Converting LiDAR Point Clouds into Simulated Environments for NVIDIA Omniverse

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Abstract

High-fidelity simulation environments can reduce both risks and costs in the deployment of robotic systems. However, raw LiDAR point-cloud data cannot be directly used in simulation platforms, creating a gap between real-world data acquisition and virtual testing. To address this challenge, a pipeline was developed that integrates point-cloud preprocessing and 3D surface reconstruction to generate simulation-ready meshes. The reconstructed environments retained a high level of photo-realism and enabled smooth execution of various functional tests for robotic systems within NVIDIA Omniverse. These results demonstrate that point-cloud–based reconstruction provides a practical pathway to creating realistic and reliable virtual environments, thereby supporting safe and cost-effective robotic research and development.

Declaration of originality

I hereby confirm that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright statement

Acknowledgments

First and foremost, I would like to express my deepest gratitude to my supervisor, Dr. Simon Watson, for his exceptional guidance and unwavering support throughout the course of this dissertation. His profound knowledge, insightful feedback, and patient encouragement have been invaluable in shaping both the direction of this project and my academic development.

Also, I would also like to thank the CRADLE Robotics and AI team for providing the high quality LiDAR dataset which is absolutely suitable for this project.

Finally, I am deeply grateful to my family and friends for their encouragement and understanding, which made the completion of this work possible.

1 Introduction

1.1 Background and motivation

In recent years, the construction of high-fidelity virtual environments has become a critical tool for the development and validation of robotic systems. This is particularly important for hazardous environment that cannot be accessed frequently, such as underground mines. A virtual environment that closely replicates real-world conditions enables realistic simulation. This approach not only reduces the risks and costs of personnel entering dangerous environments but also enables tasks to be simulated in advance, thereby improving efficiency and safety.

LiDAR point clouds can capture the real-world geometry with high precision, but they cannot be fed directly into simulation engines. The main challenge is turning this raw data into a mesh that not only keeps the geometric detail but is also ready for simulation. This project developed a practical workflow to bridge this gap and provide a reliable way to build efficient, high-fidelity virtual environments for advanced simulation platforms.

NVIDIA Omniverse was selected as the simulation platform in this project because it offers key advantages beyond those of traditional simulators such as Gazebo. With its photorealistic visual fidelity and high-precision physics simulation, Omniverse is capable of producing highly realistic virtual world and accurately simulating dynamic interactions.

1.2 Aims and objectives

The primary aim of this project is to develop and evaluate a methodology for transforming raw LiDAR point cloud data from an underground mine into a high-fidelity virtual environment within NVIDIA Omniverse, which is suitable for realistic simulation.

To achieve this aim, the following specific objectives will be pursued:

- Investigate and implement pre-processing techniques for point cloud data, including denoising, filtering, and segmenting the raw LiDAR data for 3D reconstruction.
- Analyse and apply different surface reconstruction algorithms to convert the processed point cloud data into a 3D mesh model.
- Establish a pipeline for importing the reconstructed models into Omniverse, including the application of materials, lighting, and scene composition to enhance environmental realism.

- Validate the constructed environment through interactive application scenarios within Omniverse (e.g., virtual inspection or equipment navigation), and evaluate its performance in terms of visual fidelity, geometric accuracy, and real-time simulation, thereby summarising the strengths and weaknesses of the proposed methodology.

1.3 Report structure

The structure of this dissertation is organised as follows. Chapter 2 reviews the existing literature on point-cloud processing, 3D reconstruction techniques, and NVIDIA Omniverse. Chapter 3 describes the research methodology in this project, including data sources, processing workflow, 3D model generation, and the environment construction in Omniverse. Chapter 4 presents the experimental results together with an in-depth discussion, covering both the quality assessment of the reconstructed models and the performance evaluation of the Omniverse scenes. Finally, Chapter 5 concludes the dissertation and points out potential directions for future research.

2 Literature review

The transformation of raw point clouds into simulation-ready models involves three key stages: outlier removal, segmentation, and surface reconstruction. In the following subsections, representative methods in each stage are reviewed and compared.

Outlier Removal: Outlier removal is an essential preprocessing step in point-cloud processing. Two commonly used approaches are Statistical Outlier Removal (SOR) and Radius Outlier Removal (ROR), both implemented in the Point Cloud Library [1]. SOR relies on neighborhood statistics, whereas ROR is based on local density. Extensions such as Fast-SOR [2] and adaptive ROR [3] improve runtime and precision in large outdoor scans. Comparative studies [4], [5] show that while overall denoising quality is similar, SOR is generally more robust to non-uniform point densities, whereas ROR is sensitive to parameter tuning. These improvements remain incremental rather than fundamental, and for the mine dataset in this project, the standard SOR provides a reliable and efficient solution

Data Segmentation: Segmentation plays a central role in point cloud processing, as it allows individual objects or regions to be isolated for further analysis. Traditional model-driven approaches, such as Random Sample Consensus (RANSAC) [6], have been widely used to detect and fit simple geometric shapes like planes or cylinders. Later extensions [7] improved efficiency and robustness in noisy datasets. Despite their reliability, these approaches are limited to predefined shapes and cannot deal with complex and non-geometric objects, such as people or equipment in mine environment.

More recently, deep learning has enabled end-to-end feature learning directly from raw point clouds. Instead of relying on handcrafted features or explicit geometric models, these networks learn to extract spatial patterns directly from point coordinates and their local neighborhoods. Architectures such as PointNet [8], PointNet++ [9], PointCNN [10], PointConv [11], and DGCNN [12] have shown strong performance on benchmark datasets by capturing both global and local geometric features. However, these methods usually require large annotated datasets and heavy computational resources, which are not available in this project. Their reliance on domain-specific training data also makes them difficult to apply directly in industrial settings where annotated scans are scarce.

For these reasons, neither traditional automatic geometric nor deep learning-based segmentation fully satisfies the requirements of this project. To ensure precise and consistent results, particularly for objects such as humans, a manual segmentation strategy was adopted. While less automated, this approach provides reliable and high-quality input for the subsequent 3D reconstruction and simulation stages.

3D reconstruction: Surface reconstruction transforms discrete points into continuous mesh models suitable for simulation. Two widely used approaches are the Ball-Pivoting Algorithm (BPA) [13] and Poisson Surface Reconstruction (PSR) [14]. BPA is efficient and detail-preserving, but it assumes uniform sampling and produces non-watertight meshes with open boundaries. In contrast, PSR is more computationally demanding but can handle noisy and non-uniform data, generating watertight and smooth surfaces. To address the tendency of PSR to oversmooth, Kazhdan and Hoppe [15] proposed the Screened Poisson variant, which introduces a fidelity term to force the reconstruction to pass closer to the input samples. This results in watertight meshes that preserve finer details while retaining the robustness of the Poisson framework. A comparison of these methods is shown in Table 1.

In summary, existing methods for outlier removal, segmentation, and surface reconstruction each provide clear strengths but also notable limitations, making them effective for specific tasks but insufficient as complete solutions. Consequently, no single method can be directly applied to generate high-fidelity, simulation-ready environments from mine point clouds, especially when both robustness and fine detail must be achieved. To overcome this gap, this project proposes a hybrid workflow that integrates selected techniques across preprocessing, segmentation, and reconstruction. This tailored approach delivers reliable denoising, precise object-level separation, and meshes that are both watertight and detail-preserving, thereby enabling accurate and practical 3D environments for simulation in NVIDIA Omniverse.

