DYNAMIC LIDAR SENSOR MODELING FOR SMOKE AND FIRE DETECTION IN RESCUE SCENARIOS

Simulating Environmental Challenges to

Enhance Sensor Robustness and Path Planning

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Date:

December 09, 2024

ABSTRACT

This project focuses on the simulation and planning of a 2D LIDAR sensor for fire rescue scenarios. The simulation incorporates sensor noise and light attenuation models to emulate real-world measurement inaccuracies. Environmental conditions such as smoke, rain, and fog were simulated to study their impact on LIDAR readings. The sensor dynamically identifies static and dynamic obstacles and detects fire based on smoke density. Results show that the sensor achieves efficient environment coverage (~80-84%) and rapid detection of fire (1 second) and human targets (1.5 seconds), despite noisy and attenuated signal conditions. These findings highlight the sensor's capability for robust mapping in challenging environments.

INTRODUCTION

In fire rescue scenarios, understanding the environment quickly and accurately is crucial for firefighter safety and mission success. This project explores the use of a 2D LIDAR sensor to simulate and assess its ability to *navigate hazardous environments*, *identify fire locations*, and *detect moving and static obstacles*. The simulation mimics real-world conditions, incorporating environmental factors such as s*moke, fog, and rain*, which significantly affect the LIDAR's performance.

The main objective is to utilize LIDAR's capabilities to perform efficient mapping and detection of critical elements, such as fire and human movement, under noisy and attenuated signal conditions. The sensor's movement is planned manually towards areas of interest, demonstrating its real-time decision-making capabilities to assist human operators in fire rescue operations.

This report expands on the midterm project by introducing new features like environmental noise modeling, sensor attenuation, and dynamic target integration. The findings demonstrate the sensor's ability to adapt to environmental challenges and provide high-accuracy point cloud data for fire rescue scenarios.

THEORY AND METHODS

LIDAR Sensor Modeling

A LIDAR (Light Detection and Ranging) sensor emits laser beams that reflect off surfaces and return to the sensor, providing precise distance measurements. The mathematical model governing the LIDAR's performance includes the following components:

1. **Distance Measurement**: The time-of-flight (ToF) of a laser pulse determines the distance to the target:

$$d = \frac{c.\Delta t}{2}$$

   where c is the speed of light, and Δt is the time it takes for the laser to return.

2. **Intensity Attenuation**: Signal intensity diminishes due to factors such as surface reflectivity (ρ), angle of incidence (α), and environmental attenuation (e.g., smoke, fog, or rain):

$$I = I_o * \rho * cos(\alpha) * e^{-k.d}$$

   where I_o is the emitted intensity, k is the attenuation coefficient, and d is the distance.

3. **Sensor Noise**: Gaussian noise is applied to simulate real-world inaccuracies:

$$d_{noisy} = d + \Theta(0, \sigma_d) \quad , \quad I_{noisy} = I + \Theta(0, \sigma_I)$$

   where $\Theta(0, \sigma_d)$ represents Gaussian noise with standard deviation σ.

The model uses simple ray tracing to simulate a real world LIDAR sensor's performance,

Figure 1 shows the output that the sensor model produces for the given sample environment.

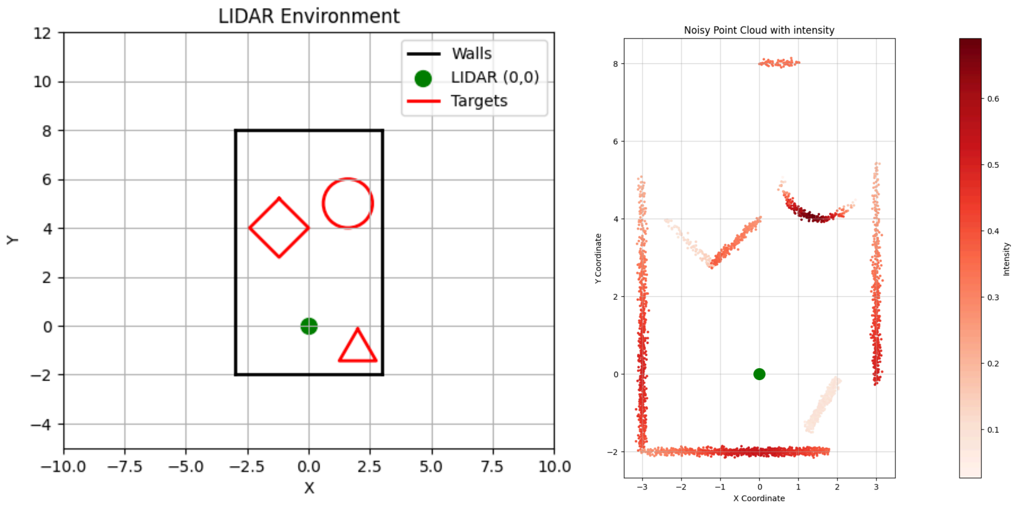


Figure 1. Point Cloud produced by the sensor model for the sample environment

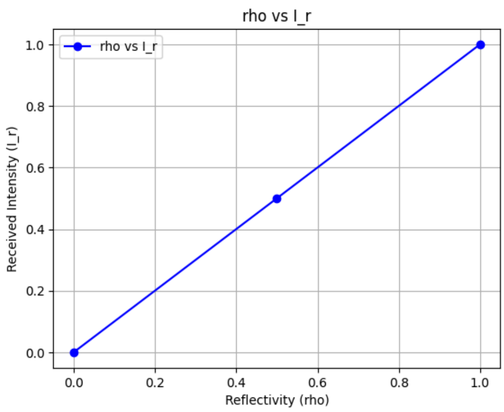


Figure 2. surface reflectivity (ρ) vs received intensity (Ir)

