/datasheet-rev7-v3p0-os1.pdf

4.2.1 Preprocessing

Since we are only interested in the comparison of the predefined objects, the recorded point clouds have to be preprocessed. For this, individual scans were extracted from the five-second recording. These scans were imported into the open-source 3D modeling tool Blender[8]. There, the background points were removed manually. Here, we defined the hull of the recorded object and placed it at the same location as in the recording. The overlapping points of the scan are assumed to be the points belonging to the recorded object. To account for the noise we increased the scale of the object. The tolerance is around $10\,cm$. This process was repeated five times for every recording. 180 point clouds of the objects at varying distances and at different times were extracted. In the simulation, we recreated the objects and recorded them with our Ray Tracing sensor.

4.2.2 Evaluation

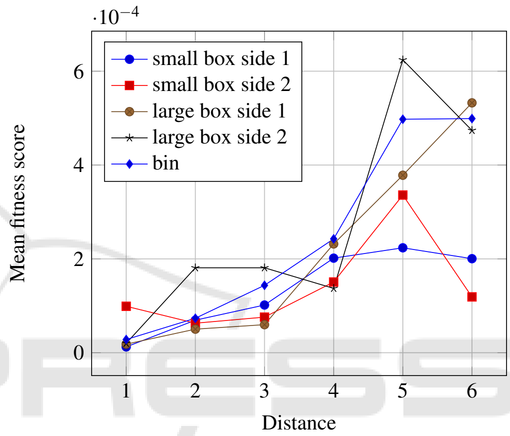
For comparing the point clouds, an iterative approach provided by the open-source *Point Cloud Library* (PCL) [9] was used. Their *Iterative Closest Point* (ICP) algorithm can be found at (ICP,). For a comparison of the point clouds, we used the fitness score value of the algorithm which represents the mean of squared distances between the source and reference point cloud. Then, we analyzed the following differences:

1. Distance of same object
2. Time
3. Objects
4. Noise of the virtual sensors

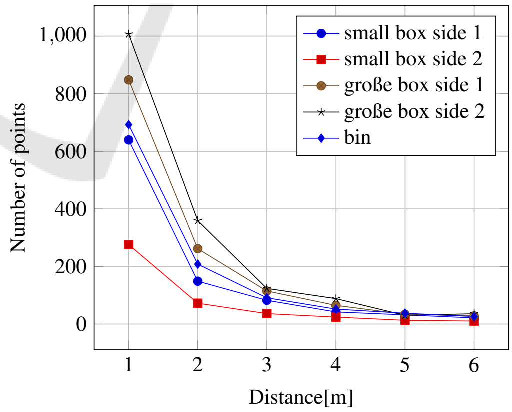
4.2.3 Results

For the first evaluation, we looked at the static noise of the real sensor at defined distances using the previously mentioned objects. In order to do this, we compared the five-point clouds of every distance with each other and calculated the fitness score using ICP. The resulting value is the mean squared distance for the object at the same distance. We repeated the process for every object at distances between $1\,m$ and $6\,m$.

The two graphs in figure 10 show the evaluation of these static aspects. The upper graph depicts the mean fitness score value per distance for the different objects. Below, the corresponding number of points of the extracted point cloud can be seen. As expected, the number of points decreases the further the object is from the sensor. At 5 meters, all objects have approximately the same number of points. When examining the graph in figure 10a one notices that the mean fitness score rises up to a certain point and then decreases. One good example is the small box side 2. At 5 meters the mean fitness score is at its highest and decreases by half for 6 meters. At first, that does not make any sense, but when considering the lower graph, one can see that at 6 meters the point cloud consists of only a few points (around 6 to 10). When looking at the recorded data, it is often the case that the small box consists of only a single scan line. Thus, the score value is smaller than expected because the point clouds consist of a single line of a few points.



(a) Mean score value the objects for different distances.



(b) Mean number of points of the pointclouds for different distances.

Figure 10: Evaluation of the real recorded point clouds. The upper graph shows the mean fitness score for every object at different distances, and the lower one the number of points for the objects. Both distances are in meters.