Table 1. Comparison of surface reconstruction methods

Method	Strengths	Limitations	Typical use cases
Poisson Surface Reconstruction	Robust to noise and non-uniform sampling; generates watertight meshes	May oversmooth surfaces; can create artificial closures in regions without data support	Large-scale structures where watertight is required (e.g., tunnels, walls)
Screened Poisson Surface Reconstruction	Watertight while preserving finer geometric details; retains robustness of PSR	Requires careful parameter tuning; higher computational cost	Watertight models that must also retain local detail (e.g., textured walls, rough rock faces)
Ball-Pivoting Algorithm	Efficient; preserves local geometric detail; intuitive radius control	Requires dense and fairly uniform sampling; produces non-watertight meshes with open boundaries	Small objects where detail is important and watertight is unnecessary (e.g., tools, human)

3 Methods

3.1 Introduction

This chapter elaborates on the complete methodology employed to transform raw LiDAR point cloud data into a functional virtual environment within NVIDIA Omniverse. The entire workflow follows a systematic pipeline, encompassing four primary stages: (1) Data Source and Description; (2) Point Cloud Preprocessing and Manual Segmentation; (3) Object-Specific Hybrid 3D Mesh Reconstruction; and (4) Virtual Environment Construction and Simulation in Omniverse. Fig.1 illustrates the steps for creating a simulation-ready mesh.

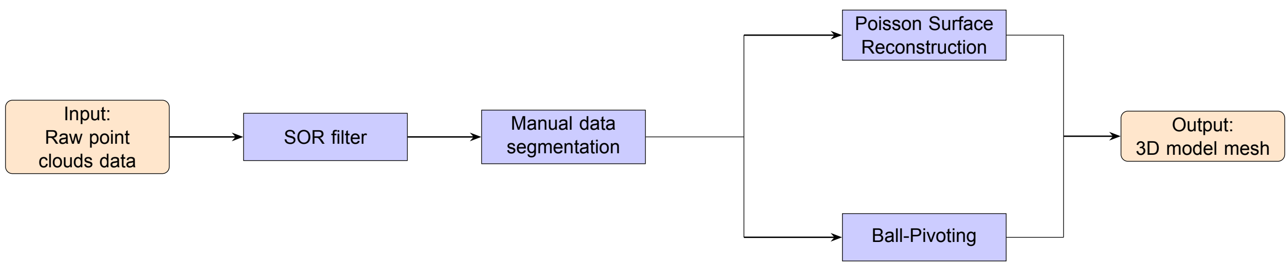
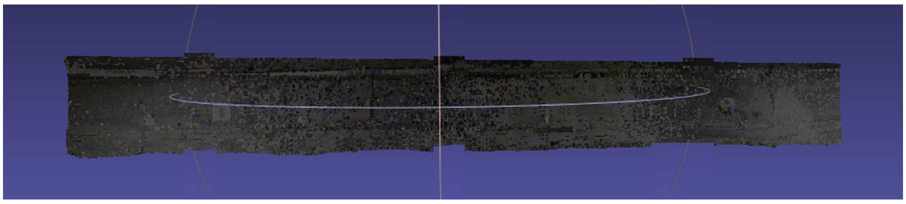
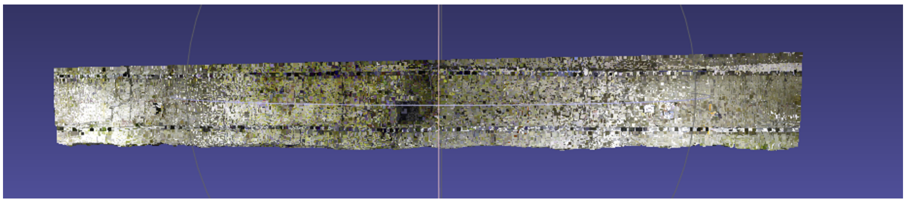


Fig. 1. Overall workflow, from point clouds data to 3D mesh

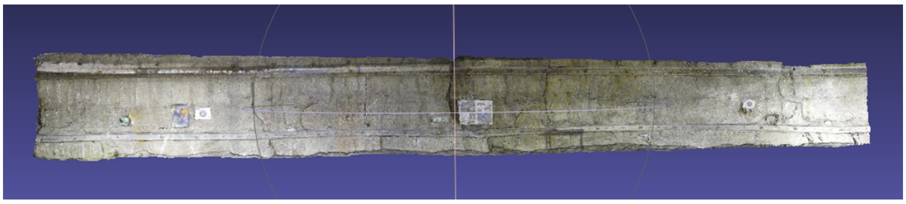
Fig.2 shows different file formats were adopted at each stages of the workflow. The raw point clouds were first exported in the industry-standard `.las` format, which efficiently stores coordinates, intensity, and classification information but lacks native support for surface normals. After preprocessing and normal estimation, the data were converted into `.e57`, a flexible exchange format capable of storing rich metadata and extended attributes such as normals, allowing 3D reconstruction. Finally, the reconstructed meshes were saved as `.ply`, a lightweight and widely supported format that preserves vertex normals, colors, and faces, and can be directly imported into NVIDIA Omniverse for simulation and visualization.



(a) `.las` (raw point cloud)



(b) `.e57` (with normals)



(c) `.ply` (mesh output)

Fig. 2. Comparison of data representations at different stages

3.2 Dataset description and source

Boulby Mine, located in North Yorkshire, is the UK's deepest mine, reaching a depth of 1.4 km. About 1.1 km below ground it hosts the Boulby Underground Laboratory, operated by the Science and Technology Facilities Council (STFC). Situated within an active polyhalite and rock-salt mine, this underground environment provides a unique and challenging setting for scientific research. Fig. 3 shows the overview of LiDAR survey and the selected section used in this project.

The point cloud dataset used in this study was provided by the CRADLE Robotics and AI team and was acquired using a Leica RTC360, a high-precision terrestrial laser scanner designed for rapid 3D reality capture. The scanner was tripod-mounted and manually repositioned at each scanning location and was triggered remotely.. All scans were performed in static mode, ensuring high stability and accuracy in the captured point clouds.

3.3 Preprocessing

All preprocessing and segmentation tasks on the point clouds were performed using the open-source software *CloudCompare v2.13.2* [16].