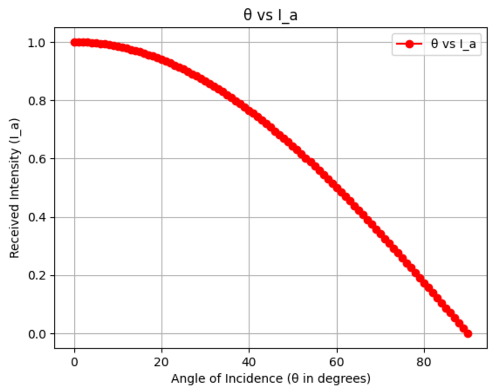


Figure 3. received intensity vs the angle of incidence (θ)

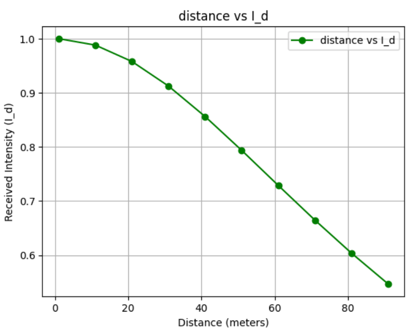


Figure 4. Decrease in Intensity due to Beam attenuation

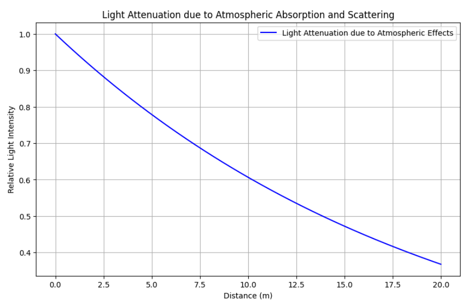


Figure 5. light attenuation due to atmospheric absorption and scattering conditions

Figures 2 to *5* illustrate the performance metrics of the modeled LIDAR sensor. *Figure 2* shows the linear relationship between surface reflectivity (ρ) and received intensity (I_r), demonstrating stronger signals for highly reflective surfaces. *Figure 3* highlights the cosine dependency of received intensity on the angle of incidence (θ), with steep angles resulting in significant signal loss. *Figure 4* depicts the exponential attenuation of intensity with increasing distance due to beam divergence and atmospheric effects. *Figure 5* showcases light attenuation under varying atmospheric absorption and scattering conditions, emphasizing the sensor's sensitivity to environmental factors. These metrics provide a comprehensive understanding of the sensor’s behavior under controlled conditions.

Multivariable Control and Sensor Movement

The sensor's movement strategy is centered on dynamically identifying dense smoke regions and tracking moving targets like humans. Dense smoke, typically surrounding the fire, is detected through increased attenuation and noise in the point cloud, while temporal changes aid in identifying dynamic targets modeled with Bézier curves.

The process operates in two phases:

1. **Quick Scanning Phase**: The sensor starts at a predefined location, rapidly scanning the environment to detect high-smoke-density areas and moving obstacles. Noise in the point cloud caused by smoke enables early identification of regions of interest.
2. **Focused Observation Phase**: After identifying high-smoke-density regions, the sensor moves toward these areas, precisely localizing the fire while avoiding obstacles. Temporal variations in smoke and noise guide this movement.

This strategy prioritizes high-risk areas while ensuring safe, collision-free navigation, effectively enhancing fire localization and data reliability for rescue operations.

MODELLING

The sensor model includes the detailed setup of the environment, the modeling of smoke and dynamic targets, and the strategy employed by the sensor to achieve its objectives in fire rescue scenarios. The modeling approach integrates environmental characteristics with sensor dynamics, ensuring a realistic simulation of the conditions faced in emergency situations.

Environment Setup

The environment for the simulation consists of two interconnected rooms separated by a door. This configuration represents a typical indoor setup, with walls and static targets like furniture modeled as obstacles. A fire source is placed in one of the rooms, emitting dense smoke that diffuses radially. The smoke is modeled using a scattering coefficient map, with the highest density near the fire center. Additionally, a dynamic target, representing a human, is introduced to simulate movement within the environment. This target follows a Bézier curve trajectory, moving from an initial position near the fire toward an escape route.

To provide a realistic representation of the fire's effects, the smoke density is spatially distributed, and its influence on the LIDAR sensor readings is accounted for through an attenuation model. The environment dynamically updates at each timestep, reflecting the changing positions of the human and the propagation of smoke. The human starts moving at the 5 second mark and moves for 2 seconds until exiting the room with the fire. *Figure 6* visually represents the modelled environment used for the simulations.

Dynamic Target Modeling

The human target in the simulation is modeled as a dynamic entity, moving away from the fire toward a safety zone. Its trajectory is represented using a Bézier curve, ensuring smooth and realistic movement.

