Joint CSCE Construction Specialty & CRC Conference 2025
Conférence conjointe spécialisée en construction de la SCGC et CRC-2025

Montreal, Quebec
July 28-31, 2025 / *28-31 juillet 2025*

Defect Detection of 3D Geometric Volume for Salvaged Masonry Units

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ABSTRACT: Climate change is a critical and urgent challenge that all countries are encountering. Civil engineering researchers have a responsibility to address this challenge. One of the approaches is to encourage, through advanced technologies, the reuse of salvaged building materials for lower carbon emissions. To aid this approach, one objective is to automatically extract damage information for salvaged masonry, including bricks, stones, timber, and concrete units. Damage degree of these types of salvaged materials can be derived from the measurement of the volumetric boundaries of their geometric shapes from 3D scans (point clouds) of those components. Therefore, this paper compares the performance of three common 3D volume computing algorithms: 2.5D volume, Mesh Volume, and 3D voxel-based Convex Hull Volume, to find a better solution. Volume loss can be calculated as the difference between the reserved volume and the complete reference volume. The "volume loss degree" of a damaged brick from its point cloud model refers to the ratio of the lost volume to the original volume of the complete brick, which quantifies the extent of the volume loss. Compared with the 2.5D volume, the percentage results of damage degree using the Mesh and 3D voxel-based Convex Hull volume algorithm are more precise, as shown in the experiment described in this paper. It is anticipated that this automatic defect detection approach would be extended to apply to more complex geometric shapes in the future, for the purpose of transforming point clouds of salvaged building components into more precise 3D enriched semantic Models.

1. INTRODUCTION

In the face of escalating global challenges such as climate change and resource depletion, the construction industry is under increasing pressure to adopt more sustainable practices. One of the most impactful ways to reduce environmental waste in construction is through the reuse and recycling of building materials. Salvaged masonry units, such as bricks, stones, timber, and concrete blocks, hold significant potential as reusable materials, offering both economic and environmental benefits (Olumo et al., 2022). However, the condition of these materials—particularly in terms of damage and degradation—need to be precisely assessed before they can be safely reused in new construction projects.

Traditionally, assessing the damage and remaining useful life of salvaged building components involves time-consuming manual inspections and subjective evaluations. To address this limitation, advanced technologies such as 3D scanning and automated damage detection systems are being explored to provide objective, consistent, and efficient assessments of these materials. One of the core challenges in this area lies in the precise extraction of damage information from the 3D point cloud data generated by these scans. The ability to compute the volume of a damaged masonry unit and compare it to its original, undamaged form is crucial for determining the degree of damage and, consequently, the material's potential for reuse.

The objective of this paper is to explore and compare various algorithms for the automatic extraction of damage information from 3D geometric data, specifically focusing on the volumetric analysis of salvaged masonry units. By evaluating the effectiveness of three commonly used volume computation methods—2.5D volume, Voxel-based volume, and Convex Hull—we aim to identify the most suitable approach for calculating the degree of volume loss in damaged masonry units. These methods rely on the analysis of point cloud data generated through 3D scanning, and their performance is assessed based on their ability to precisely reflect the degree of damage as a ratio of lost volume to the original volume of an undamaged reference model.

In the following sections, we first present the methodology used to preprocess the 3D point cloud data and segment the individual masonry units for analysis. Next, we detail the volume computation algorithms under comparison, followed by an experiment using a standard, undamaged brick model as the reference for volume loss calculations. Through these experiments, we aim to demonstrate the viability of these algorithms for automating the defect detection process and providing precise, quantifiable damage assessments that can be used to guide the reuse of salvaged masonry materials. Finally, we discuss potential improvements and future directions for this research, including further validation of accuracy, the application of these methods to more complex and varied building components, and the application to automatic materials sorting systems.