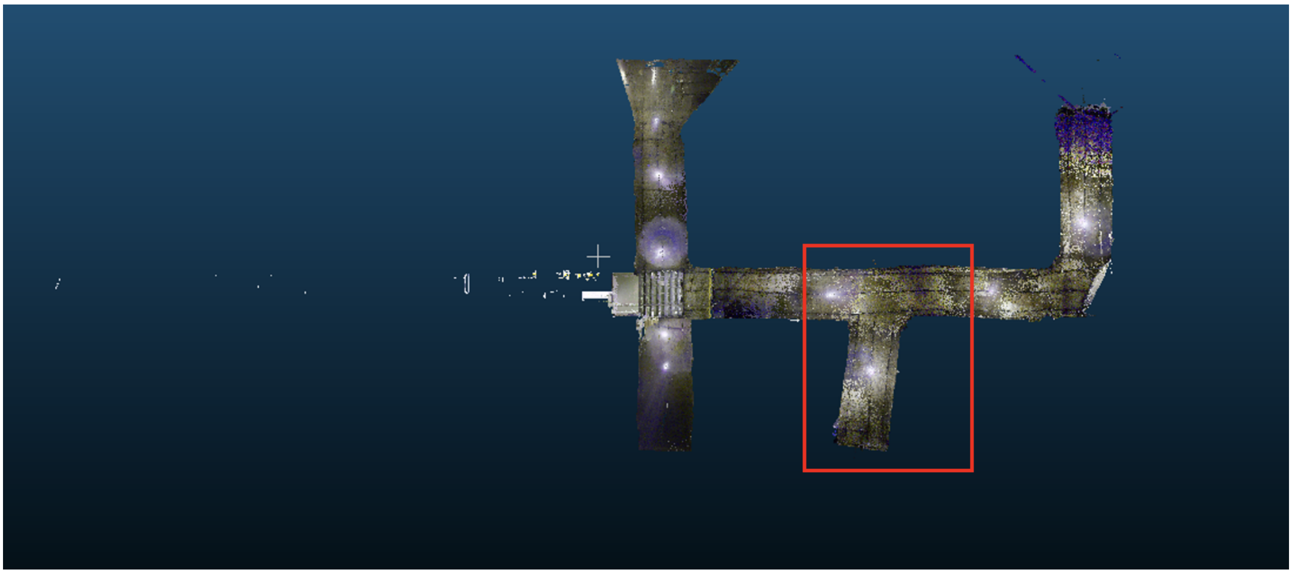


Fig. 3. Overview of the Boulby Mine LiDAR survey. Only the red-highlighted section was used for reconstruction in this project.

3.3.1 Statistical Outlier Removal Filtering

The Statistical Outlier Removal (SOR) filter is a statistical method designed to remove outliers from point cloud data. Its core idea is to evaluate the distribution of distances between each point and its neighbors, and then remove points that significantly deviate from the majority, assuming a Gaussian distribution of distances.

For each point p_i in the point cloud, the mean distance to its k nearest neighbors is computed as:

$$d_i = \frac{1}{k} \sum_{j=1}^{k} \|p_i - p_j\|, \tag{1}$$

where p_j represents the neighbors of p_i, and $\|\cdot\|$ denotes the Euclidean distance.

The set of all d_i values is assumed to follow a Gaussian distribution with mean μ and standard deviation σ. A point is considered an outlier if its mean distance satisfies:

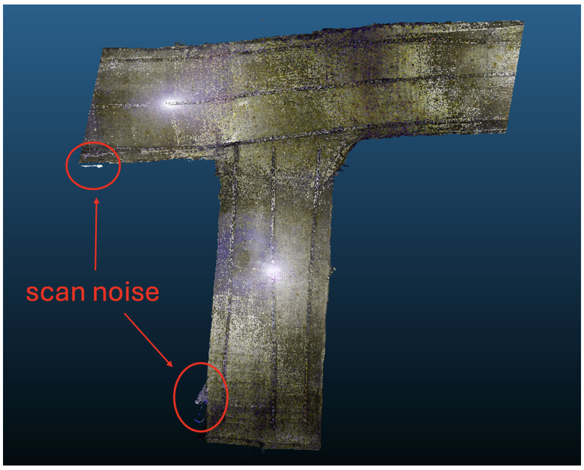
$$d_i > \mu + \alpha \cdot \sigma, \tag{2}$$

where α is a user-defined standard deviation multiplier.

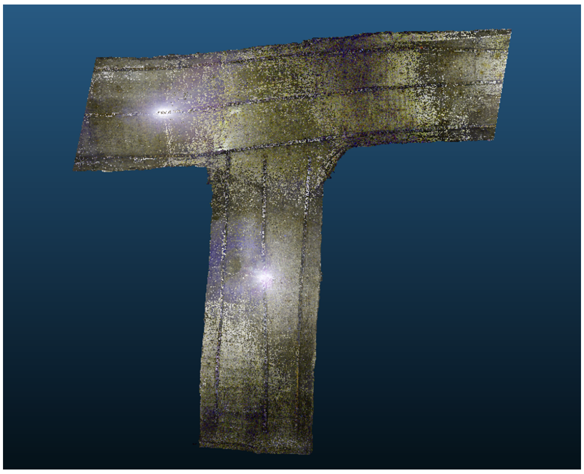
Number of neighbors (k): Defines the number of nearest neighbors used to estimate the mean distance. Larger values of k yield more robust results but increase computational cost.

Standard deviation multiplier (α): Controls the strictness of the filter. Smaller values of α remove more points, while larger values retain more points.

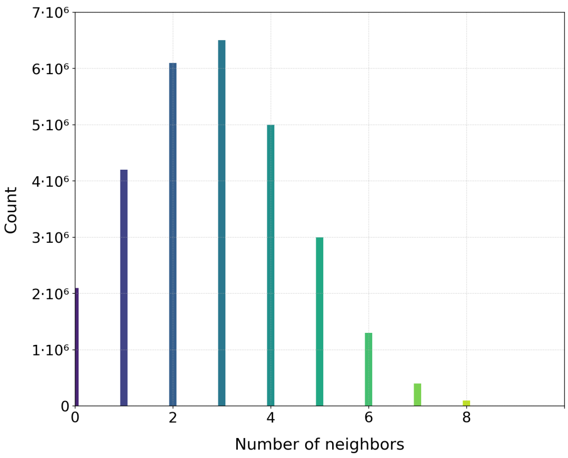
After applying the Statistical Outlier Removal (SOR) filter with the parameters set to $k = 20$ nearest neighbors and a standard deviation multiplier of $\alpha = 1.5$, it can be observed that the circled regions in the raw point cloud, which clearly are noise points, were effectively removed (Fig. 4a, Fig. 4b). Consequently, the total number of points was reduced from 28,639,263 to 25,802,581, indicating that approximately 2.8 million outliers were eliminated. In addition, the density distribution histograms highlight the improvement in data quality (Fig. 4c, Fig. 4d). Before filtering, a relatively large number of points had only 0–2 neighbors within a neighborhood radius of $r = 0.01$, which are likely to correspond to isolated or sparse points. After SOR filtering, the number of points with 0–2 neighbors was reduced by roughly half, and the overall distribution became more uniform and concentrated. This demonstrates that isolated noise points were effectively removed, thereby enhancing the robustness of subsequent reconstruction and registration processes.



