INVESTIGATING APPLICATIONS OF MACHINE LEARNING IN CONSTRUCTION COMPLIANCE SYSTEMS

With 3D Point Clouds

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Abstract. Modern construction compliance techniques are flawed and relies on human-centred techniques to identify disparities in construction. Emerging technologies such as machine learning provides effective solutions that can outperform any current compliance checking techniques. This paper investigates the applications of machine learning in construction documentation and compliance checking. An analysis system is created from a neural network which is trained on artificially generated construction scenarios. After the system has learnt the features of a building schedule through the process of machine learning, it categorises collected point clouds using self-defined 'shape grammar'. By performing 3D scans on site or remotely through UAVs, a high definition point cloud is created which, using the analysis system, can examine the point cloud and separate it into different categories; a process called semantic segmentation. The virtual model can then be directly compared against the digital or planned model using the dimensions of model features. The system proposed can produce a compliance check or quantitative score as well as flagging key areas that require intervention. The outcome aims to produce a system which is effective in maintaining the compliance of a building during development and overall lowers the risks of structural collapse, in order to define construction liabilities and increase the safety of property inhabitants.

Keywords. Compliance, Machine Learning, Point Cloud.

1. Introduction:

The development of a building or structure begins with a design proposal, which includes construction plans and digital models which are load tested and run through construction simulations to ensure the safety and integrity of the structure. During the construction stage, oversights and purposeful shortcuts can create problems in the final product which can cause structural failures, collapses and potential threats to building inhabitants. Unfortunately, it is difficult to accurately regulate and monitor progress during the construction; where most quality assurance checks by third parties or regulating bodies are performed after the construction has already completed (ABCB, 2018). At times, inspections are performed on site during the construction phase, but it is difficult to make exact measurements, especially if the structure is in an unstable state where direct examination is not possible. Additionally, it is difficult to inspect areas of the structure where manual measurements are logistically impossible such as external facades and enclosed foundations.

There have been instances in history where issues in construction compliance has cause of structural failure. Notably, the Sampoong department store failure in South Korea 1995. The building started showing cracks and eventually the roof gave way due to the main columns collapsing causing a total structural failure. An investigation further revealed that cost reductions and construction malpractice actioned by corrupt officials caused the construction of the building to be crippled. Simple construction changes resulted in a devastating outcome after this tragic event unfolded, international building regulations and building codes were revised and enforced to ensure such a tragic event would not happen again. However, these issues are still occurring, where in Australia the Opal Tower in Sydney Olympic park experienced the same cracking in the structure of the building. An investigation was performed by NSW planning, which revealed that structural failure was caused by non-compliant support beams and errors during construction, along with several other design failures. Major structural failure was avoided in this instance due to the fast response rate and evacuation of residents. However, a system is essential to prevent oversights and negligence in all stages of building development.

A real-time compliance checking system would be the preferred method of regulating building standards and quality during construction. A potential solution to this problem is to create a neural network which utilizes 3D model data which have features that are pre-categorized. Once converted into a 3D Point cloud, the artificial dataset has been created which can then be fed into the neural network to create a standalone shape grammar. Unlike RGB segmentation (Lawin et al, 2017) conducted in "Deep Projective 3D Semantic Segmentation", the neural network will classify based on point relations and neighboring context. By having this newly created shape grammar, the system should be able to look at a real 3D point cloud and apply classifications to point clusters based on previous information using the inference engine. The system can be scaled or tested on various levels of detail (LOD), which means that each stage of the construction process; from LOD 100 (Conception model) to LOD 500 (As built model) (NATSPEC NBP001, 2013). The advantages of this system are that models can be archived following the construction process; changes can be made if an issue is flagged and that measurements can be made virtually instead of on site if required for later amendment. This solution will save time and money as well as increasing the safety and reliability of the building.

2. Research Aims

The aim of this research is to investigate the applicability of machine learning in the context of compliance checking systems within the built environment.

3. Research Questions

How can emerging technologies like machine learning be used to improve compliance checking processes?

What are the limitations in utilizing machine learning or machine centered analysis systems in comparison to human centered approaches?