2. LITERATURE REVIEW

The reuse of salvaged materials, especially masonry units such as bricks, stones, timber, and concrete blocks, is an emerging practice aimed at reducing the environmental impact of construction projects. This practice is gaining momentum in response to global challenges like climate change, waste generation, and resource depletion. As the construction industry seeks to become more sustainable, developing methods for efficiently evaluating the condition and potential for reuse of salvaged materials has become a critical research area. One of the most promising techniques for material assessment involves the use of 3D scanning and digital image processing technologies to capture detailed information about the geometry and internal damage of building components.

2.1 3D Scanning and Point Cloud Data in Construction

The use of 3D scanning technology, particularly LiDAR (Light Detection and Ranging) and photogrammetry, has become widespread in construction for creating digital representations of physical objects. These techniques generate point clouds, which are collections of data points in three-dimensional space that represent the surface of an object. Several studies have explored the potential of 3D point cloud data for various applications in construction, such as structural health monitoring, building information modeling (BIM), and the assessment of damage in salvaged materials.

For example, Kassotakis et al. (2021) highlighted the role of 3D scanning in capturing detailed geometries of masonry units, enabling more accurate assessments of their condition. Similarly, Chen et al. (2021) demonstrated how point cloud data could be processed to detect cracks and other forms of damage in concrete structures. These studies emphasize the importance of developing reliable algorithms that can automatically extract useful information from point cloud scans, such as the degree of damage or volume loss, to facilitate decision-making in construction and demolition projects.

2.2 Volume Calculation Algorithms for Point Cloud Data

One of the key challenges in assessing the condition of salvaged masonry units is precisely calculating the volume of the damaged components. Several algorithms have been proposed for this purpose, each with its strengths and limitations.

2.2.1 2.5D Volume Approach

The 2.5D approach to volume computation is a simpler method that involves fitting a plane to the point cloud data and calculating the distance of each point from the plane. This approach has been employed in several studies, such as in the work of Santos et al. (2013), where it was used for the estimation of surface roughness and volumetric loss in damaged concrete structures. While the 2.5D method is computationally less expensive than most other methods and can provide quick estimations, its precision is often limited when dealing with complex 3D shapes or highly irregular surfaces.

2.2.2 Mesh Volume Approach

The mesh volume approach involves converting the point cloud data into a continuous surface representation using a triangular or tetrahedral mesh. This method reconstructs the object's geometry by connecting discrete points into a network of polygons, enabling more precise volume estimation. One common technique for mesh generation is the Delaunay triangulation, which ensures well-formed, non-overlapping triangles that accurately approximate the object's shape. Mesh-based volume estimation has been widely applied in various domains, including structural health monitoring and digital reconstruction. For instance, Park et al. (2020) demonstrated that meshing techniques provide accurate volume calculations for fragmented and irregularly shaped objects.

2.2.3 3D Convex Hull Approach

The convex hull method is a geometric algorithm that generates the smallest convex shape (hull) that encloses all the points in the point cloud. This approach has been found to be effective in accurately estimating the volume of irregular objects, as it can be applied to a wide variety of shapes and is less sensitive to the noise and outliers commonly found in point clouds. The work of Wu et al. (2024) demonstrated the advantages of convex hull-based volume estimation for 3D objects, showing that it outperforms simpler methods like the 2.5D and voxel approaches in terms of accuracy for complex geometries. Moreover, the convex hull method has been successfully applied in the context of damage detection in construction materials, as seen in the studies of Yuan et al. (2022), who used convex hulls to quantify material loss in concrete beams.

2.3 Research Gaps in Defect Detection of Salvaged Masonry Units

While the application of 3D scanning and volume computation methods to defect detection in salvaged masonry units is promising, there are several challenges that remain to be addressed. The first is the preprocessing and segmentation of point cloud data, which often involves dealing with noise, incomplete scans, and occlusions. Effective filtering and segmentation algorithms are crucial to obtaining accurate representations of individual masonry units from large, unorganized point cloud datasets. Several studies have proposed methods to improve segmentation, such as the region growing algorithm (Lu et al., 2014) and clustering-based techniques (Li et al., 2017) in medical research area, but robust and automated segmentation for complex building materials is still an ongoing research topic.