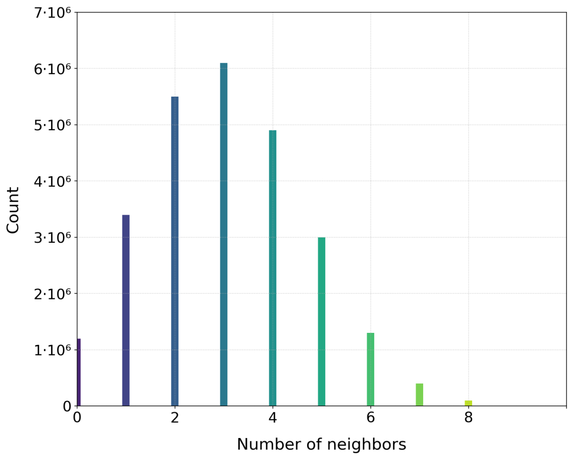
(a) Raw point cloud



(b) SOR filtering



(c) Density distribution (raw)

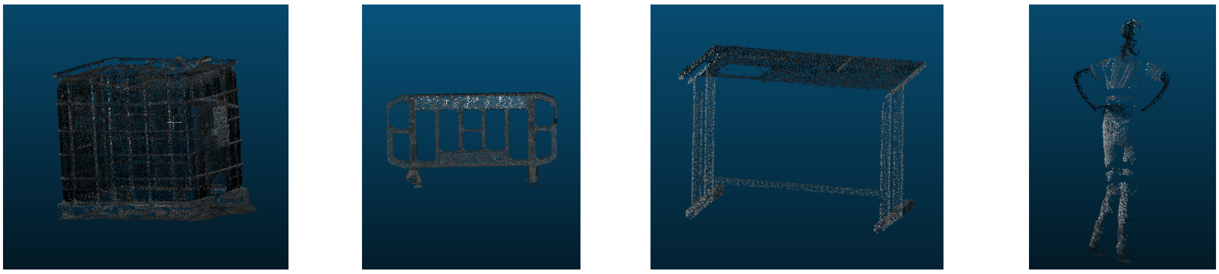


(d) Density distribution (SOR)

Fig. 4. Comparison of raw and filtered point clouds. In image(a), there are few obvious noisy points in the circle areas. After SOR filtering, the noise is removed as the (b) shows. Image (c),(d) shows within a neighborhood radius of $r = 0.01$, most points have 2–4 neighbors. Points with only 0–1 neighbors are likely noise. Their count decreases after applying SOR (d).

3.3.2 Data Segmentation

Manual segmentation strategy was employed to ensure the highest level of semantic accuracy and object-level independence. Using *CloudCompare*, the operator manually separated each object of interest in the point cloud—such as walls, floors, boxes, and human models—into distinct subsets based on visual assessment. Each object was then exported individually to prepare for subsequent independent mesh reconstruction.



(a) Box **(b)** Barrier **(c)** Table **(d)** Person

Fig. 5. Segmented subsets results: (a) box, (b) object, (c) table, and (d) person. Manual segmentation can provide object-level accuracy.

3.4 3D reconstruction

The 3D mesh reconstruction was carried out using the open-source mesh processing software `MeshLab` (Ver. 2013.12) [17]. In this project, a hybrid reconstruction strategy was adopted, in which either the Screened Poisson surface reconstruction or the Ball-Pivoting algorithm was selectively applied according to the characteristics of each point cloud subset.

3.4.1 Screened Poisson Surface Reconstruction

In order to better preserve the fidelity of the input point cloud, a screening term is added into the standard Poisson reconstruction energy. This term penalizes deviations of the implicit function from zero at the sample positions, ensures it passes through the input points $p \in \mathcal{P}$ as closely as possible. The resulting energy is defined as

$$E(\chi) = \int \|\nabla\chi(p) - \vec{V}(p)\|^2 \, dp + \frac{\alpha \cdot \text{Area}(\mathcal{P})}{\sum_{p\in\mathcal{P}} w(p)} \sum_{p\in\mathcal{P}} w(p)\,\chi^2(p) \tag{3}$$

where $\vec{V}$ is the vector field induced by the input normals, $\mathcal{P}$ is the set of input points, $w(p)$ denotes their weights, and $\alpha > 0$ is a parameter balancing smoothness and data fidelity. In this pipeline, we set $\alpha = 4$, an empirical value that provides a good balance in most cases and $w(p) = 1$ for all $p \in \mathcal{P}$, which assumes uniform confidence.

Minimizing this energy is mathematically equivalent to solving the *Screened Poisson equation*:

$$(\Delta - \alpha I)\chi = \nabla \cdot \vec{V} \tag{4}$$

where Δ is the Laplace operator and I is the identity operator. The solution χ is discretized using finite elements on an adaptive octree and then converted into a mesh by extracting the zero-level isosurface.

Implement The algorithm requires oriented normals as input, the first step is to compute consistent normals for the point cloud. In *MeshLab*, `Filters → Normals, Curvatures and Orientation → Compute normals for point sets` defines how many nearest neighbors are used to approximate the local tangent plane. A smaller neighborhood size makes the normals more sensitive to noise but can capture fine geometric details, while a larger neighborhood provides smoother and more robust normals at the cost of potentially oversmoothing small-scale features.

In MeshLab, the reconstruction was carried out via `Filters → Remeshing, Simplification and Reconstruction → Screened Poisson Surface Reconstruction`. Most parameters were left at their default values, consistent with the assumptions in our formulation ($w(p) = 1$, $\alpha = 4$). The reconstruction mainly depends on two parameters:

Reconstruction Depth controls octree resolution and balances detail versus computation cost, a larger depth enables the recovery of finer details but increases memory consumption and computation time, whereas a smaller depth produces a smoother surface with lower resolution. Fig. 6 illustrates the result of varying reconstruction depth. In this project, the reconstruction depth was set to 14.

Minimum Number of Samples regulates local sampling density to smooth noise or retain detail. The default value of 1.5 generally sufficient for denoised point clouds.

An important characteristic of the screened Poisson reconstruction is that it always produces a *watertight* surface. This is advantageous for our application, as tunnel walls, floors, and ceilings can be robustly represented as continuous meshes that are suitable for simulation and navigation. However, watertight may also introduce extra surfaces in regions without data support. To address this, we manually removed the extra geometry, leaving only the parts corresponding to the actual environment.

(a) Reconstruction Depth=8 **(b)** Reconstruction Depth=10 **(c)** Reconstruction Depth=14

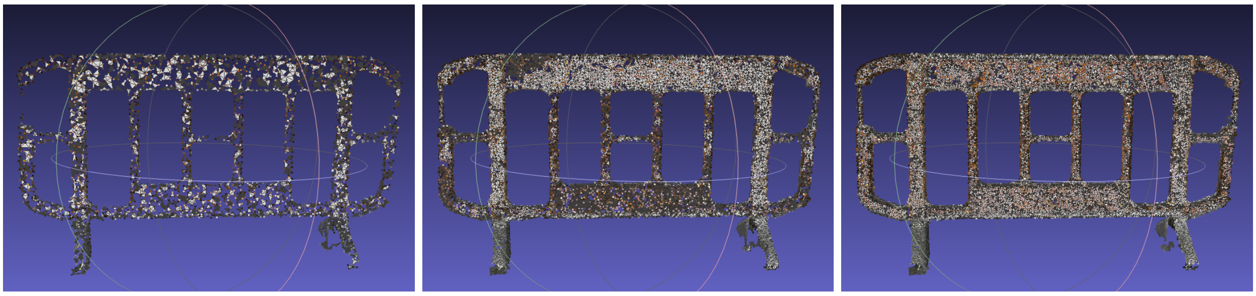
Fig. 6. Results of Screened Poisson Surface Reconstruction with different reconstruction depths. Increasing depth can produce better details but also increases computation and memory usage.

3.4.2 Ball-Pivoting algorithm

The Ball-Pivoting Algorithm reconstructs a triangle mesh by simulating a ball of radius r that "rolls" over the point cloud. Whenever the ball simultaneously touches three points without enclosing others, a triangle is generated. Starting from an initial position, the ball is incrementally pivoted around mesh edges to discover neighboring triangles until no further connections can be formed. The choice of ball radius is critical: it should be related to the average point distance, since a smaller ball radius will capture fine details but might leave holes if your points are far apart. A larger radius will bridge gaps but might smooth over small features. In this way, BPA naturally adapts to the density of the input data but assumes a relatively uniform sampling of the surface.