For comparing the simulated point cloud with the real recordings, we have to define a noise value based on the simple model defined in 3 using centimeter as

[8]https://www.blender.org
[9]https://pointclouds.org/

units. To do this, we compared the mean fitness score of the small box using the ray tracing sensor with different noise values at different distances. The graph in 11 shows the results. As expected, the mean fitness score between consecutive scans of the same object decreases with a higher noise value. This aspect is intensified by the distance because the number of points decreases the further the object is away from the sensor which can be seen in graph (d) of figure 13. Comparing those values with the real sensor recordings in figure 10 shows that the noise of it is neither linear nor constant and we have to use different values for different distances. Having this in mind, we increase the noise value by one centimeter for every meter in distance for which the results of figure 11 roughly align with the real recordings in figure 10 for the small box. In our tests, we focused on the ray-tracing sensor since we expect that it returns the best results in the scenario. Additionally, as explained in subsection 3.2, small objects can not be detected by the particle sensor and the camera based sensor. Figure 13 shows the complete evaluation for all objects at different distances using the ray tracing LiDAR sensor and the noise model explained above. The similarity in the virtual and real sensor is higher than initially expected since our linear noise model is very simple and does not account for effects like reflection. Nevertheless, the curves match in basic shape and also in the absolute values besides a few outliers. These results, however, do not show the direct comparison of the virtual pointcloud and the real one, they only quantify the relative accuracy of the sensors and show that our ray tracing LiDAR with corresponding parameters has similar properties to a real sensor.

Finally, we compared the pointclouds of the virtual sensor to the real data. The results can be seen in figure 12. Here, the mean fitness score between the pointcloud of the real sensor and the ray tracing sensor per object and distance can be seen. Note that the scaling of the y axis is 10^{-3} instead of 10^{-4} which was the value for the other graphs. It can be seen that the graphs show a roughly linear behavior and are constantly rising with some outliers. The fitness score ranges between a few millimeters at 1 meter and around twelve centimeters at 6 meters. The high fitness score of the small box side 2 comes from an offset of the recorded object in the y axis of around 5 centimeter.

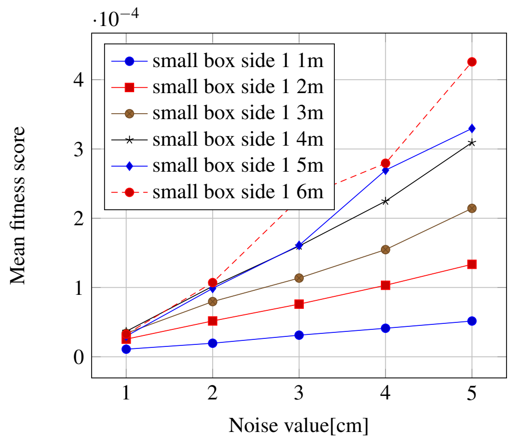


Figure 11: Mean fitness score value of the small box per distance in the simulation using the ray tracing sensor using different noise values. The noise values are in centimeter.

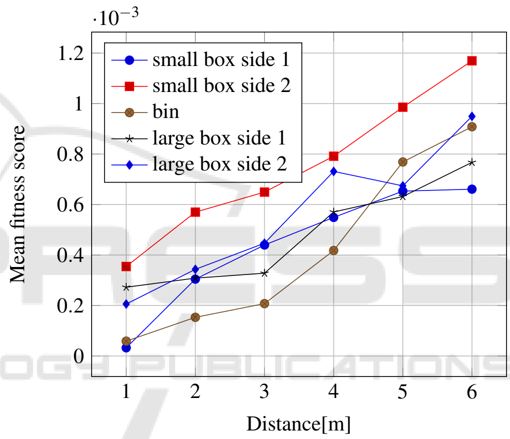


Figure 12: Comparison between the real sensor and the virtual ray tracing based LiDAR sensor for the different objects and different distances. The noise model assumes that for every meter one centimeter of noise is added to the current noise value.