Another challenge is the variability in the shape and size of masonry units, which can complicate volume computation. Masonry units often exhibit irregular geometries and surface imperfections that may not be easily captured by traditional volume calculation algorithms. Recent advancements in deep learning and machine learning algorithms, as explored by several researchers like Zar et al., (2024), have shown promise in enhancing segmentation and volume calculation for irregular and damaged structures, although these techniques are still in the early stages of development.

3. METHODOLOGY

The methodology for this research is focused on the automatic detection of defects in salvaged masonry units using 3D point cloud data. Specifically, the goal is to compare different algorithms for volume computation, namely the 2.5D volume, Mesh Volume, and 3D Convex Hull volume algorithms, to assess their accuracy and efficiency in quantifying the degree of damage in salvaged masonry components. The general workflow includes three major steps: data acquisition, preprocessing, and volume computation.

3.1 Data Acquisition

The first step in the methodology is the collection of 3D point cloud data for the salvaged masonry units. This data is typically obtained using 3D scanning technologies such as LiDAR or structured light scanning. These methods capture the geometries of individual components by recording the positions of points on their surfaces in three-dimensional space. The point cloud data contains information about the external geometry of the units, which can be used to detect damage based on volumetric differences from the original undamaged geometry. Salvaged masonry units were acquired to be utilized in the research project. They include 3 types of brick and 1 type of stone from one local salvaged materials vendor (The Timeless Material Company) and 3 types of brick from the Architecture School of the University of Waterloo. The total number of bricks is 160 while the total number of stones is 30. This reasonably large number and diverse types of masonry units is a sufficient sample population. It may be sampled, proportioned, randomly mixed, and scanned to create a rich database of 3D point cloud scans. The masonry units set from which the subset used for this experiment is selected is specified in Table 1.

Table 1: Types and groups of masonry units

masonry type	masonry types	masonry numbers
bricks	brick_type1	50
	brick_type2	50
	brick_type3	50
	brick_type4+5+6 (Cambridge)	10
	total	160
stones	stone_type1	30
total		190

The database of 3D point cloud scans is acquired using the Lidar scanner. Selecting groups of masonry units with varying degrees of damage or ratios of types of units is facilitated by the relatively large total of 190 and by their accessibility in an indoors section of the UW structures lab on the main campus where they are stacked. Therefore, one type of brick or stone is divided into 10 groups. Each group consists of one type of brick and one type of stone. The number of bricks in each group is five while the number of stones in each group is three (see Table 2). They are re-arranged and re-scanned in an ordered number of scenes. The number of scenes for every group is 15 to capture data, as shown in Figure 1. The first scene consists of 5 bricks and 3 stones. The second scene consists of 7 bricks and stones. The third scene consists of 6 bricks and stones. In this way, the 7th scene consists of 2 bricks and(or) stones. The remaining 8 scenes merely contain single units (brick or stone) in this group. This arrangement is intended to serve multiple purposes including the experiments described here and future classification research. One point-cloud scan model file was captured once for each scene. The result is an initial training data set of 120 labelled scans. This set can be expanded as necessary.

Table 2: The collected 3D scan data of bricks and stones

scene	types	units	total scan arrangement
1	brick1+stone	5+3	15
2	brick1+stone	5+3	15
3	brick1+stone	5+3	15
4	brick1+stone	5+3	15
5	brick1+stone	5+3	15
6	brick2+stone	5+3	15
7	brick3+stone	5+3	15
8	brick_type4+5+6 (Cambridge)	10	15