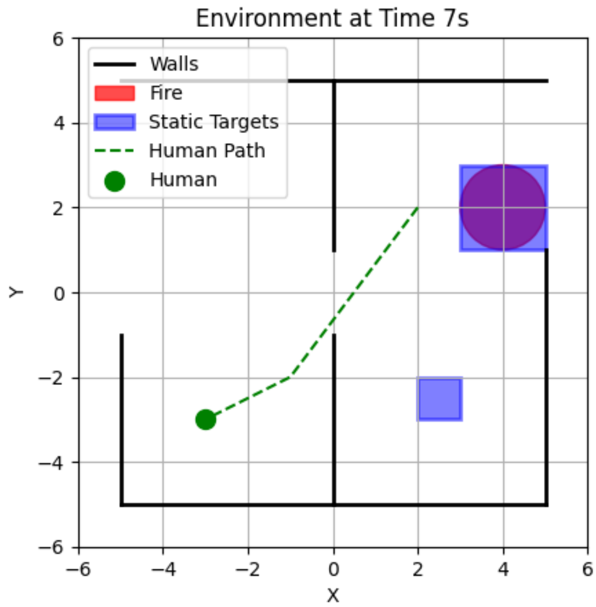


Figure 6. Modelled Environment

The simulation updates the human's position at each timestep, allowing the sensor to track their movement dynamically.The interaction between the human target and the environment is integrated into the sensor's data processing. Temporal changes in the point cloud, caused by the moving target, are used to distinguish dynamic obstacles from static ones. This capability is essential for real-time monitoring and decision-making in fire rescue scenarios.

Smoke Density and Attenuation Modeling

The smoke generated by the fire is modeled to create localized attenuation and noise in the LIDAR sensor's readings. A scattering coefficient map is used to represent the spatial variation of smoke density. The coefficients are highest near the fire and gradually decrease with distance. These values directly influence the intensity of the reflected LIDAR signals, leading to visible attenuation in the point cloud. *Figure 7* shows the smoke density map generated for our environment. This map accurately modells the diffusion of smoke through open doors in the environment.

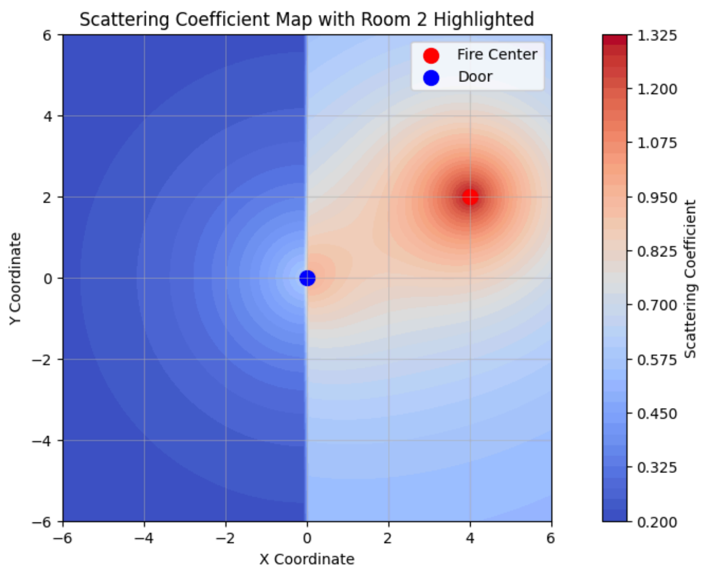


Figure 7. Smoke Density Map

The simulation also accounts for the temporal variations in the smoke's effects. As the fire intensifies and smoke spreads, the LIDAR readings near the fire exhibit higher noise levels, making these regions identifiable in the point cloud. This behavior is critical for identifying high-risk areas and prioritizing them for observation and rescue efforts.Based on the given environment the sensor produces the following point cloud in *Figure 8* from a position (1 , 0) in the environment, at time $t = 0$. Sensor noise not illustrated to better visualize the smoke.

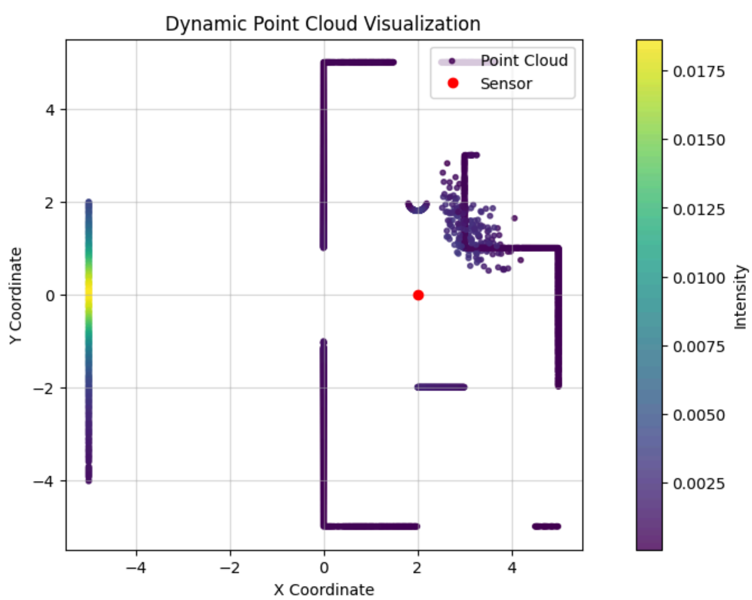


Figure 8. Generated Point Cloud

Sensor Strategy

The sensor employs a two-phase strategy to achieve its objectives. In the *quick scanning phase*, the sensor starts from an initial position and rapidly scans the environment. This phase aims to identify key regions, such as areas with dense smoke or moving targets. By analyzing the noise and attenuation in the point cloud, the sensor can detect the fire and dynamic targets early in the simulation.