4. Methodology

The overarching methodology this research project adopts is an adapted form of action research applied in a design technology context. Action research typically iteratively cycles through four keys phases of planning, acting, reflecting, and adapting. This is reflected in the research project described here in the way that the initial action plan will be written up with various documentation procedures detailed. The initial testing results will be quantified and scored in a scientific manner; however, it will then be evaluated as a potential replacement of traditional workflow processes. After evaluations have been made in early testing, further refinement will be added to increase effectiveness or relevance in context to design development. This process closely follows the "Application of AR Criteria to a DR Exemplar" as detailed by (Cole et. 2005) where action research drives the criteria and design research forms the assessment and outcome reflection. To generalise the research methods, parts of the research covers traditional scientific research with a hypothesis and aim, however; focuses on human centred use of the research in the context of design. To conclude, by detailing action research using the characteristics of “Process Model, Structure, Typical Involvement and Primary Goals” (Baskerville, 1999), the resultant can be assessed using design research criteria (Cole et. 2005). It is expected that the case study will go through several iterations however the research aims will remain the same throughout experimentation.

5. Background Research/Literature review

5.1 PREVIOUS CASE STUDIES:

5.1.1 A 3D Point-cloud-based Verification of As-built Construction Progress

There have been several studies that have explored methods in documenting the construction process; notably in “A 3D Point-cloud-based Verification of As-built Construction Progress” (Shih & Wu, 2005). The paper explores the collection of a 3D point cloud to monitor the construction process, and then represent the data digitally. The technique collects a two point clouds, one earlier in construction schedule, and one in a later time. By using the technique of a Boolean intersection function, they can isolate the differences between each scan, revealing the progress between two timeframes. This is effective for archival processes and datalogging, and can be used for manual observational differences, however, is not sufficient in detailing inconsistencies on a large scale. Additionally, any large changes during the initial foundation stage such as facades or large envelope and changes in LOD will result in inconsistencies and problems as scans are only performed on surface level. The data generated from these scans are still generic in value and are not categorized to specific parts. Consequently, the automation involved in such a process is limited to clusters of points and any meaningful information retrieved from the Boolean set would still have to be further analyzed by human experts. In the effectiveness of checking for construction compliance, it is only able to “provide geometric property for dimension related checks” (Shih & Wu, 2005) which is only effective up to LOD 200 representation of geometry (NATSPEC NBP001, 2013). The authors acknowledge these limitations by stating that it “only illustrated its usefulness in solving one single construction aspect which is the reversed working process of design verification by as-built data” and further specified the limitations in function due to factors in data manipulation requiring manual interaction. (Shih & Wu, 2005)

5.1.2 Automated floor plan reconstruction from Point clouds

In another research project exploring the viability of automated 3D models of interior spaces using the point cloud method (Budrion and Boehm 2010), focuses are on sweeping techniques. This technique aligns points to flat planes which are then intersected to create a floor plan. The method is quite effective in automating the process of scanning to floor plan but still does not identify individual features of a structure and planar features such as windows may be incorrectly identified as walls as a result. The paper includes in depth information about the segmentation techniques and goes well in depth to the problems and solutions encountered for each method. The result is a system that fully automates the conversion of a point cloud to a floor plan with wall heights. This still isn't effective enough as the overall level of detail remains at around LOD 200. Noisy data and very precise geometry is filtered out during the sweeping process so the accuracy of more complex forms will not be converted correctly. However, this technique will be useful in creating a floor plan for when the original design models are no longer available (Budroni & Boehm, 2010).

5.1.3 Extracting shape grammar from 3d point clouds

The missing aspect of these two studies is the differentiation of individual parts of a building; to understand how the feature exists in the form of curves and ratios. The paper "From Point Cloud to Shape Grammar to Grammatical Transformations" (Countinho, et al, 2013), formed a potential solution to this problem. By utilizing a pre-constructed dataset of 'Shape Grammar', smaller compositions of form can define larger features, which can then be constructed in place of the associated point clusters. The issue with this approach is that a predefined set of shape grammar must be created before any sections of form can be classified. The study was performed with Portuguese architecture based on the shape grammar written by Leon Battista Alberti in classic architectural treatise "De re aedificatoria" (Alberti, 1485). By then converting Alberti's work into a modern shape grammar definition (Stiny & Gips, 1972) it could then be applied on the 3D structure. In modern buildings, not all structures follow the same rules and it is difficult to have one universal shape grammar. The paper mentions this limitation "The code to automate the shape recognition proved to be helpful but improvements are necessary, namely the generation of mesh surfaces directly from the PCM in a complete automated way" (Countinho et al, 2013, p.662).

