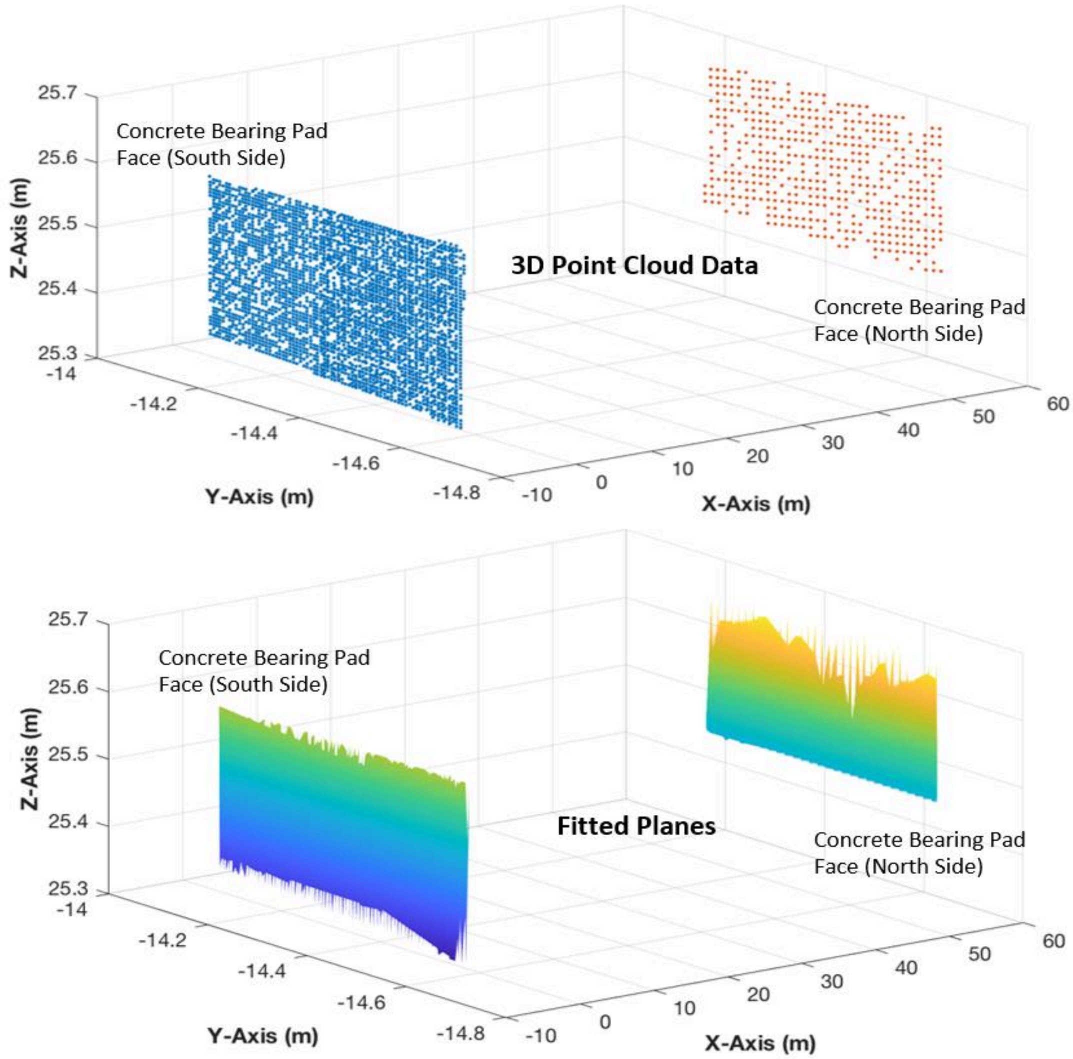

Figure 3. 3D point cloud data (on top) and the fitted planes (on bottom) for North and South concrete pad outer faces

The distance between the concrete pads was also computed within the CloudCompare software environment for the validation of the computational algorithm. First, the CloudCompare's plane fitting tool created individual planes for each concrete pads' outer faces. Then, the "compute cloud/mesh distance" algorithm provided the minimum, average and maximum distances between the two planes. The standard deviation for the computed distances was negligible. Similar measurements were observed for both cases (using the computational algorithm and CloudCompare's compute cloud/mesh distance algorithm), further validating the used computational algorithm.

The perpendicular distances were computed between the 6 pairs of concrete pads located on north and south abutment for milestone_2 and milestone_3. From plane-plane distance computation, it was observed that the distance between concrete pads increased for each pair after the installation of two additional girders (milestone_3) compared to milestone_2.