In the *focused observation phase*, the sensor adapts its trajectory to move closer to the fire while avoiding obstacles. The sensor prioritizes regions with high smoke density, as indicated by increased noise in the point cloud. This approach enables precise localization of the fire and supports the identification of potential survivors. The sensor's movement strategy is designed to balance efficiency and safety, ensuring comprehensive coverage of critical areas. *Figure 9* depicts the identification of the noisy low intensity region of smoke during the initial quick scanning phase of the sensor.

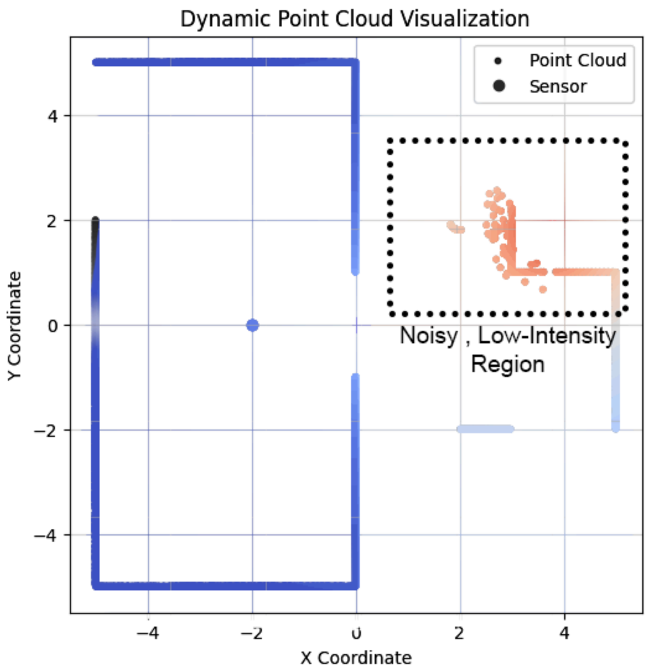


Figure 9. Identification of smoke using noise

RESULTS

The simulation results demonstrate the effectiveness of the LIDAR sensor in identifying key elements of a dynamic, smoke-filled environment and highlight its performance under varying environmental conditions such as smoke, fog, and rain.

Fire and Human Detection Times

Fire Detection Time	Human Detection Time
0.8 seconds *(some amount of the smoke needs to be unoccluded)*	**1.5 Seconds** *(after human starts moving)*

Table 1. Detection Times

The sensor's ability to detect fire and humans was evaluated based on temporal changes in the point cloud. The fire was successfully detected within the first second of simulation due to the heavy smoke density surrounding the fire. The localized attenuation and noise patterns in the point cloud served as clear indicators. The dynamic target (human) was identified at 1.5 seconds after the human started moving. The human's movement, modeled via Bézier curves, caused distinctive temporal changes in the point cloud, aiding in detection.

Coverage Efficiency

Coverage efficiency refers to the percentage of the environment scanned by the LIDAR sensor during a given time step. It is a measure of how effectively the sensor captures spatial data from the environment.

This metric is calculated by dividing the number of unique points detected by the sensor in a given time step by the total possible points that could be scanned within the sensor's 360° field of view. The result is then expressed as a percentage:

$$Coverage\ Efficiency\ =\ (\frac{Points\ Detected}{Maximum\ Possible\ Points})\ \times\ 100$$

The *maximum possible points* were determined based on the sensor's resolution. Higher coverage percentages indicate a more comprehensive scan of the environment, which is critical for detecting obstacles, fire, and dynamic targets efficiently.

Coverage Efficiency (Quick Scan)	Coverage Efficiency (Focussed Observation)
80 - 82%	**83 - 84%**

Table 2. Coverage Efficiency

The sensor maintained high coverage efficiency throughout the simulation. During the quick scanning phase (first 4 seconds), the sensor achieved approximately 80-82% coverage while moving from Room 1 to Room 2. This phase allowed efficient mapping of the environment and identification of areas of interest. In the focused observation phase (last 3 seconds), the sensor localized the fire with consistent coverage of 83-84%, ensuring accurate data collection near the fire.

Point Cloud Visualizations

The LIDAR sensor's real-time point cloud visualizations serve as a comprehensive tool for understanding the environment, showcasing the sensor's capability to adapt dynamically to changing conditions. These visualizations provide spatial data on static obstacles, dynamic targets, and regions of dense smoke.