6. Case Study

6.1 INTRODUCTION

To preface, machine learning is used as it can quickly identify patterns and learn shape contexts quickly and automatically. The method structure will be as follows;

Artificial Preparation: Randomly generate models with simple features, apply simulated points on interior surfaces and categorising the points based on collided features. Point clouds are usually generated from LIDAR scanners, which rapidly fire laser beams and records the distance and angle of projection, a similar technique is used in artificial preparation to replicate the behaviour of LIDAR scanners.

Machine Learning: Import created point databases from artificial preparation, train the neural network with the artificial point databases and evaluate the accuracy with uncategorised point clouds.

Compliance Checking: Export categorised points, perform compliance checking comparisons with original models and run real point clouds through the neural network

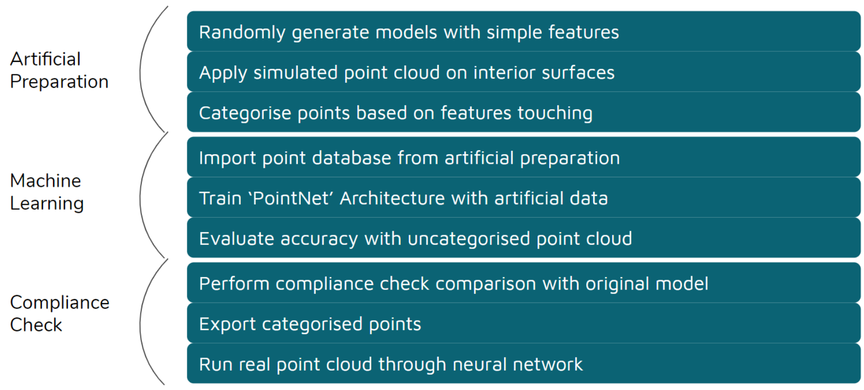

Figure 1. Method Diagram

6.2 TESTING ENVIRONMENT SETUP

For a neural network to be able to create inferences, it requires to be trained on a range of data that will encompass all different types of features it will encounter. This data needs to have the same structure for the remainder of testing. Since categorised point cloud data is difficult to source, especially those with the same data structures, it will be artificially generated for consistency and ease of training. The time scale of this project is limited to several weeks so the time training allocation to machine learning model is of greatest priority.