5 CONCLUSIONS

In subsection 3.1 we presented a system for adaptable virtual sensors in Unreal Engine utilizing the adapter pattern. Its benefits are easy integration of new sensors as well as adaptable communication interfaces. After that, we showed common LiDAR simulations also introducing a new type of LiDAR simulation method and showed that this approach is faster than the current methods, but lacking behind in level of detail. Although this method might be not applicable for every use case, since e.g. the resolution is not invariant to the position of the viewer, and the accuracy is worse than other methods, we are certain, that the performance improvement (of ∼4x compared to Ray Tracing) enables LiDAR sensors on much larger scales. Lastly, we conducted experiments for comparing a common sensor implementation (ray-tracing based) to a real sensor and evaluated the pointclouds using the iterative closest points algorithm.

5.1 Further Research

For further research, there are some aspects depending on the virtual sensor that can be improved. It is possible to further improve the particle LiDAR approach using Hardware ray traces. Additionally, instead of only considering the geometry of the scene, we plan on developing a weighting of the sensor signals based on the material of the surface to account for a more accurate physical model. This weighting is predestined for the depth camera based approach explained in subsection 4.1.2 since properties of materials can be accessed in the same way as the scene depth in Unreal Engine. Another important aspect is reflection, based on materials as well as the surface normal. Here, the approaches vary based on the sensor type, using ray-tracing it is easy to calculate reflections. For the depth based approach, only single reflections can be calculated easily since Unreal Engine provides a normal map of the scene similar to the scene depth and the material properties. For all sensors more work has to be invested into the noise model to reflect physical properties of a LiDAR sensor.

REFERENCES

Dosovitskiy, A., Ros, G., Codevilla, F., López, A. M., and Koltun, V. (2017). Carla: An open urban driving simulator. *ArXiv*, abs/1711.03938.

Fang, J., Yan, F., Zhao, T., Zhang, F., Zhou, D., Yang, R., Ma, Y., and Wang, L. (2018). Simulating lidar point cloud for autonomous driving using real-world scenes and traffic flows.

Hossny, M., Saleh, K., Attia, M., Abobakr, A., and Iskander, J. (2020). Fast synthetic lidar rendering via spherical uv unwrapping of equirectangular z-buffer images. *ArXiv*, abs/2006.04345.

Hurl, B., Czarnecki, K., and Waslander, S. L. (2019). Precise synthetic image and lidar (presil) dataset for autonomous vehicle perception. *2019 IEEE Intelligent Vehicles Symposium (IV)*, pages 2522–2529.

ICP. Website of pcl icp implementation. https://pointclouds.org/documentation/classpcl_1_1_iterative_closest_point.html. Accessed at 13.02.2023.

Manivasagam, S., Wang, S., Wong, K., Zeng, W., Sazanovich, M., Tan, S., Yang, B., Ma, W.-C., and Urtasun, R. (2020). Lidarsim: Realistic lidar simulation by leveraging the real world. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 11164–11173.

Stachowiak, H. (1973). *Allgemeine Modelltheorie*. Springer Verlag, Wien, New York.

Vierling, A., Sutjaritvorakul, T., and Berns, K. (2019). Dataset generation using a simulated world. In Berns, K. and Görges, D., editors, *Advances in Service and Industrial Robotics Proceedings of the 28th International Conference on Robotics in Alpe-Adria-Danube Region (RAAD 2019)*, pages 505–513.

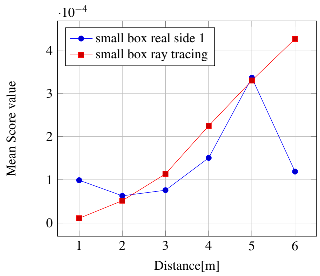
Wang, D., Watkins, C., and Xie, H. (2020). Mems mirrors for lidar: A review. *Micromachines*, 11.

Wang, Y., Chao, W.-L., Garg, D., Hariharan, B., Campbell, M. E., and Weinberger, K. Q. (2019). Pseudo-lidar from visual depth estimation: Bridging the gap in 3d object detection for autonomous driving. *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 8437–8445.