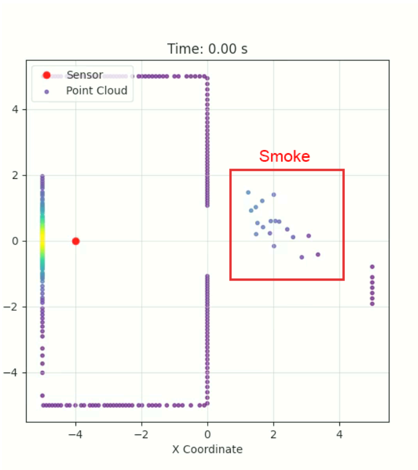
In the quick scanning phase, the point cloud captures critical elements such as the *fire*, *static targets* like walls and furniture, and the *moving human*. As the human moves through the environment, temporal changes in the point cloud allow the sensor to track their movement effectively. For instance, the human's trajectory from Room 2 to Room 1 introduces distinct patterns in the data, helping distinguish dynamic elements from static ones.

As the sensor transitions into the focused observation phase, the point cloud density near the fire increases. This refined data collection is instrumental in localizing the fire and providing a clearer understanding of the high-risk areas. Noise and attenuation caused by dense smoke near the fire are prominently visible in the point cloud, emphasizing the sensor's ability to identify and prioritize critical regions.

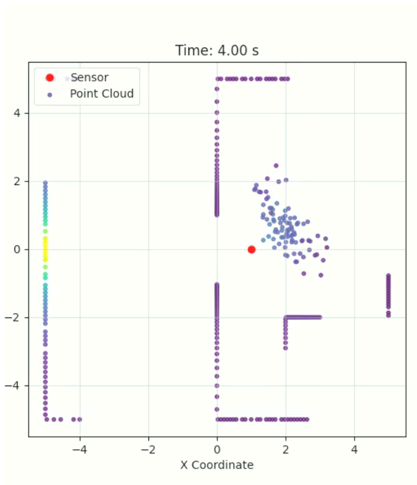
Figure 10 shows the point clouds at different timesteps illustrate how the sensor captures the evolving environment. The human's movement, combined with the static layout and smoke density variations, provides a dynamic test case for the sensor's capabilities, showcasing its robustness in tracking and prioritizing data collection.

Trajectory Planning and Execution

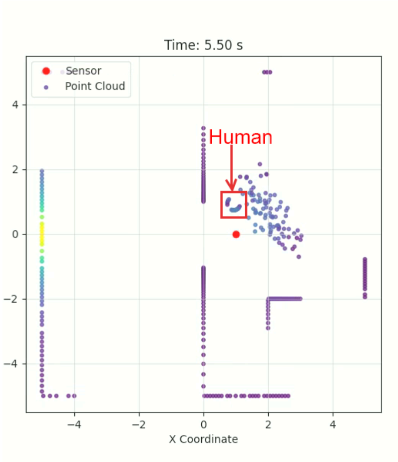
The sensor's trajectory is guided by an adaptive path planning algorithm that detects and prioritizes regions of low intensity in the point cloud, indicative of high smoke density.



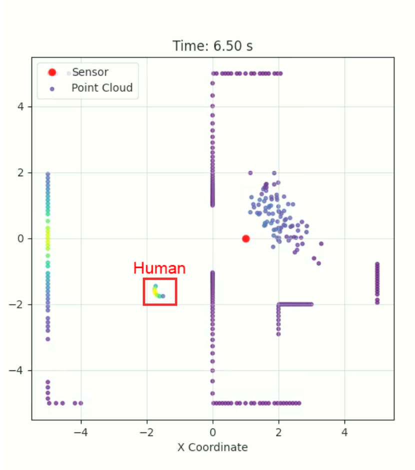
t = 0 sec



t = 4 sec



t = 5.5 sec



t = 6.5 sec

Figure 10. Point Cloud Visualization

Unlike the simplified linear path used for initial point cloud visualizations, this trajectory planning algorithm dynamically adjusts the sensor's movement based on real-time environmental data.The algorithm analyzes attenuation patterns in the point cloud to identify areas with dense smoke, often surrounding the fire. The sensor moves toward these regions while avoiding static obstacles like walls and furniture and dynamically steering clear of moving targets, such as the human. The trajectory balances the need for detailed data collection near the fire with effective obstacle avoidance.

Figure 11 shows several visualizations of the sensor's trajectory starting from different points within the environment, overlaid on the environment map, illustrating how the sensor moves toward the fire while navigating around obstacles and dynamic elements. These maps highlight the real-time adaptability of the trajectory planning algorithm, showcasing its efficiency in gathering critical information near the fire. This approach demonstrates the sensor's ability to support rescue operations by prioritizing high-risk areas and maintaining collision-free navigation.