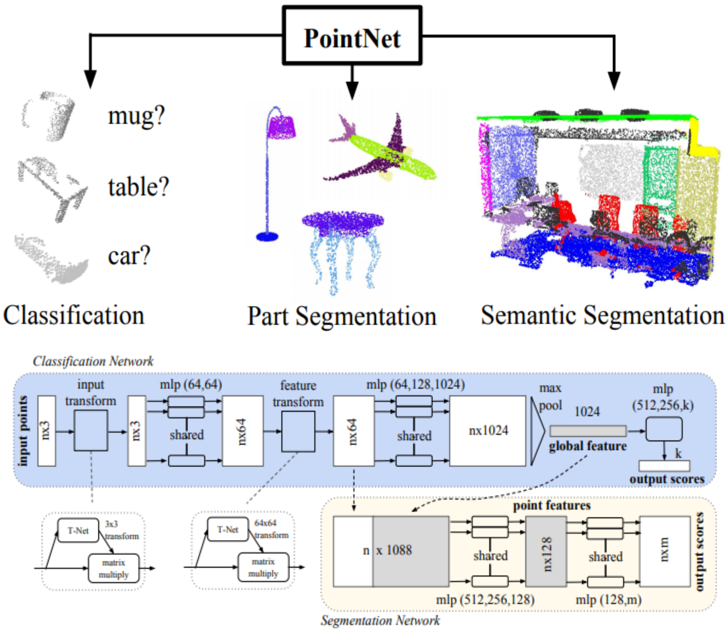

Figure 2. The Pointnet Architecture

6.2.1 Introduction to Pointnet

The architecture created for the model is using the Pointnet Architecture created by Stanford researchers. The Pointnet architecture is used as it has the best effectiveness in differentiating objects within a 3D array. The structure uses unordered lists, local and geometry contexts for the interferences. Pointnet uses 'Tensorflow' for the majority of its code, which is a python library. The base inputs for the Pointnet architecture is a simple (x,y,z) database array. For that reason, the output from the initial data generation should be generic and not contain additional data such as RGB values. Many point clouds are produced in a HD5 data format, which includes images mapped on points to give them a colour value. Instead the data for this project will be produced in Rhino Grasshopper, as it can be an automated process.

In order to keep things simple, the type of features is typical of a room. This includes; Walls, Windows, Window Frames, a roof, a floor and a door. These features are put into a dictionary of categorical value, which can represent the feature by a number. The specifications of this room are constrained to certain bounds, but the value is generated randomly using a seed. These features are organised into a simple value to represent the category that a point is touching. After the room is generated, the point within the middle of the room will extend outwards in random directions is a spherical projection. The amount of directions is set to the amount of points required per dataset. After these points are created, they are matched into the categories they are touching, a simple point could be (x,y,z,c) where c is the categorical value. These points are then exported into a csv format to be read by the Pointnet architecture. After this has been repeated many times, it can then be trained for several epochs.

6.2.2 Room Generation

The rooms are generated using generated floor plans which have several constraints. The door is placed randomly on one of the rectangles walls and is also constrained to a maximum ratio 1/5 of the wall length. Window frames have a thickness between 50 and 100mm and the window to wall ratio is calculated based on the bounds of the lower and upper walls. Glazing thickness is set between 10mm to 50mm and is always inside the window frames. The height of the window is set randomly, and the upper and lower walls are set based on the height constraint of the room. After all features of the room have been generated, they are merged with {Boolean union}.

6.2.3 LIDAR Simulation

Using the merged form of the room, a bounding box is created so a center point can be extracted from the object. From the center point, a sphere is created, and points are randomly placed on the sphere surface. This allows a line to be drawn from the bounding box center outward in the direction of the points on the sphere. This simulates the behavior of a stationary LIDAR scanner emitting laser beams.

6.2.4 Point interception

After the lines are created from the Lidar simulation, an intersection is performed between the lines and the original geometry of the merged room features. This creates multiple intercepting points as there is an outer and inner side to a feature. For the purposes of this case study, only the interior points are selected as they represent the constraints of a LIDAR scanner.

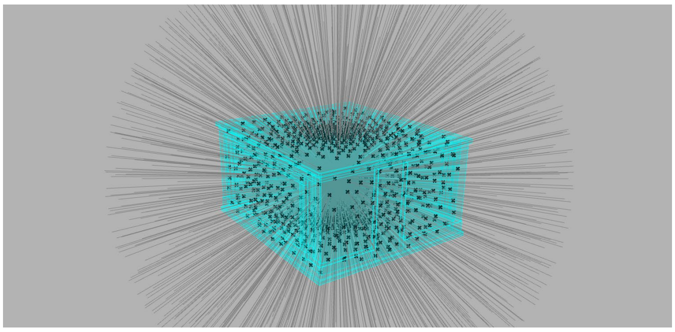

Figure 3. LIDAR simulation point interception.

6.2.5 Point Categorisation

After the points are generated, they are compared to the individual features of the room and tested for collisions. It is assumed that if a point is colliding with the face of a feature, it is part of the point group that will recreate the feature. This is repeated for all features, and then combined to create a list of points touching each feature. Very rarely, a single point can be categorized as touching two features when the intercepting line touches the edge between two objects. For consistency, these instances are removed to avoid problems during training.

6.2.6 Point Database

The database of points is created with a csv (comma separated values) file format, the table of points have 4 columns, x, y, z (which defines the location of the points) and c (The category of the feature). When all points of a room have been written to the csv file, the next seed generates a new room. A new line (Line feed) is written to the csv to separate between the different room data.