total	120

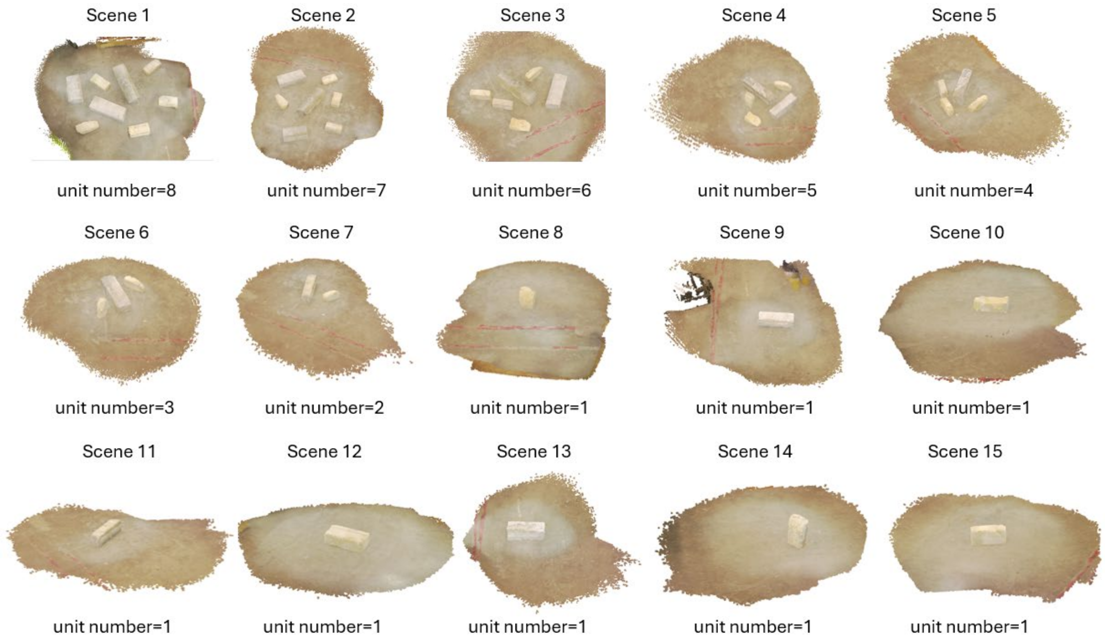

Figure 1: Total 15 scenes in an example group

In this study, the point cloud data is obtained for both damaged and undamaged masonry units. A standard undamaged brick model is selected as the reference for volume comparisons. The model is generated by scanning an intact brick, which is used as a baseline for calculating damage in the subsequent steps. The point cloud data for the damaged bricks is processed and analyzed to extract meaningful damage information.

3.2 Preprocessing and Segmentation

In this approach, the procedure begins with reading the point cloud data (PCD) from a specified file using Open3D. The main goal is to segment the point cloud into two main parts: the ground plane and the objects above it, such as bricks. First, the ground plane is segmented using the RANSAC algorithm with a specified distance threshold and a maximum number of iterations. This process identifies the points belonging to the ground and separates them from the non-ground points. These ground and non-ground point clouds are then saved as separate files. Next, the non-ground objects are further processed using the DBSCAN clustering algorithm. This unsupervised method groups nearby points based on a given radius (epsilon) and minimum number of points, thus identifying distinct clusters of objects. Each cluster, corresponding to an individual object such as a brick, is saved as a separate point cloud file. The segmentation results are stored in an organized directory structure, and information logs are generated throughout the procedure to track the saved files.

3.3 Volume Computation Algorithms

The procedure for estimating the volume of a 3D object from point cloud data in this study involves three distinct algorithms: 2.5D-based, mesh-based, and 3D convex hull voxel-based algorithms. Initially, the point cloud data is loaded using the Open3D library. For the mesh-based algorithm (mesh_volumn), the point cloud is processed using an Alpha Shape method to create a mesh, followed by the computation of its convex hull. The volume is then derived from the convex hull, which represents the smallest convex boundary enclosing the object. In the 3D convex hull algorithm (voxel_volumn), which includes a voxelization step, the point cloud is downsampled to a voxel grid, reducing the data's complexity. A convex hull is computed from the downsampled points, and its volume is calculated, providing an efficient estimation of the object's volume. Lastly, the 2.5D-based algorithm (cal_25D_volumn) employs Principal Component Analysis (PCA) to fit a plane to the point cloud, then projects the points onto this plane to compute a 2D convex hull area. The volume is approximated by multiplying this area with the average height of the points above the plane. These three algorithms offer different balances between accuracy and computational cost, with the mesh and convex hull algorithms being more robust for complex geometries, while the 2.5D algorithm is less computationally demanding.