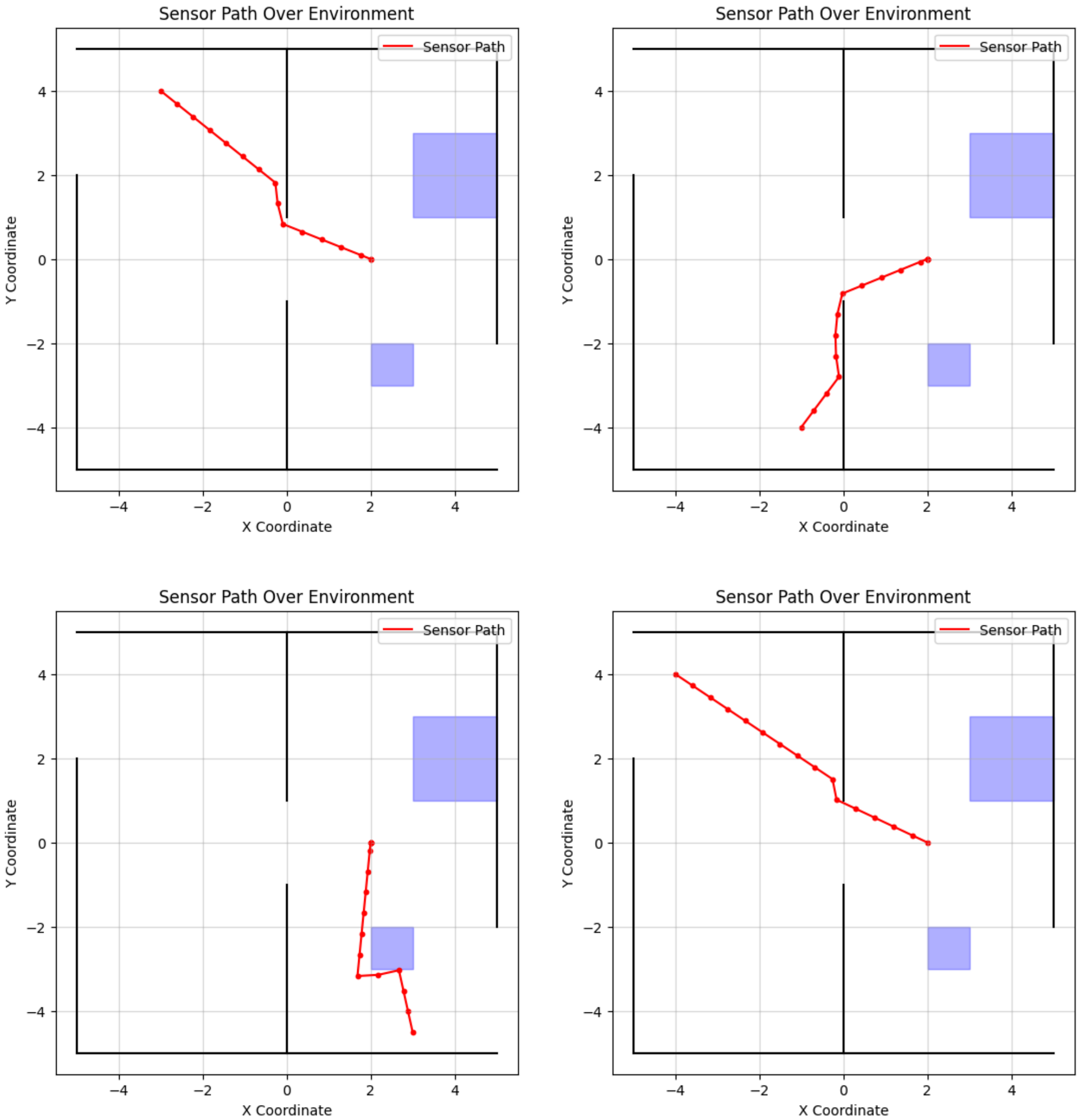


Figure 11. Sensor Trajectories

Environmental Condition Scenarios

The isolated effects of smoke, fog, and rain on LIDAR intensity are simulated to evaluate the sensor's robustness under varying environmental challenges. For these simulations, only the mentioned variables are considered to clearly visualize their impact on intensity loss, while other factors influencing intensity (such as surface reflectivity and angle of incidence) are ignored.

- **Smoke:** *Figure 12* . Dense black smoke near the fire introduces significant attenuation and noisy point cloud data. The resulting intensity loss clearly highlights the fire's location, as the dense smoke regions are readily identifiable.
- **Fog:** *Figure 13*. Uniform attenuation across the environment leads to a gradual decrease in intensity with distance. This is visible as a consistent dimming effect throughout the sensor's field of view, reflecting the scattering nature of fog.
- **Rain:** *Figure 14*. Random scatter due to raindrops introduces sporadic noise in the intensity readings, particularly at medium and long distances. This scatter mimics real-world challenges, where raindrops partially reflect or refract LIDAR beams, affecting measurement accuracy.

This illustrates the intensity loss under these environmental conditions, emphasizing the isolated impact of each variable on the sensor's performance. These visualizations demonstrate how the LIDAR sensor handles specific challenges in smoke-filled, foggy, or rainy conditions.