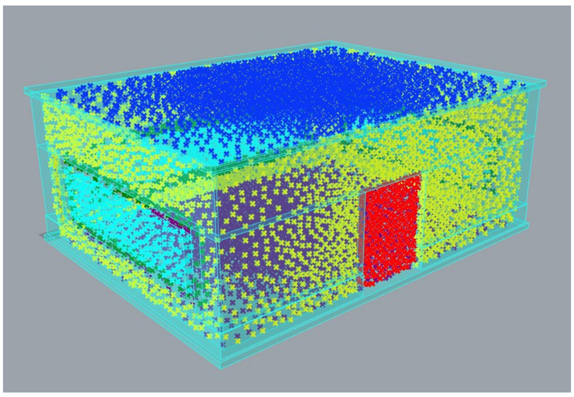

Figure 4. Categorised point clouds.

6.3 TESTING

The first iteration of this process was with a point set size of 1000. The initial test did not yield a great accuracy and the algorithm could not recognise more than two features. There were additional issues within the model generation to cause the point set size to exceed the set number of 1000 points, this was revised afterwards to lead to the second iteration.

The second iteration was still tested with a point set size of 1000. The training script was revised to handle an infinitely sized database, testing still did not yield substantial results. An additional problem appeared where the loss becomes static and drops to a local minima. This was fixed by employing Pointnet's custom loss function as opposed to Tensorflow's built in loss function.

The third iteration was tested with a point set size of 10000. The training script finally started to show results, attaining an accuracy of around 95% after 20 epochs. The training session was run to 200 epochs, but still yielded the same results comparable to 20 epochs.

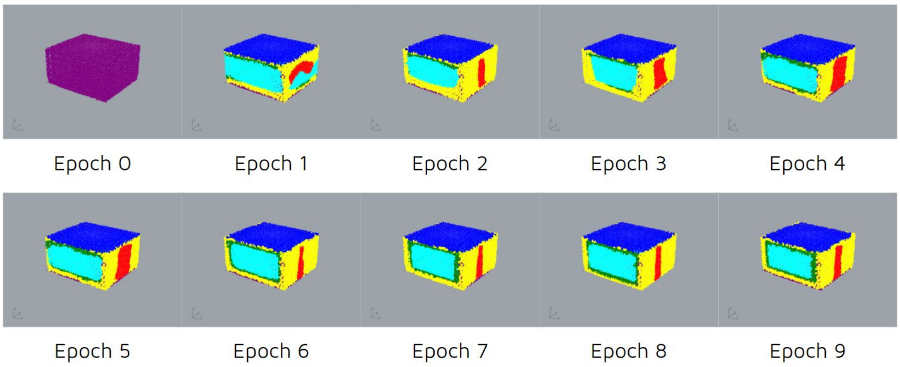

Figure 5. Model visualisations Epoch 0 – 9

No further revisions were made on the training sections, the only additions were to add a function for saving the trained models and a function for testing and evaluating an uncategorised dataset afterwards.

To test the accuracy and applicability of the trained model, a new generic data set without categorical values were run through the neural network. When evaluating the test data it produced accuracies of over 90%.

The third section of testing Is the compliance test. During the generation of the data set, a 3D model was saved of the respective model. After a point cloud model has been processed through the feature detection, it is then reimported into the rhino grasshopper environment. Using a model reconstruction script, the original geometries can be compared to the reconstructed models from the point cloud. This represents the compliance checking process, as any irregularities are flagged and shown on the system.

6.3 COMPLIANCE CHECKING SYSTEM

The reconstruction technique aligns the angle of the point cloud to the original geometry, and then creates bounding boxes purely by the points within a certain category. Bounding boxes are defined by three domains in each dimension (x,y,z). When compared to the bounding box of the original features, a compliancy calculation can be performed by the sizes of domains. For example, a door is compliant when the size of the x and y domains of the reconstructed object are the same as the original domains. For a room this technique is sufficient as there is a limited amount of geometries, however, in large scale this becomes less accurate. If the compliance checking method is extended to a larger scale, the reconstruction technique needs to separate the different kinds of features as well as each feature itself. As an example, three doors on the same x or y axis will have the same bounds as two doors provided that the extents are the same. This becomes an issue as the compliance technique will falsely flag it as correct whereas it should be incorrect. Another issue that the reconstruction technique has is that point cloud collisions are usually planar. This is an issue as compliance checking must be performed on all dimensions of a feature. A door could be flagged as compliant if it is the right height and width but could be off by thickness.