Table 2 shows the computed average plane-plane distance between the outer face of concrete pads for 6 girders after the placement of first and second pairs of girders.

Table 2. Concrete pad to Concrete pad distances for 6 girders

Girder	Milestone_2 (m)	Milestone_3 (m)	Difference (mm)
1	54.1471	54.1866	39.5
2	54.1957	54.2216	25.9
3	54.2015	54.2373	35.7
4	54.2116	54.2239	12.3
5	54.1716	54.2428	71.2
6	54.2075	54.2617	54.2

The average increment in plane-plane distance for 6 measured pairs of concrete pads was 39.8mm with the standard deviation of 20.8mm. The maximum increase in the distance observed was 71.2mm for girder 5 and the minimum was 12.3mm for girder 4. This increase in the distance between the outer face of concrete pads suggests that either one or both the abutments have moved away from each other due to the addition of girders as no spatial change was noticed between the concrete pads of the same abutment. The authors plan to collect more 3D point cloud data to pinpoint the movement of each abutment as well as to see if these observed changes have any influence on the service life of bridge structure.

CONCLUSION

From this pilot study, the authors observed that the 3D laser scanner could be effective for an accelerated bridge construction projects' quality control as well as for proper documentation of as-built condition for future inspection and maintenance planning. The 3D point cloud data analysis concluded that no significant deviation was noticed in the first two girders even after the installation of the second pair of girders. Similarly, there was no significant deviation on the abutments between milestone_2 and milestone_3. However, the authors observed the change in the distance between concrete bearing pads on which the girders rested between the 3D point cloud from milestone_2 and milestone_3 respectively. Additional analysis also concluded that there was no lateral displacement between the concrete pads of the same abutment between the 3D point cloud data collected during milestone_2 and milestone_3. This suggests that with the addition of load in the form of two more girders, the abutment has undergone minor displacements which could be further verified by measuring the distance between concrete pads after placing additional girders. This method provides an easy way for engineers to identify, visualize, and interpret the deformations.

Limitations

The major limitation of this research paper was lack of design parameters defining the permissible deviations for each structural element. Such design parameters will be obtained from the structural designer of the bridge and comparison will be used to check whether the deformations or deviations noticed in bridge elements are within the permissible limits or not. Besides, the authors only compared the bridge structures between two milestones in this paper. An additional comparison should be performed for other milestones to analyze the pattern of change. For this, the authors plan to further analyze the behavior of bridge elements for other construction milestones and after addition of service load (vehicular live load).

Future Work

The future work includes the identification and separation of structural deformations and construction deviations to allow rectification of error before carrying out further construction works. More scans will be collected after the completion and during the construction to create the as-built model which will serve as the basis for future inspection. During its service life, the authors plan to collect 3D point cloud every two months for spatiotemporal analysis of bridge structure to monitor if the spatial changes identified during construction are deteriorating and interfering with the structural functioning of the bridge post construction. Such continuous monitoring can help in making better decisions during the rehabilitation process of the bridge structure.

The researchers will also focus on developing an automated structural health monitoring model which would control the quality of bridge structure during construction, create the as-built model, service life inspection and identification and prediction of possible structural deformations by collaborating with the bridge structural engineers.

In addition, the future work includes the development of an automated model that will identify all important structural deformations and defects so that the structural engineers will be able to retrofit the bridge structure before failure. The use of laser scanner for crack identification has already been validated by researchers (Laefer, Truong-Hong, Carr, & Singh 2014). Furthermore, the actual deflection of the bridge girders computed from the 3D point cloud data will be compared periodically with time-dependent deflection (including creep and shrinkage) computed by the bridge structural engineers. And if the actual deflection is more than the expected one, the structural engineers will be able to conduct full inspection to find any abnormalities in the bridge. This will help in increase the overall lifespan of the bridge by preventing the possible crack formations and failure of the bridge in advance.

REFERENCES

Akinci, B., Boukamp, F., Gordon, C., Huber, D., Lyons, C., & Park, K. (2006). A Formalism for Utilization of Sensor Systems and Integrated Project Models for Active Construction Quality Control. *Automation in Construction*, *15*(2), 124–138.

Böhm, J., & Becker, S. (2006). Automatic marker-free registration of terrestrial laser scans using reflectance features. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *36*(5/W17), 338–344.