In practice, we employed the BPA implementation in *MeshLab* `Filters → Remeshing, Simplification and Reconstruction → Surface Reconstruction: Ball Pivoting`. The key parameter is the **pivoting ball radius**, which can be specified either in absolute units or as a percentage of the model's bounding box diagonal in the MeshLab interface. In this project, a practical workflow is to first press *Apply* without adjusting the settings, letting the software estimate a reasonable starting radius. If the resulting mesh shows excessive holes, then reduce the ball radius and apply again. Fig. 7 shows the result of different radius applied.

In this pipeline, most individual objects inside the mine were reconstructed using the Ball-Pivoting Algorithm. Environmental structures such as walls, floors and ceiling require watertight reconstruction to avoid holes and ensure complete surfaces, but objects inside the mine do not have this requirement. For these objects, the Ball-Pivoting Algorithm is preferred as it preserves fine details and achieves higher data fidelity.



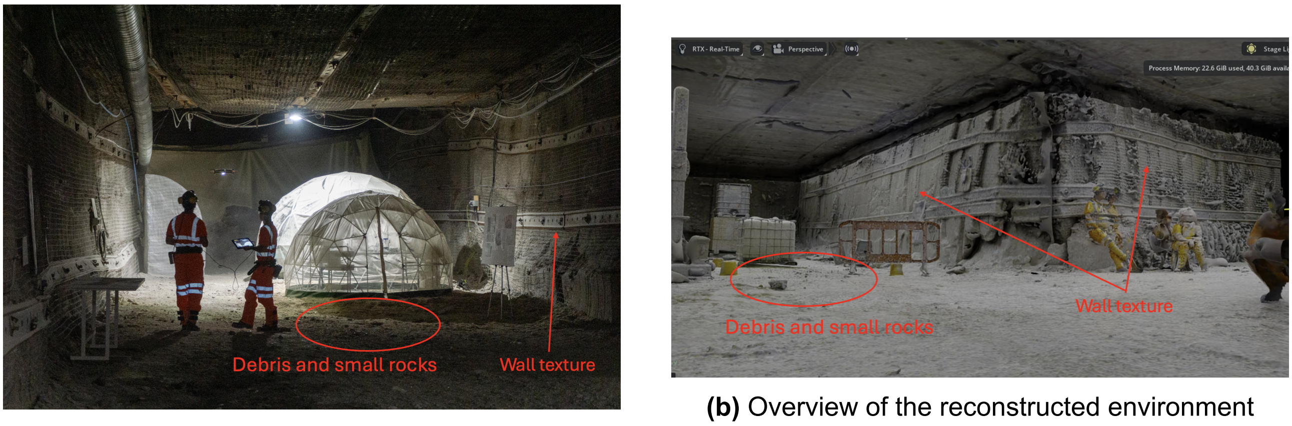
(a) Radius = 5% of bounding box. **(b)** Radius = 2% of bounding box. **(c)** Radius=0.5% of bounding box.

Fig. 7. Results of Ball-Pivoting Algorithm with different radius (percentage of bounding box). Smaller radius captures more fine details but may leave holes, while larger radius produces smoother surfaces that fill gaps.

4 Results and discussion

4.1 Introduction

Fig. 8 presents the comparison between real world and reconstructed environment. Although the two images are from different areas of the mine, they share several features—such as small ground debris and wall textures—illustrating the photorealism of the reconstruction. This also highlights the photorealistic visualization capability of Omniverse. In the following subsections, the simulation environment is analyzed based on its functional aspects through tests of interactivity, geometric fidelity, perception, and physical feasibility.



(a) Real photo of the mine

(b) Overview of the reconstructed environment generated from LiDAR data.

Fig. 8. Photorealistic reconstruction in Omniverse (b) reproduces debris and wall textures comparable to the real scene (a).

4.2 Environment Interactivity

Firstly, environment interactivity is evaluated. Fig. 9 demonstrates dynamic object-level modifications. Specifically, experiments were conducted by duplicating and removing individual objects within the environment, simulating real-world scenarios such as adding obstacles, or replicating structures for diversity testing. The results indicate that the constructed environment preserved geometric and topological consistency while responding in real time to object insertion and deletion. This demonstrates that the environment is not merely a static model but can function as an interactive platform for further simulations and testing. However, the manual segmentation mentioned in subsubsection 3.3.2 cannot eliminate the object's shadow on the ground when the object itself is removed.

(a) Original **(b)** Bright orange barrier removed. **(c)** Bright orange barrier duplicated.

Fig. 9. Environment interactivity tests (a) original scene, (b) Bright orange barrier removed, and (c) Bright orange barrier duplicated.

4.3 Geometric Fidelity

The geometric accuracy of the reconstructed environment was quantified using a point-to-mesh distance analysis between the generated mesh and the original LiDAR point cloud. Fig. 10 shows the histogram of signed distances, demonstrates that the reconstruction process successfully preserved the underlying geometry with minimal deviation. This indicates that most reconstructed surfaces closely align with the input point cloud. Fig. 11 illustrates the spatial distribution of the errors, showing that deviations mainly occur inside the mine, especially in blocked regions and in areas corresponding to human. Meanwhile, the overall structural components, such as walls and floors, remain well preserved. These results confirm that the reconstruction achieved high geometric fidelity.

4.4 Perception Validation

To validate whether the reconstructed environment can be perceived by sensors, we conducted perception experiments using both LiDAR and camera-based detection. Fig. 12 illustrates the simulated LiDAR scanning results within the simulated environment in Omniverse, showing that the reconstructed scene can be reliably sensed. This confirms that the generated mesh not only provides visual realism but also maintains sufficient geometric properties to support sensing. Human detection was performed using an Intel RealSense D455 RGB–D camera. The algorithm converts RGB frames to HSV and thresholds the yellow range to segment the subject's safety vest, thereby localizing the person in the scene. The person-to-camera distance is then obtained from the depth

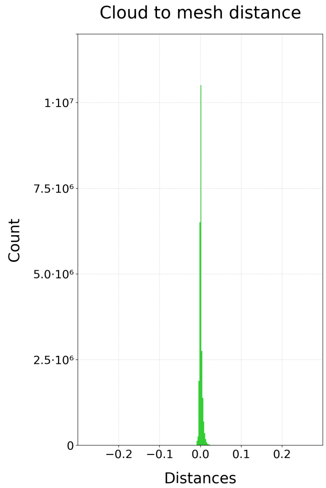


Fig. 10. Point-to-mesh distances between the reconstructed mesh and the point cloud. The majority of points lie within a very narrow range around zero, indicating that the reconstructed mesh closely matches the input geometry.