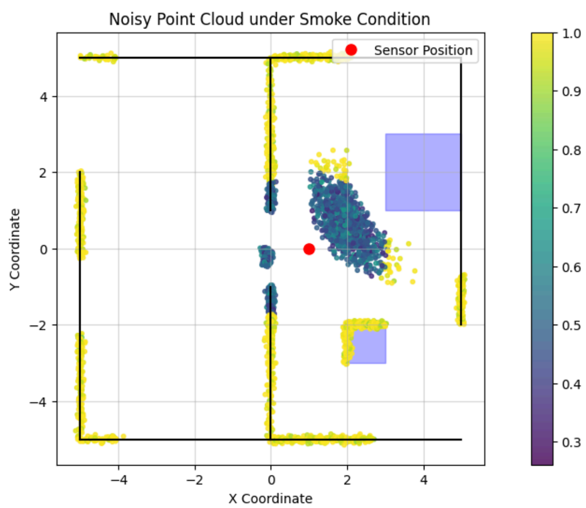


Figure 12. Effects of smoke

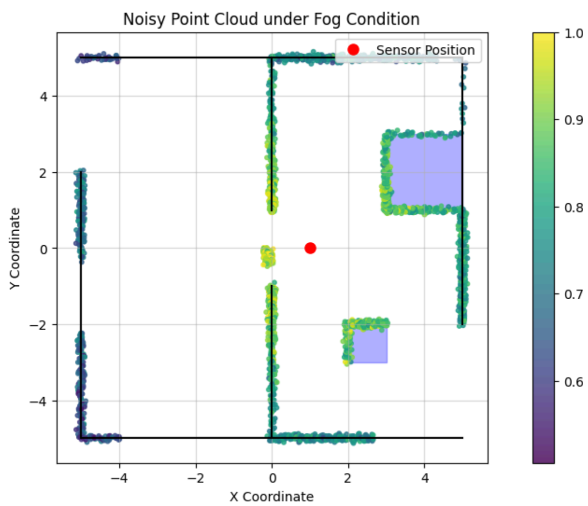


Figure 13. Effects of fog

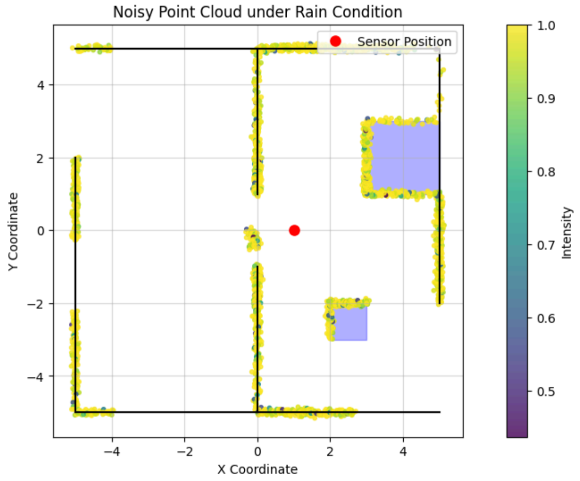


Figure 13. Effects of rain

FUTURE WORKS

Future work on this project could focus on integrating an RGB camera with the LIDAR sensor to enhance the system's ability to differentiate and classify objects. While LIDAR excels at providing geometric and depth data, an RGB camera would add crucial contextual information such as color and texture. This fusion would improve the detection of dynamic obstacles like humans, enabling better identification through visual patterns alongside motion data. In smoke-filled environments, where LIDAR can struggle with attenuation and noise, an RGB camera could complement detection by capturing areas where smoke is visible, aiding in localizing fire or escape routes.

This sensor fusion could also support the development of machine learning models that process and classify combined LIDAR and RGB data for real-time decision-making. For example, integrating visual features with depth information could refine object classification and prioritize high-risk areas in rescue operations. By aligning data from both modalities, this approach would create a richer understanding of the environment, improving the system's performance in adverse conditions.

CONCLUSION

The simulated LIDAR sensor demonstrates exceptional performance in dynamic fire rescue scenarios, achieving rapid detection and effective mapping of critical elements such as fire and human targets. The sensor identifies the fire within 1 second and tracks dynamic targets like humans by 1.5 seconds, showcasing its capacity for prioritizing high-risk areas.

Through real-time point cloud generation, the sensor adapts to varying smoke density and obstacle configurations, maintaining consistent coverage of 80-84% across operational phases. Environmental simulations further validate the sensor's robustness, with visualized intensity losses due to smoke, fog, and rain highlighting its adaptability to real-world challenges.

The sensor’s trajectory planning algorithm ensures efficient and collision-free navigation toward dense smoke regions while avoiding obstacles and dynamic targets. This capability, combined with the precision of the point cloud data, emphasizes the sensor's potential for improving situational awareness in rescue operations.

Future work could involve integrating additional sensors, such as RGB cameras, to enhance decision-making and enable autonomous navigation, ensuring even greater utility in complex rescue scenarios. This study highlights the vital role of advanced sensor models in critical applications, offering a foundation for robust, real-world implementations.

REFERENCES

[1] Heiden, E., Liu, Z., Ramachandran, R.K., & Sukhatme, G.S. (2020). Physics-based Simulation of Continuous-Wave LIDAR for Localization, Calibration and Tracking. 2020 IEEE International Conference on Robotics and Automation (ICRA), Paris, France.

[2] Yang, X., Wang, Y., Yin, T., Wang, C., Lauret, N., Regaieg, O., Xi, X., & Gastellu-Etchegorry, J.P. (2022). Comprehensive LiDAR simulation with efficient physically-based DART-Lux model (I): Theory, novelty, and consistency validation. Remote Sensing of Environment, 272, 112952.