Catbas, F. N., Ciloglu, S. K., Hasancebi, O., Grimmelsman, K., & Aktan, A. E. (2007). Limitations in structural identification of large constructed structures. *Journal of Structural Engineering-Asce*, *133*(8), 1051–1066. https://doi.org/10.1061/(ASCE)0733-9445(2007)133:8(1051)

Ellirtgwood, B. (1987). Design and Construction Error Effects on Structural Reliability. *Journal of Structural Engineering*, *113*(2), 409–422. https://doi.org/10.1061/(ASCE)0733-9445(1987)113:2(409)

Golparvar-fard, M., Bohn, J., Teizer, J., Savarese, S., & Peña-mora, F. (2011). Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques. *Automation in Construction*, *20*(8), 1143–1155. https://doi.org/10.1016/j.autcon.2011.04.016

Ham, Y., Han, K. K., Lin, J. J., & Golparvar-Fard, M. (2016). Visual monitoring of civil infrastructure systems via camera-equipped Unmanned Aerial Vehicles (UAVs): a review of related works. *Visualization in Engineering*, *4*(1), 1–8. https://doi.org/10.1186/s40327-015-0029-z

Hu, X., & Wang, B. (2013). A Wireless Sensor Network-Based Structural Health Monitoring System for Highway Bridges. *Computer-Aided Civil and Infrastructure Engineering*, *28*, 193–209. https://doi.org/10.1111/j.1467-8667.2012.00781.x

Kalasapudi, V. S. (2017). Robust Registration Algorithm for Performing Change Detection of Highway Bridges Using 3-D Laser Scanning Data. *Eleventh International Bridge and Structures Management Conference*, (April), 243. Retrieved from www.TRB.org

Kalasapudi, V. S., & Tang, P. (2015). Automated tolerance analysis of curvilinear components using 3D point clouds for adaptive construction quality control. *Congress on Computing in Civil Engineering, Proceedings*, *2015–Janua*(January), 57–65. https://doi.org/10.1061/9780784479247.008

Kalasapudi, V. S., & Tang, P. (2017). A Robust Registration Algorithm for Automatic and Reliable Geometric Change Detection of Bridges using 3D Laser Scanning Data, *09*, 2017.

Kang, C. (2017). Application of GPS and Remote Sensing Image Technology in Construction Monitoring of Road and Bridge, (Ssme), 337–342.

Laefer, D. F., Truong-Hong, L., Carr, H., & Singh, M. (2014). Crack detection limits in unit based masonry with terrestrial laser scanning. *NDT and E International*, *62*, 66–76. https://doi.org/10.1016/j.ndteint.2013.11.001

Li, L., Ma, Z. (John), Griffey, M. E., & Oesterle, R. G. (2010). Improved Longitudinal Joint Details in Decked Bulb Tees for Accelerated Bridge Construction: Concept Development. *Journal of Bridge Engineering*, *15*(3), 327–336. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000067

Liu, W., Guo, H., Li, H., & Li, Y. (2014). Using BIM to improve the design and construction of bridge projects: A case study of a long-span steel-box arch bridge project. *International Journal of Advanced Robotic Systems*, *11*(1), 1–11. https://doi.org/10.5772/58442

Sedek, M., & Serwa, A. (2016). Development of new system for detection of bridges construction defects using terrestrial laser remote sensing technology. *Egyptian Journal of Remote Sensing and Space Science*, *19*(2), 273–283. https://doi.org/10.1016/j.ejrs.2015.12.005

Shi, Y., Xiong, W., Kalasapudi, V. S., Geng, C., Zhang, C., & Tang, P. (2017). Automated Change Diagnosis of Single-Column-Pier Bridges Based on 3D Imagery Data Ying. *Computing in Civil Engineering*, 91–98. https://doi.org/doi:10.1061/9780784407943

Stamos, I., & Leordeanu, M. (2003). Automated Feature-Based Range Registration of Urban Scenes of Large Scale. *CVPR (2)*, 0–6.

Yang, H., Xu, X., & Neumann, I. (2016). Laser Scanning-Based Updating of a Finite-Element Model for Structural Health Monitoring. *IEEE Sensors Journal*, *16*(7), 2100–2104. https://doi.org/10.1109/JSEN.2015.2508965

Zhou, J., Li, X., Xia, R., Yang, J., & Zhang, H. (2017). Health Monitoring and Evaluation of Long-Span Bridges Based on Sensing and Data Analysis : A Survey. *Sensors*, *17*(3), 603. https://doi.org/10.3390/s17030603

A 3D Irregular Packing Algorithm Using Point Cloud Data

Yinghui Zhao[1] and Carl T. Haas, F.ASCE[2]

[1]Ph.D. Candidate, Dept. of Civil and Environmental Engineering, Univ. of Waterloo, ON N2L 3G1, Canada. E-mail: yinghui.zhao@uwaterloo.ca
[2]Professor, Dept. of Civil and Environmental Engineering, Univ. of Waterloo, ON N2L 3G1, Canada. E-mail: chaas@uwaterloo.ca