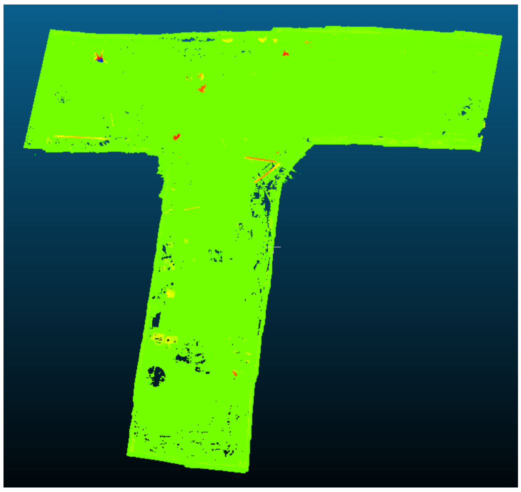


Fig. 11. Point-to-mesh error distribution of the reconstructed model. The color map indicates the magnitude of the distance error, with green representing small errors, yellow medium errors, and red large errors.

image of the depth camera. As shown in Fig. 13, the system successfully identified and localized a person in the environment, demonstrating that the reconstructed environment can support higher-level perception tasks, such as object recognition. Together, these results establish that the environment is not only geometrically accurate but also sensor-ready, enabling robotic applications such as navigation and human-rescue tasks.

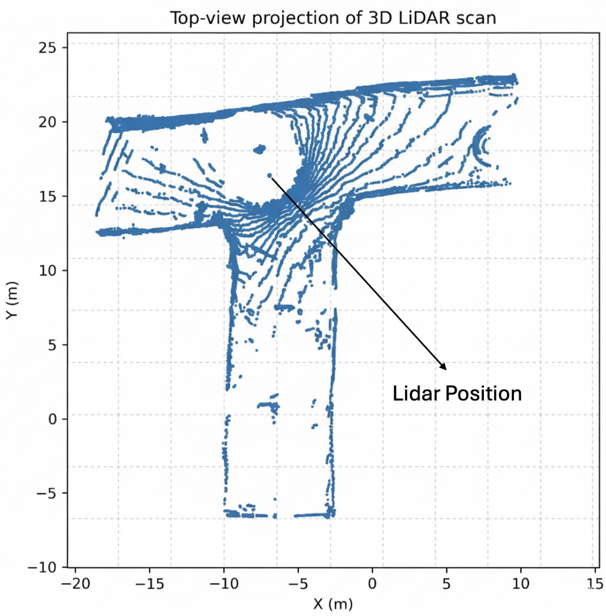


Fig. 12. Top-view projection of simulated 3D LiDAR scan result in the simulation environment. The surrounding environment can be detected by LiDAR.

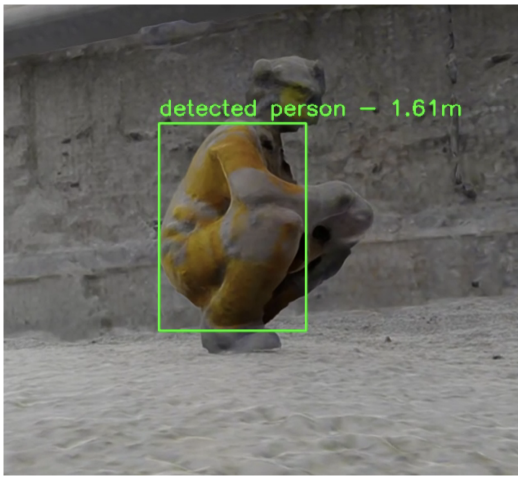


Fig. 13. A human in the environment was successfully detected and localized based on the color of the safety vest.

4.5 Physics and Collision

The physical feasibility of the reconstructed environment was evaluated through collision tests, as illustrated in Fig. 14. Collision boxes and rigid bodies were assigned to the mesh so that the robot could interact with the environment during navigation. In the simulation, the robot correctly stopped when it encountered walls or obstacles, showing that the reconstructed environment can provide reliable collision responses. This confirms that the environment is not only visually and geometrically accurate but also physically consistent enough to support robotic navigation experiments.

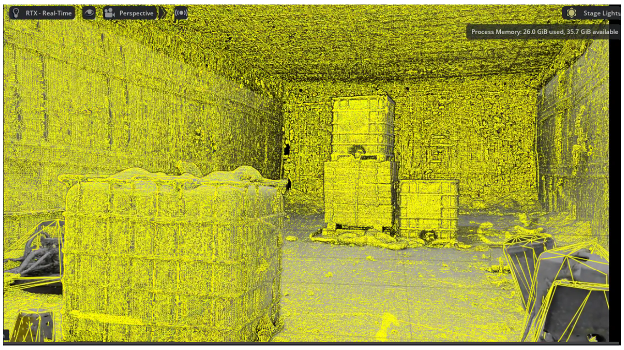


Fig. 14. Collision boxes added to the reconstructed environment.

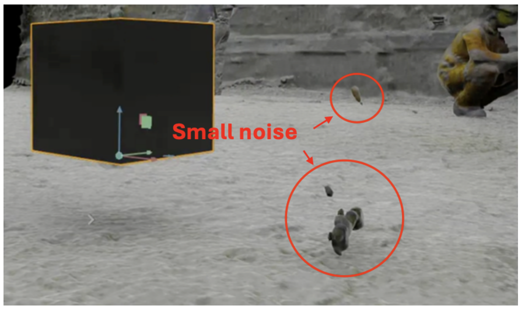


Fig. 15. Small residual noise from Screened Poisson reconstruction, which required manual removal during post-processing.

4.6 Discussion and Limitation

Based on the above evaluations, the proposed pipeline demonstrates the ability to transform raw point cloud data into a simulation-ready environment that maintains photorealism and high-fidelity physics within Omniverse, thereby supporting a variety of robotic simulation tasks. However, the current approach cannot be fully automated, which means that reconstructing very large-scale environments still requires a large amount of time. Although the point cloud was denoised, the Screened Poisson reconstruction method still produced a small number of residual noise in Fig. 15, particularly when generating large surfaces, which had to be manually removed. In this project, some human meshes appeared incomplete due to limitations in scan quality, likely caused by subject movement during scanning or blind spots that prevented full coverage. These issues could be mitigated by improving LiDAR scanning precision or applying mesh repair techniques during post-processing.

5 Conclusions and future work

This study has demonstrated that raw LiDAR point clouds can be transformed into simulation-ready environments in NVIDIA Omniverse, allowing robots to operate in high-fidelity digital world that closely approximate real conditions in hazardous settings such as underground mines. By demonstrating the creation of a high-fidelity environment, the project confirms that Omniverse provides a powerful platform for conducting realistic and reliable robotic simulations. Future work should focus on developing more automated and robust reconstruction pipelines, minimizing reliance on manual intervention and enabling the automated handling of complex environments. It will also be important to ensure that the environment can adaptively respond to conditional changes—for example, removing an object should simultaneously remove its associated shadow—to maintain consistency in both geometry and visual realism. Another key contribution of this work is that it provides a solid foundation for developing digital twins. To achieve digital twin will require real-time data integration, continuous synchronization with the physical environment, and scalable dynamic updating.

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Appendices

A Project outline

MSc Dissertation Project Outline

Yu-Chuan Liao
MSc in Robotics
Supervisor: Dr. Simon Watson

June 30, 2025

1 Motivation

The convergence of real-time graphics and physics-based simulation is paving the way for an industrial metaverse, where high-fidelity digital twins serve as virtual proving grounds for complex systems. This paradigm shift is particularly critical in the robotics industry, which faces increasing complexity in robotic simulations and a heightened demand for effective simulation between virtual and physical environments. Traditional simulation platforms are frequently limited by a lack of physical fidelity and suboptimal accuracy. Addressing these shortcomings, NVIDIA Omniverse is engineered with a core focus on high fidelity, delivering both physics-based precision and photorealistic visuals.