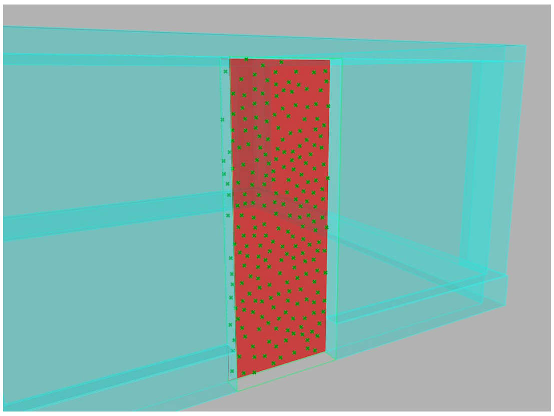

Figure 6. Reconstructed door(red) made from points(green) tested against original geometry(blue)

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Problems with doors:
Length is off by 8mm
Height is off by 20mm
Problems with walls:
Width is off by 280mm
Length is off by 280mm
Height is off by 2mm
Problems with window frames:
Width is off by 211mm
Length is off by 426mm
Height is off by 2mm
Problems with glazing:
Width is off by 124mm
Length is off by 240mm
Height is off by 2mm
Problems with roof:
Width is off by 382mm
Length is off by 380mm
Problems with floor:
Width is off by 429mm
Length is off by 412mm
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Figure 7. Compliance checking output flags from Rhino Grasshopper

6.4 REAL WORLD TESTING

As a measure for real world testing, a 3D Point Cloud was collected using the Zeb Revo scanner, a handheld portable Lidar scanner. A simple room was scanned and processed though Cloud Compare and MeshLab software. Since the neural network was trained on a fixed number of points, it was required that the same amount of points was fed into the system for categorisation. The initial point cloud collected was a total of over 23 million points. Noise was removed in Cloud Compare, and then the point resolution was also reduced in the same software. After the data was exchanged from Cloud Compare to Meshlab, it needed to be cleaned of internals since interior objects and features were not included in the training data. The interior points were taken out manually and the point definition was reduced once more to around 10 thousand.

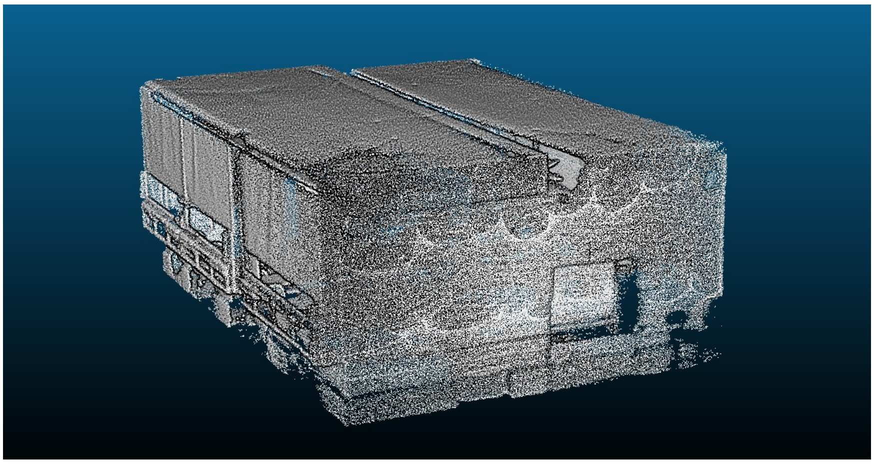

Figure 8. Collected point cloud.