3.3.1 2.5D Volume (PCA and 2D Convex Hull)

The 2.5D volume calculation leverages Principal Component Analysis (PCA) to model the point cloud data. PCA is applied to the point cloud to fit a plane, with the third principal component representing the normal vector of the plane. The algorithm projects the points onto this plane and computes the convex hull of the projected points, which provides the area of the object's base. Additionally, the algorithm calculates the distance from each point to the plane, which corresponds to the height of the object at that point. The average height is then multiplied by the base area to estimate the volume. This method is referred to as "2.5D" because it approximates the 3D volume by considering the object as a 2D shape using the 2D convex hull algorithm extruded along the height dimension.

3.3.2 Mesh Volume (Alpha Shape Method) Algorithm

The mesh volume calculation algorithm utilizes the concept of Alpha Shapes to generate a 3D mesh from the input point cloud data. First, the algorithm reads the point cloud and computes a 3D mesh using an alpha shape, which is a generalization of the convex hull for point sets. The alpha parameter controls the level of detail in the resulting mesh. Once the mesh is generated, vertex normals are computed to facilitate further geometric analysis. Subsequently, the algorithm computes the convex hull of the mesh, which is the smallest convex shape that encloses the entire mesh. The convex hull's volume is then calculated, providing an estimate of the volume of the point cloud's 3D structure. This method is useful for approximating the volume of irregular objects represented by point clouds.

3.3.3 Voxel Volume (3D Convex Hull After Voxelization) Algorithm

The 3D convex hull algorithm involves first down-sampling the point cloud using voxelization, which reduces the number of points based on a specified voxel size. By discretizing the point cloud into voxels, the algorithm simplifies the computational process and makes it more efficient. After voxelization, a convex hull is computed for the down-sampled points. The convex hull serves as a boundary that encompasses all the points in the cloud. The volume of this convex hull is then calculated, which gives an approximation of the point cloud's volume. This voxel-based method is particularly effective for large point clouds where computational efficiency is a concern.

3.4 Volume Loss Degree

To quantify the damage, the volume loss is calculated as the difference between the volume of the damaged brick and the volume of the reference brick (complete brick), as Equation 1 demonstrates. This is done by computing the volume of the damaged unit using one of the three algorithms and subtracting it from the volume of the undamaged reference unit.

The degree of volume loss, or the missing degree, is expressed as the ratio of the lost volume to the original volume of the reference brick. The Volume Loss Degree equation calculates the percentage of volume lost in a damaged brick relative to its original complete state. Given the volume of the complete reference brick and the volume of the damaged brick, the equation is expressed as:

$$[1]\ \text{Volume Loss Degree (\%)} = [\text{Volume(reference brick)} - \text{Volume(reserve of damaged brick)}] \,/\, \text{Volume(reference brick)} \times 100$$
$$= \{1 - [\text{Volume(damaged brick)}/\text{Volume(reference brick)}]\} \times 100$$

This equation quantifies the volume loss due to damage by subtracting the damaged brick volume from the reference volume. The result is the volume loss. Dividing this volume loss by the reference complete volume represents the degree of missing volume. This percentage is a straightforward measure of how much of the brick's original volume has been compromised. A higher damage degree indicates a greater loss of volume, while a lower degree suggests less significant damage. This damage degree provides a clear, quantitative measure of the extent of the damage to the salvaged masonry unit.

The error has been validated using 2 scene datasets containing 18 complete type 3+4+5 bricks from the Cambridge campus among 3 algorithms. A standard complete brick could be served as the reference model, with its ground truth volume probably calculated using the 3D Oriented Bounding Box (OBB) algorithm by authors' previous work or realistic measurement (length × width × height). In the error statistics phase, the Shapiro-Wilk test was applied to distinguish the accuracy of 3 algorithms (see Figure 2) (Zhang et al., 2022) (Hanusz et al., 2016). The p-value (greater than 0.05) in 3D mesh volume or 3D convex hull algorithm illustrates that the volume error may be normally distributed, which fits the expected sampling results. Besides, the error range is less than 0.0002 square meters if an algorithm between the two is applied, which can perhaps be accepted, too. Since the convex hull algorithm's strength in capturing geometric boundaries was more evident in irregularly shaped masonry units, the validation experiment shows that the precision of the 3D convex hull algorithm is a little higher than that of the mesh volume algorithm. However, both of them have much better performance in volume loss degree computation compared with 2.5D volume. The equation is expressed as:

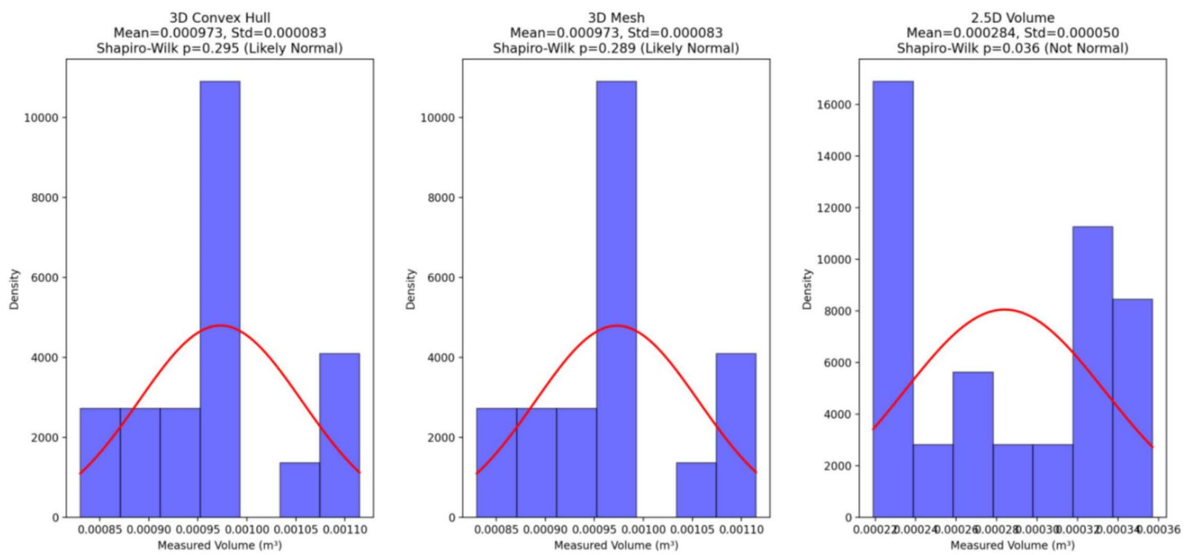

Figure 2: The Shapiro–Wilk test of volume errors using three algorithms

[2] Average Volume Loss Degree (%) = [Volume Loss Degree (3D Mesh) + Volume Loss Degree (3D Convex Hull)]/2

The results revealed that the 3D Convex Hull algorithms consistently produced precise volume estimates that were so close to the 3D Mesh algorithm estimates that if both are found to be accurate in subsequent volume loss ground truth validation experiments, the choice between them would depend on computational efficiency more. However, ground truth validation for the accuracy of damaged masonry units may use displaced liquid or sand volume measures of other damaged types of bricks and stones later. The aim is to compare with the algorithm estimates of volume loss, which will be reported in the presentation of this paper to improve the accuracy.

4. EXPERIMENT RESULTS

For this project, considering comparing the three above volumetric computation algorithms for defect detection of salvaged masonry units, four types of brick and three types of stone were scanned using a high-resolution 3D scanner. Pre-processing (including noise filtering, segmentation, and normalization) and post-processing (including error statistics and algorithm optimization) steps were applied to ensure an accurate volume loss representation of each unit. The computed volumes and volume loss percentages were visualized and tabulated in test scenarios, showing distinct differences between the units due to varying defect levels and geometries in Figure 3 and Table 3. Given the computational efficiency and observed fidelity of the Average Volume Loss Degree for detecting defects and assessing volume loss, it is likely to be the algorithm used to measure volume damage of salvaged masonry units as the broader research program in which it plays a part of advances. Future work will aim to optimize the algorithm for improved computational efficiency, further validate its accuracy, and expand its applicability to more complex building components.