In this project, we leverage the Omniverse platform for robotic simulation, utilizing pre-existing data acquired from a high-precision LiDAR scanner. This methodology aims to substantially reduce the gap between simulation and reality, facilitating experimentation that is safer, more cost-effective, and highly scalable.

2 Scope

The scope of this project is centered on the end-to-end process of reconstructing a high-fidelity, photo-realistic environment within NVIDIA Omniverse and subsequently using it as a validation platform for robotic simulation. The process begins with leveraging pre-existing spatial data from high-specification LiDAR systems to create a functional digital twin of a real-world location. The primary emphasis is placed on achieving a high degree of realism and physical accuracy in this reconstructed environment.

Following the successful reconstruction and validation of the environment, a pre-defined robotic model will be deployed to simulate and analyze its physical interactions with the surroundings. This serves as a practical demonstration of the environment's utility and fidelity.

Key In-Scope Activities

- Processing pre-existing LiDAR datasets for simulation, including their conversion into optimized 3D meshes or point clouds.
- Importing and meticulously reconstructing the environment in NVIDIA Omniverse, with a focus on configuring accurate terrain geometry, material properties, and physics-based interactions.
- Deploying a standardized robotic model into the completed environment to execute a series of defined simulation scenarios.
- Analyzing simulation data, such as collision events and path traversal, to assess the environment's impact on robotic operations.

This project does not include the development, training, or comparative performance evaluation of robotic control algorithms and the design or modification of the robotic model itself.

3 Aims

The principal aim of this project is to develop and evaluate a methodology for creating high-fidelity digital twins from real-world sensor data using NVIDIA Omniverse, and to assess its efficacy and utility as an advanced simulation platform for robotic systems.

4 Objectives

To achieve the stated aim, the project will pursue the following objectives:

- To process pre-existing 3D spatial datasets, originally captured via LiDAR and camera systems, to prepare them for ingestion into the simulation platform.
- To reconstruct the processed data within NVIDIA Omniverse to create a high-fidelity digital twin, focusing on the accurate configuration of its geometry, materials, lighting, and physics properties.
- To integrate and configure a standardized robotic model within the reconstructed environment using the NVIDIA Isaac Sim application.
- To conduct a quantitative evaluation of the end-to-end workflow, assessing the reconstructed environment's realism and the simulation platform's usability for robotic applications.

B Risk assessment

MANCHESTER 1824
The University of Manchester

General Risk Assessment Form

Date:	Assessed by:	Checked by:	Location:	Assessment ref no	Review date:
01/07/2025	Yu-Chuan Liao	Dr. Simon Watson	Home/Nancy Rothwell Building		
Task / premises: Working for MSc Dissertation in home and Nancy Rothwell Building					