By running the collected point cloud through the neural network several findings were observed. Initially after 500 rooms were examined in the first epoch. The real point cloud was identified with a ceiling floor and walls. There were instances where glazing was forced on areas that did not have windows; however, no window frames were identified. Subsequent epochs revealed that 'overfitting' occurred, as the neural network identified doors on areas that there were none. These issues were likely due to the imperfect data, as the actual location of points had noise and were not of certain accuracy. This is likely the causation of glazing appearing in areas of flat planes off axis from the wall. The machine learning section could have been improved by feeding it imperfect noisy data from the beginning, but due to the limitations of software and actual data it was not performed in this case study. Future tests could analyse patterns in the noise or distortion and can be applied during the model creation or simulation.

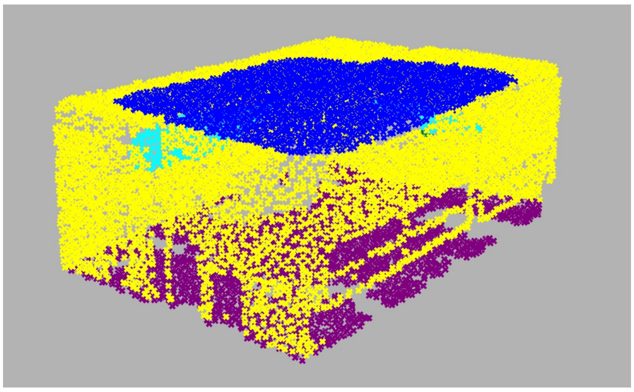

Figure 9. Real point cloud evaluated by inference system.

7. Discussion

This research project has investigated the ways machine learning can be used with 3D point clouds to check the geometric integrity of a structure or building. The study has created a working pipeline which has shown the effectiveness of the techniques employed. The initial findings have shown that a neural network is capable to learn the features of a room or structure and create classifications based on unclassified data. This classified data can then be compared to an original geometry to prove if a feature is compliant and if there are any issues present. This approach is highly effective in comparison to human centered approaches as it can perform a holistic evaluation rather than focus areas that a traditional approach performs. As shown in the time scale of the case study, a solution which utilizes machine learning can be adapted in a short time scale and be improved over iterations rapidly. The implications of using machine learning is that over time, the system does not need manual intervention to improve accuracy and effectiveness. If developed and placed within a workflow, it can completely replace traditional methods and drastically improve the accuracy and fidelity of construction. This system can even be combined with construction management to prevent disparities from occurring from the beginning.

The limitations of this study are that it has not focused on the initial data collection techniques. Large scale 3D Point cloud scanners are currently immobile and are limited to one perspective of scanning. This is an issue as the system requires a high level of detail from the point cloud before it becomes effective. This problem could be resolved by employing new emerging techniques such as UAV and handheld collection systems, that can scan from multiple perspectives. Since the trained data was digitally generated and not collected, it does not serve as a full product or representation of a real training sequence. Additionally, in order to reduce the required computational power, the scope of a dataset was reduced relative of a collected point cloud. However, as a concept it proves that it is possible for a neural network to learn the shape grammar of defining features.

This study will benefit construction and planning industry as it more accurately ensures the fidelity of construction. The workflow process can also be automated and provides high potential in further development. Furthermore, this study has also explored the potential of 3D point clouds and the segmentation techniques in machine learning, which can have other applications within building and feature analysis. Additional research also be performed on the flagging and analysis system, which can be developed to perform more complex compliance checks.

8. Conclusion

Building compliance should be a top priority as it involves the safety of society and ensures the delivery of a basic human need. There are several challenges in creating a compliance checking system. As architecture designs become precedingly more complex, it is essential for buildings to be structurally sound. With emerging technologies such as machine learning we can better regulate the construction process and ensure the quality of the delivered product; however, machine learning provides an efficient and highly scalable solution during or after building construction. As demonstrated in this research, in a short scale of time existing machine learning technologies were implemented into new applications not previously experimented with. The machine learning in this instance proved to be effective in identifying the features of a building in a 3D point cloud, which by reconstructing into the original geometries, can amend construction issues by comparing the two models. The reconstruction technique is simple but already proves the effectiveness when outlining disparities between inferenced geometry and original geometry. By further developing this pipeline it could be easily developed into industry workflows, ensuring better safety in the built environment. The ongoing development of new construction compliance systems should be essential to maintaining the security of buildings and the trust of all inhabitants of modern buildings.

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