[3] Tessema, L.S., Jaeger, R., & Stilla, U. A Mathematical Sensor Model for Indoor Use of a Multi-Beam Rotating 3D LIDAR. Photogrammetry and Remote Sensing, Technical University of Munich (TUM), Germany, Center for Applied Research, Karlsruhe University of Applied Sciences.

[4] Negrut, D., & Serban, R. Physics-Based Sensor Models for Virtual Simulation of Connected and Autonomous Vehicles. Department of Mechanical Engineering, University of Wisconsin-Madison.

[5] Chevrier, M., & Campanella, G. LIDAR Pulsed Time of Flight Reference Design. Texas Instruments, TI Designs.

[6] Huntington, A., & Williams, G.M., Jr. Lidar Effective Range. Allegro MicroSystems. Retrieved from www.allegromicro.com.

[7] Espineira, J.P., Robinson, J., Groenewald, J., Chan, P.H., & Donzella, V. (2021). Realistic LiDAR With Noise Model for Real-Time Testing of Automated Vehicles in a Virtual Environment. IEEE Sensors Journal, 21 (8), 9919-9926.

[8] Mei, L., Zhang, L., Kong, Z., & Li, H. (2018). Noise modeling, evaluation and reduction for the atmospheric lidar technique employing an image sensor. Optics Communications, 426, 463–470.

[9] Yu, R., Li, X., & Bi, T. (2024). Modelling and validation of LiDAR noise distribution in fog and rain. Measurement, 229, 114472.

[10] Hahner, M., Sakaridis, C., Dai, D., & Van Gool, L. (2021). Fog Simulation on Real LiDAR Point Clouds for 3D Object Detection in Adverse Weather. Proceedings of the IEEE International Conference on Computer Vision (ICCV).

[11] J. R. Spletzer and C. J. Taylor, Sensor planning and control in a dynamic environment. Proceedings of the 2002 IEEE International Conference on Robotics and Automation (ICRA), Washington, DC, USA, 2002, pp. 676–681, vol. 1.

[12] Starr, J.W., & Lattimer, B.Y. (2014). Evaluation of Navigation Sensors in Fire Smoke Environments. Fire Technology, 50(6), 1459–1481.

APPENDIX A

Code Implementation

This appendix provides the Python code used for the simulation, modeling, and analysis of the LIDAR sensor and its environment. The code is organized into sections for clarity and ease of understanding.

Refer to the Python Notebookk File "*Appendix A_Code Implementation.ipynb*" submitted with this report

APPENDIX B

This section provides the mathematical foundations for the LIDAR sensor modeling, trajectory planning, and intensity calculations. These models are integral to the sensor's ability to navigate and analyze the environment effectively.

B.1 LIDAR Intensity Model

The intensity of light detected by the LIDAR sensor is influenced by surface reflectivity, angle of incidence, distance, and environmental conditions such as smoke, fog, or rain. The following equation models the received intensity:

$$I = \frac{I_0 * \rho * cos(\alpha)}{1+\left(\frac{2d}{divergence}\right)^2} * exp(-\ \sigma * d)$$

Where:

- I_0 : Initial Emitted Intensity
- ρ : Surface reflectivity.
- α : Angle of incidence (degrees).

- d : Distance to the target.
- $divergence$: Laser beam divergence.
- σ : Scattering coefficient based on environmental conditions

This model accounts for:

1. **Surface reflectivity** (ρ): Determines how much light is reflected back to the sensor.
2. **Angle of incidence** (α): Affects the amount of light returned to the sensor.
3. **Distance attenuation**: Reduces intensity due to beam spreading over distance.
4. **Scattering effects** (σ): Simulates environmental challenges like smoke, fog, and rain.

B.2 Path Planning and Navigation

The sensor's trajectory is guided by a path planning algorithm that prioritizes regions with high smoke density and avoids obstacles. The trajectory is calculated iteratively:

1. **Vector Calculation**: The direction vector from the sensor to the target is normalized:

$$Direction\ Vector = \frac{Target\ Position - Sensor\ Position}{||Target\ Position - Sensor\ Position||}$$

2. **Next Position**: The sensor moves incrementally along the calculated direction vector:

$$Next\ Position = Sensor\ Position + Step\ Size * Direction\ Vector$$

3. **Collision Avoidance**: If the next position intersects with an obstacle, the trajectory is recalculated to avoid collisions while maintaining progress toward the target.

B.3 Bézier Curve for Human Motion

The movement of dynamic targets (e.g., humans) is modeled using a Bézier curve:

$$P(u) \;=\; (1 - u)^2 * P_0 + 2u(1 - u) * P_1 + u^2 * P_2$$

Where:

- P0, P1, P2: Control points representing the human's start, control, and end positions.
- u: Time parameter, normalized between 0 and 1.

B.4 Environmental Conditions

The impact of environmental conditions is modeled using scattering coefficients (σ):

1. **Smoke**:

$$\sigma_{smoke} = \; base \; + \; localized\ density$$

High scattering near the fire due to dense smoke.

2. **Fog**:

$$\sigma_{smoke} = uniform\ density$$

Consistent attenuation across the field of view.

3. **Rain**:

$$I = I_0 * (1 - p_{rain})$$

Sporadic noise added based on rain probability (p_{rain}).