ABSTRACT

The cutting and packing (C&P) problem has been extensively studied as it has a wide variety of applications in many industries. Good packing solutions can effectively reduce manpower and production costs. However, approaches for packing 3D irregular shaped items common in construction are very limited. In this paper, a heuristic algorithm to pack a set of irregular shaped items into a box-shaped container with the objective to maximize the contact area between objects has been proposed as one step required for alternative packing solutions. A 3D scanner is employed to obtain the geometric information of items. The heuristic algorithm determines the rotation and translation of each item, moves the objects into close proximity, and fits the objects together automatically using point cloud representation. This is a new approach. Experiment results show that the proposed approach has the potential to support good packing solutions of realistic items in a reasonable time.

INTRODUCTION

The Cutting and Packing (C&P) problem has a wide application in the medicinal, materials science, chemical, mechanical engineering, shipbuilding, aircraft construction, transportation, and garment industries. The basic problem is to find the optimal packing layout in order to optimize an objective. The C&P problem with 3D irregular shapes became a significant research interest in recent years. One of the main driving forces for research in the 3D irregular packing problem comes from the 3D printing industry. Three-dimensional printing, also known as additive manufacturing, is a type of manufacturing method that produces 3D shapes by adding layers. Three-dimensional printing is rapidly growing and has massive potential in many industries including medical instruments, aerospace, and robotics. Three-dimensional printing also has a promising outlook in the construction industry, its application including buildings and bridges. For example, the office building for Dubai Future Foundation was printed by Winsun, a Chinese 3D printing architecture Company. Benefits arise through the possibility of packing several parts into one build chamber and simultaneously printing them by batch production (Wu et al. 2014). As the use of 3D printing is mainly focused on off-site fabrication, C&P problem can help decease transportation costs for the prefabricated parts.

Another application of C&P problem in construction industry lies in facility decommissioning and disassembling. Take the decommissioning of a nuclear power plant as an example. The packing of nuclear waste produced by the decommissioning phase highly affects the final number of containers required, manpower required, the manipulation complexity, and consequently their effect on costs. Further, the C&P problem can be more generally applied in the construction industry, such as assisting in the placement of construction materials on construction sites, improving transport efficiency of building tools or fabricated construction assemblies by increasing space utilization of trucks, and reducing the storage space of the construction waste. Despite all the promising applications, as far as we know, no research has been done on the C&P problem in the scope of the construction industry.

This paper describes a novel packing algorithm for 3D irregular objects using scanned point cloud data. In the current study, a solution for the 3D irregular packing problem using the principle of maximum contact surface between objects to minimize the packing volume is proposed. A collision detection method developed for point cloud models is proposed and multiple orientations for each object are taken into consideration.

The paper is organized as follows. A brief introduction of the existing 3D irregular packing approaches is given in section 2. Section 3 explains the proposed collision detection algorithm for point cloud models, followed by the description of the maximum contact surface principle in section 4. The 3D irregular packing algorithm is described in detail in section 5. Experiment results are shown in section 6. Finally, section 7 contains concluding remarks.

RELATED WORK

Heuristic methods: Heuristic algorithms, which aim to find an optimized, "good enough" solution in an acceptable amount of time, are often used to deal with packing problems. Bortfeldt and Wäscher (2013) asserted that heuristic algorithms, in particular metaheuristics, are and will remain the most important class of algorithms for solving the container loading problems in the foreseeable future. Liu et al. (2015) proposed a packing algorithm called HAPE3D, a heuristic algorithm aiming at minimizing the total potential energy of the packing, which can be hybridized with a simulated annealing algorithm to further improve the packing quality by optimizing the sequence of the packing. Wu et al. (2017) introduced a genetic algorithm based two-step packing procedure: (1) determine the sequence of packing and orientation for each small item by genetic algorithm; and (2) place items into the container one-by-one using a modified bottom-left-fill placement heuristic, which is an extended method from the bottom-left heuristic for the 2D packing problem. Yao et al. (2015) introduced a relaxed placement method using level-set representation of small items. The idea is to slowly reduce the size of the container and remove the collision area using level set function. Another contribution of their research is that they tried to incorporate the cutting process into the packing through iteration between these two processes. Vanek et al. (2014) also managed to combine cutting and packing together. They use iteration between height field based packing and Tabu-search sequence optimization.