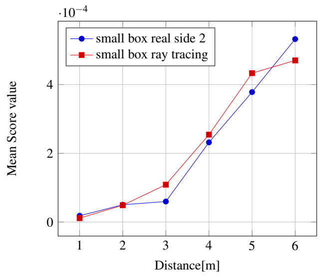
Wolf, P., Groll, T., Hemer, S., and Berns, K. (2020). Evolution of robotic simulators: Using UE 4 to enable real-world quality testing of complex autonomous robots in unstructured environments. In Rango, F. D., Ören, T., and Obaidat, M., editors, *Proceedings of the 10th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2020)*, pages 271–278. INSTICC, SCITEPRESS – Science and Technology Publications, Lda. ISBN: 978-989-758-444-2, DOI 10.5220/0009911502710278, Best Poster Award.

APPENDIX

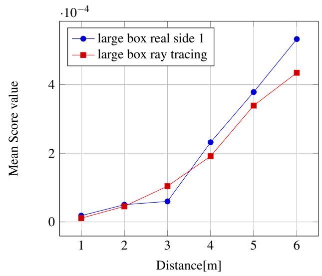
Figures



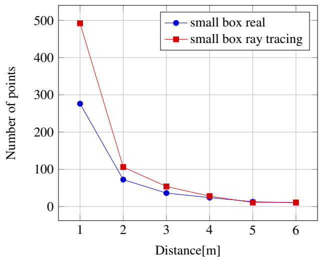
(a) Mean fitness score of the small box side 1.



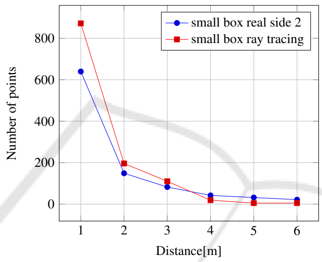
(b) Mean fitness score of the small box side 2.



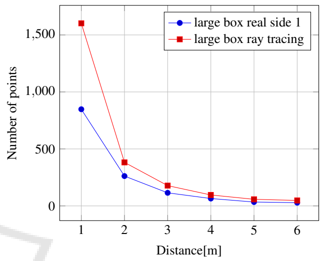
(c) Mean fitness score of the large box side 1.



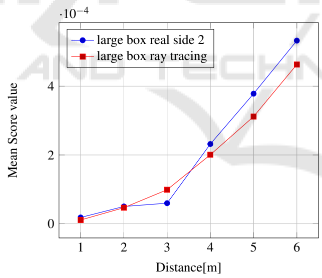
(d) Mean number of points for the small box side 1.



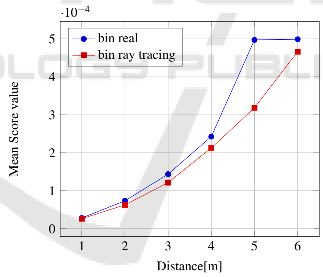
(e) Mean number of points for the small box side 2.



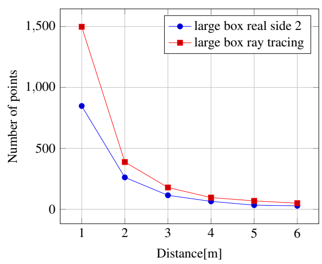
(f) Mean number of points for the small box side 1.



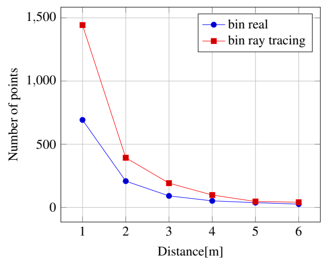
(g) Mean fitness score of the large box side 2.



(h) Mean fitness score of the bin.



(i) Mean number of points large box side 2.



(j) Mean number of points of the bin.

Figure 13: Results for the ray tracing LiDAR sensor in the Unreal Engine with different objects. The upper graphs(a-c and g-h) show the mean fitness score whereas the graphs below (d-f and i-j) shows the number of points for the object. Both, the real data and the virtual data is shown.