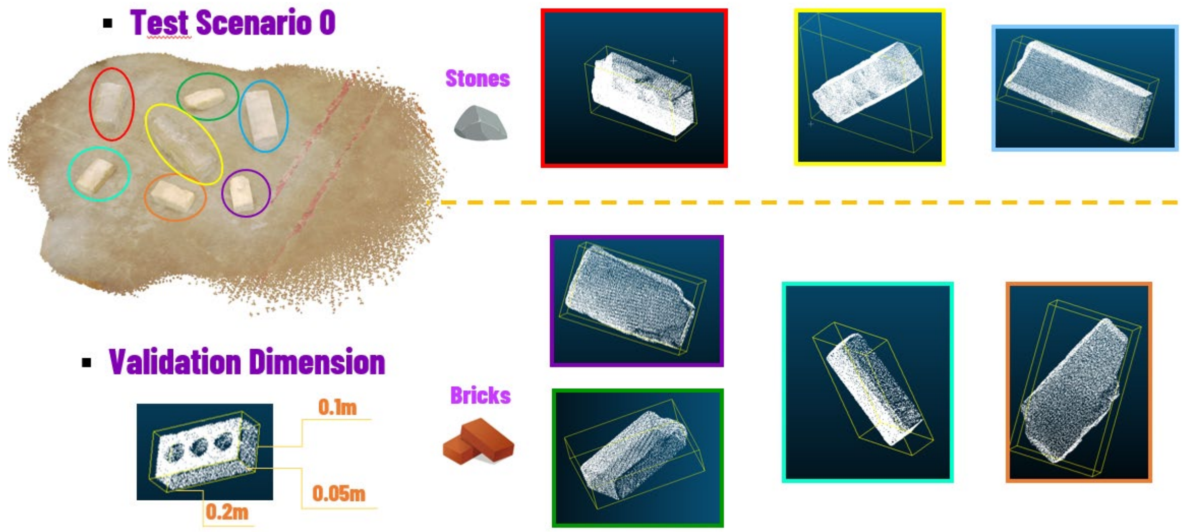

Figure 3: The segmentation results of a divided 3D scan scenario into masonry units

Table 3: The test results of reserved volume degree calculation using 3 algorithms

Unit Number	Masonry Type	Reference Complete Volume	Reserved Volume of Damaged Masonry Units (unit: m^3)			Average Volume Loss Degree
			2.5D	3D Mesh	3D Convex Hull	
0	Stone	0.007000	0.001113	0.004201	0.004196	40.02%
1	Stone	0.007000	0.001771	0.006215	0.006213	11.23%
2	Brick	0.001510	0.000273	0.001102	0.001100	27.09%
3	Brick	0.001510	0.000293	0.001061	0.001061	29.74%
4	Brick	0.001510	0.000192	0.000987	0.000986	34.67%
5	Stone	0.007000	0.001312	0.004978	0.004975	28.91%
6	Brick	0.001510	0.000166	0.000916	0.000915	39.37%

5. DISCUSSION

The three algorithms (2.5D Volume, Mesh, and Voxel-based 3D Convex Hull) each have unique approaches for estimating the volume of point cloud data, and their precision and deviations can vary depending on several factors, such as the point cloud density, the quality of the data, and the choice of parameters. Below is a discussion of the performance and deviations for each method.

5.1 2.5D Volume (PCA and 2D Convex Hull)

The 2.5D volume calculation method uses Principal Component Analysis (PCA) to fit a plane to the point cloud data and then calculates the convex hull of the projected points to estimate the area, which is then used to calculate the volume. This method is particularly useful when the object has a relatively flat structure with height variation, as the projection onto the plane simplifies the calculation. The accuracy of this method depends on the assumption that the points can be effectively projected onto a 2D plane. If the object deviates significantly from a 2D structure or has a large height variation, this method may provide a less accurate approximation of the volume.