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Working from home	Lone working	Home working staff Isolated,	1. Please refer to the University Lone Working policy and guidance for more information 2. Please refer to the new University Working at Home guidance 3. Please refer to the new University Wellbeing Support website 4. Staff are able to have regular direct contact with line manager and colleagues via phone, Teams, Zoom or email	Low	A
Working from home	Poor posture, repetitive movements, eye strain, from long periods looking at DSE (display screen equipment)	Staff, students, visitors Back strain (due to poor posture). Repetitive Strain Injury (RSI) to upper limbs. Eye strain.	1. Please refer to the DSE policy, guidance and poster for more information on how to set up your workstation properly 2. Complete DSE Self-Assessment for your home working at least every 2 years but sooner if any changes or pain is experienced. 3. Complete Homeworking self-assessment checklist 4. Set up workstation to a comfortable position with good lighting and natural light where possible 5. Take regular breaks away from the screen 6. Regularly stretch your arms, back, neck, wrists and hands to avoid repetitive strain injuries. Refer to seated exercises 7. Set up a desktop working space where possible and try to avoid working on a laptop without a docking station, separate keyboard or mouse 8. Small equipment purchases of up to £50 to assist with working from home, contact local administration for more details. 9. If experiencing ill-health issues contact your local DSE assessor or local safety advisor who will perform a full DSE assessment. 10. Occupational health referral where issues cannot be resolved from full DSE assessment. 11. DSE users should have regular eye tests, follow guidance 12. FSE run monthly DSE awareness sessions on Teams	Low	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Working from home	Stress / Wellbeing	Home working staff Psychosocial effects Work / Life imbalance Anxiety Poor performance Fatigue & Tiredness	1. Please refer to Stress Prevention and Management toolkit for policies and guidance 2. Please refer to new University guidance for Managing teams working from home 3. Please refer to Seven rules of home working published by AMBS 4. Please refer to Guidance for Managers and Guidance for Staff 5. Complete training Work Related Stress: Identification, Prevention & Management (Online) 6. The University Stress Assessment tool can be used to highlight the main factors for an individual that are recognised as having the potential to lead to work-related stress 7. Projects, work plans and objectives to be discussed and agreed with line manager regularly 8. Refer to full FSE Stress Risk Assessment 9. Regular contact meetings with manager and peers via Teams, Zoom, email and phone 10. Define working hours, set a start & close daily routine, and prioritise your tasks. 11. Individual may self-refer to Occupational Health Service or to the Counselling and Mental Health Service 12. Manager / Employee consultation, wellbeing focused	Low	A
Use of electrical appliances	Misuse of electrical appliance, faulted electrical appliance.	Home working staff Electric shock, burns and fire	1. All office equipment used in accordance with the manufacturer's instructions 2. Visual checks before use to make sure equipment, cables and free from defects 3. University IT equipment brought home should already be PAT tested, small electrical items can be tested through the FSE I&F team 4. The domestic electrical supply and equipment owned by the employee is the responsibility of the employee to maintain 5. Liquid spills cleaned up immediately 6. Defective plugs, cables and equipment should be taken out of use	Med	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Moving around the home office	Obstructions and trip hazards	Home working staff Slips, trips and falls causing physical injury	1. Floors and walkways kept clear of items, e.g. boxes, packaging, equipment etc 2. Furniture is arranged such that movement of people and equipment are not restricted 3. Make sure all areas have good level of lighting 4. Reasonable standards of housekeeping maintained 5. Trailing cables positioned neatly away from walkways 6. Cabinet drawers and doors kept closed when not in use	Med	A
Working from home	Fire	Staff Home Working Risk of burns, smoke inhalation, asphyxiation	1. In the event of a fire evacuate out of the building and call the fire brigade on 999 2. All waste, including combustible waste, removed regularly 3. Heaters located away from combustible materials and switched off when not in use, don't leave heaters unattended 4. Avoid daisy chaining and do not overload extension leads 5. Test smoke alarm routinely and replace batteries every 6-12 months 6. Please refer to fire brigade Home Fire Safety and Smoke Alarms	Med	A
Working from home	High risk activities	Staff Home Working Personal injuries / accidents	1. Only office activities with IT equipment and associated peripherals are carried out without further specific risk assessment	Low	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Working from home	Manual handling	Staff Home Working Back pain bruises, sprains, strains, fractures.	1. When ordering goods the intended recipient must first check the weight and dimension of the delivery. Please use page 7 of the HSE weight guide to help determine if the item is too large, bulky or heavy to be received at home by the recipient. Item should only be delivered to a home address if it is below 25kg and can be comfortably carried by the recipient 2. Staff are trained via SLD courses (TLCO510 or TLCA500 as appropriate), and familiar with correct handling technique and seek assistance when needed 3. Use kinetic lifting techniques e.g. feet apart, load held close and in front of the body. If lifting off the floor, bend knees and keep the spine neutral. 4. Ensure there is a firm grip on the item whilst moving 5. Ensure trip hazards are removed on route from the front door to where the item is to be located. 6. Do not store large, heavy, fragile or cumbersome items at height (e.g. on high shelves or on top of cabinets/bookcases etc.)	Low	A
Working on campus	COVID infection through close contact or the contact with surfaces which may have been contaminated by previous users	Staff, students, visitors Infection of respiratory illness	• COVID restrictions have ceased in the UK. • Face coverings and hand sanitisers remain available at main entrances of University buildings.	Med	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Working on campus	Building fire	Staff, students, visitors If present within the building during a fire Burns, Smoke inhalation	• Induction arrangements cover security and fire awareness and include how to locate and use a fire door to exit the building and the location of the fire assembly point(s). • All new staff should complete fire awareness e-training TLCF100. • Fire Action notices are displayed around the building • Fire alarm system are in place and tested weekly on day at time to enable users to identify the sound of the alarm, see fire action notice at entrance to buildings. • Fire evacuation practices are carried out annually as a minimum • Building users are empowered to activate the fire alarm if a building evacuation is necessary during an emergency • Induction covers the importance of maintaining clear fire exit routes and keeping the doors closed unless essential. Induction also covers the need for high general housekeeping standards. • Ready access to fire extinguishers is available for use by trained users. • Staff 'hosts' are responsible for the safety and evacuation of visitors. • Evacuation marshals attend suitable training and assist where possible during evacuations during normal working hours. Requests to work out of hours include emergency action in case of fire and use of fire routes and doors.	Med	A
Working on campus	Injuries or ill health	Staff, students, visitors	• First aiders are available and First Aid Notices are displayed around the building • All Campus Security staff are first aid trained. Security contact details are 0161-306-9966. This telephone number can be found on the back of staff/student ID cards. • AEDs/ Defibrillators are located throughout campus, please see map for nearest location	Med	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Use of office electrical equipment, both Personal and University Owned	Electric shocks Fire Damage to other electrical equipment Misuse of electrical appliance, faulted electrical appliance.	Staff, students, visitors Burns, Smoke inhalation,	• All University electrical equipment will undergo Portable Appliance Testing. • Staff are discouraged from bringing in own electrical equipment as maintenance cannot be assured. • Personal Equipment will also need to undergo portable appliance testing before use within UoM buildings. • Any damaged equipment should be taken out of service and either replace or repaired. • All equipment whether personal or UoM owned must comply with relevant standards such as the British Standard or EU standards. • All equipment should be used in accordance with the manufacturer's instructions. • Liquid spills near electrical equipment should be cleaned up immediately. • Extension cables should be avoided as much as possible. Daisy-chaining is not permitted. • Visual checks before use to make sure equipment, cables and free from defects • Defective plugs, cables equipment etc. should be taken out of use and be reported for repair/replacement.	Low	A
Use of display screen equipment Repetitive/prolonged use of equipment or tasks	Incorrect posture whilst using DSE Incorrect workstation set up Prolonged use without breaks Electrical hazards	Staff, students, visitors Musculoskeletal injuries/disabilities Limb disorders Eye strain Headaches Back pain Repetitive strain Fatigue Electric shock	• Please refer to the DSE policy, guidance and poster for more information on how to set up your workstation properly • Complete DSE Self-Assessment for a Safety Advisor to review and report back with any recommendations or actions. • Seats should be stable and adjustable to provide comfort • Set up workstation to a comfortable position with good lighting and natural light where possible • Take regular breaks away from the screen. • Regularly stretch your arms, back, neck, wrists and hands to avoid repetitive strain injuries. Refer to workstation exercises here • Provision of adjustable equipment and furniture available following DSE assessment • Refer to use of electrical equipment. • Any work of a repetitive nature must be subject to a separate risk assessment in consultation with a Safety Advisor	Low	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Working on campus and traversing around the buildings	Building defects and poor housekeeping	Staff, students and visitors. Discomfort while working and physical injuries if building defects cause an accident Slips, trips and falls	• Defects or concerns can be reported to Estates Helpdesk by calling 0161 275 2424 or using the on-line reporting form Estates Helpdesk • Reasonable standards of housekeeping should be maintained and checked on regularly. • Floors kept clean, dry and clear of obstructions particularly exit routes. Spillages to be cleared immediately • Cabinet drawers and doors are kept closed when not in use. Items should be stored securely to avoid items falling or people colliding with protruding items. • Trailing cables must be positioned neatly away from walkways or secured and highlighted with hazard tape. • Fan heaters or air conditioning units should not be brought into the space unless facilitated by Estates. • Waste bins are supplied for general and recyclable waste reducing the build-up of rubbish in corridors and spaces. • All communal spaces should be treated with respect and House services will be conducting regular cleaning of these spaces. • Adequate lighting is based on identified activities/tasks in the areas as deemed sufficient during building design specification. • Emergency lighting will turn on if standard lighting system is faulty to ensure there will always be light in the areas.	Med	A

Activity	**Hazard**	**Who might be harmed and how**	**Existing measures to control risk**	**Risk rating**	**Result**
Working out of hours	Potential for lone-working Changes to the environment during evenings and weekends	Staff, students, visitors More vulnerable. Difficulty in contacting help/assistance	• Out of hours working to be approved by line manager/ Academic Supervisor beforehand. • Minimise the duration and frequency of working out of hours. • Carry a charged up mobile phone on person at all times. • Be aware of out of hours safety protocols, including security contact telephone numbers, evacuation and first aid information. • General building and campus support will be reduced out of hours. • Inform someone beforehand of the planned lone working (time, location and duration). Set up a buddy system so you contact someone at regular intervals (within the building if possible or by telephone /emails/ Teams etc.) • Accompanied buddy is for high-risk activities = Work with another person in the same area in close proximity • Remote buddy is for low-risk activities = Regular contact with another person via visits, phone, texts or emails • SafeZone app can be set with a check-in timer during out of hours use. Should the timer not be switched off, security and/ or remote buddy will be alerted to call occupant. • In an emergency or if in need of first aid call Campus Security on 0161 3069966 •	Med	A

Activity	Hazard	Who might be harmed and how	Existing measures to control risk	Risk rating	Result
Work pressures	Stress	Staff, students, visitors Stress related illness (causes may include: pressure of work, insufficient support from colleagues/line management)	• Please refer to Stress Prevention and Management toolkit for policies and guidance • Please refer to Guidance for Managers and Guidance for Staff • Complete training Work Related Stress: Identification, Prevention & Management (Online) • The University Stress Assessment tool can be used to highlight the main factors for an individual that are recognised as having the potential to lead to work-related stress • Projects, work plans and objectives to be discussed and agreed at annual PDR or more frequently if required. • Refer to full FSE Stress Risk Assessment • Regular contact meetings with manager and peers, Skype, Zoom, Phone • Define working hours, set a start & close daily routine, and prioritise your tasks. • Individual may self-refer to Occupational Health Service or to the Counselling and Mental Health Service	Low	A

Action plan

Ref No	Further action required	Action by whom	Action by when	Done