The main source of deviation in the 25D volume calculation is the assumption of the object's geometry and the fit of the PCA plane. If the object’s shape deviates from the ideal 2D structure, the method might introduce significant error. Additionally, this method uses the convex hull to approximate the base area, which might not fully capture the object’s true base if the projected points are sparse or irregular. Since the method approximates the height using the average distance of points from the plane, it may not account for local variations in height, leading to potential underestimation or overestimation of volume.

5.2 Mesh Volume (Alpha Shape Method)

The mesh volume method uses alpha shapes to create a mesh surface that approximates the object represented by the point cloud. The accuracy depends on the chosen alpha parameter, which controls the resolution of the mesh. A smaller alpha value can result in a finer mesh, capturing more details, while a larger alpha can simplify the geometry, potentially losing finer features. For highly detailed objects, the mesh volume method can provide accurate results, especially when the alpha value is optimized for the point cloud.

The main source of deviation in the mesh volume method is the choice of the alpha parameter. If the alpha is too large, the mesh might be overly simplified, leading to an underestimation of volume. If the alpha is too small, the mesh might overfit the data, resulting in a more complex shape and possible overestimation of volume. The mesh provides a good approximation of the volume, but this may not perfectly represent the actual object if the mesh is not adequately representative of the object’s true geometry.

5.3 Voxel Volume (3D Convex Hull After Voxelization)

The voxel volume method downscales the point cloud using a voxel grid, where the density of the voxels influences the accuracy of the volume calculation. A smaller voxel size will yield a more detailed representation of the point cloud, while a larger voxel size will reduce the level of detail but also reduce computational complexity. The accuracy of this method is generally reasonable for large, uniform objects, as the voxelization process tends to smooth out small irregularities in the point cloud. However, this method may struggle with very detailed or highly irregular objects, especially when important features are lost during voxel downsampling.

The accuracy and deviation are heavily influenced by the voxel size. A larger voxel size leads to a coarser representation and higher deviation from the true volume, while a smaller voxel size increases computational cost and can result in an overestimation of volume if not properly calibrated. Since the voxel volume method uses the convex hull of the downsampled points, it may still introduce some deviation from the actual volume, particularly for non-convex or complex shapes where the convex hull might not be an accurate fit.

5.4 Algorithm Evaluation

Mesh Volume is generally accurate for well-defined, non-complex objects but may struggle with irregular shapes if the alpha value is not carefully chosen. 3D voxel-based Voxel Volume is computationally efficient and works well for large datasets, but it can introduce significant error if the voxel size is not carefully calibrated. 2.5D Volume Calculation is most effective for objects with significant flatness but might have a high deviation if the object has complex 3D structures or irregular features.

6. CONCLUSION

This paper compares the performance of three common 3D volume computing algorithms: 2.5D volume, Mesh, and voxel-based 3D Convex Hull to find a better solution. The 3D Convex Hull algorithm has demonstrated its ability to provide accurate and reliable volume computations for salvaged masonry units, making it an essential tool for quantifying volume loss and defect detection. By precisely and effectively capturing the geometric boundaries of different kinds of 3D geometrical shapes, this method can prove to be particularly advantageous for evaluating salvaged masonry components with complex surfaces. Its precision, though computationally demanding, establishes it as the preferred choice for applications requiring detailed defect analysis. Compared with the 2.5D volume and Mesh approaches, the percentage result of damage degree using the 3D voxel-based Convex Hull algorithm is more precise, as shown in the validation analysis. It is anticipated that this automatic defect detection approach would be optimized to apply to more complex geometric shapes in the future for the purpose of transforming point clouds of building components into more precise enriched semantic models.

In conclusion, while significant progress has been made in the development of algorithms for volume computation and damage detection in 3D point cloud data, there remains a need for further research to refine these methods and expand their applicability to more complex and diverse masonry units. That might also be a great opportunity for the rapid reuse of salvaged mass timber in North America. Therefore, the continuous evolution of scanning technologies and computational algorithms holds the key to more sustainable practices in the reuse of building materials and the reduction of construction waste.

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