Mathematical modeling: Mathematical modeling refers to the methodologies that attempt to formulate the packing problem into a mathematical programming problem. Due to the complex characteristics of the irregular shapes and the multiplicity of objectives, there are only a few methods that attempt to find the exact or optimal solutions to the problem. Stoyan et al. (2005) extended phi-function into three dimensions to pack three-dimensional convex polytopes into a parallelepiped. However, as polytopes can only be translated, the rotation is not allowed. Stoyan et al. (2016a) developed a non-linear programming model using ready-to-use phi-function, to search for local optimal solution for two-dimensional irregular packing problem with continuous rotation. Romanova et al. (2018) proposed a non-linear programming formulation to manage the concave polyhedra packing problem with continuous rotations using quasi phi-functions introduced by Stoyan et al. (2016b). The complexity of generating phi-functions for arbitrary shapes is the major limitation of this approach.

To address the shortcoming identified for phi-functions, the use of point cloud representation is proposed as leading to a class of solutions to optimize the C&P problem of 3D objects. Point cloud models are increasingly used to measure complex geometry or environment in various fields, including environmental surveying and robotics. As 3D scanners are becoming more affordable, point clouds have also became a popular tool for shape representation, which allows high precision and rapid geometry acquisition for objects without existing synthetic models. Comparing with other previously developed packing algorithms, the proposed packing algorithm does not require a pre-designed CAD model, the point cloud representation is easy and rapid to acquire, and it is more consistent with the actual shape of the objects. For this reason, the proposed packing algorithm would be suitable for construction components (with careful tolerance management).

COLLISION DETECTION METHOD

Little literature (Figueiredo et al. 2010; Pan et al. 2013) exists on determining collision between point clouds. In this research, the 3D irregular packing problem of unknown geometries is addressed. Three-dimensional scanning technology is employed to collect raw data, and a novel collision detection method in the context of the packing problem using point cloud is proposed. Building upon the sphere assembly model (Li and Zhao 2009) and the bubblepack algorithm in PFC3D (Particle Flow Code, a discrete element modeling framework available for three-dimensional programs), every point in the point cloud can be represented by a sphere.

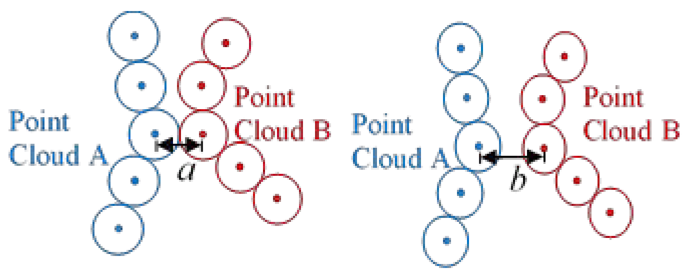

Figure 1. Collision detection method

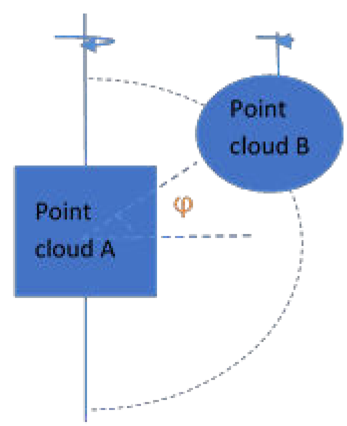

Figure 2. Rotation and starting points for point clouds

Consider two point clouds A and B, which have m and n points respectively. To determine if these point clouds are intersecting, two parameters a and b are defined as shown in figure 1, which are empirical values dependent on the density of the point cloud. The value a denotes the diameter of spheres that represent each scanned point, which is also the minimum distance between point cloud A and point cloud B when they are as close to each other as measurement error might allow without collision and yet not connected. Value b denotes another critical distance. When the distance between two point clouds is greater than b, the two point clouds are considered to be separate. Let d_{ij} define the distance between i^{th} point in point cloud A and j^{th} point in cloud B, where $i \in [1,m]$, $j \in [1,n]$. Let d_i define the minimum distance between point i in point cloud A and point j in point cloud B, $d_i = \min(d_{ij})$, where $i \in [1,m]$, $j \in [1,n]$.

In the situation where two point clouds are approaching each other. For point i in point cloud A, if distance d_i from this point to point cloud B is:

- $a < d_i < b$, the distance between this point and point cloud B is appropriate, this point is in contact with point cloud B;
- $d_i > b$, this point is far from point cloud B;
- $d_i < a$, this point is inside point cloud B;

For point cloud A and B:

- Collide, $\exists d_i < a$;
- Separate, $\forall d_i > b$; and
- Contact, $\forall d_i > a \cap \exists d_i < b$.

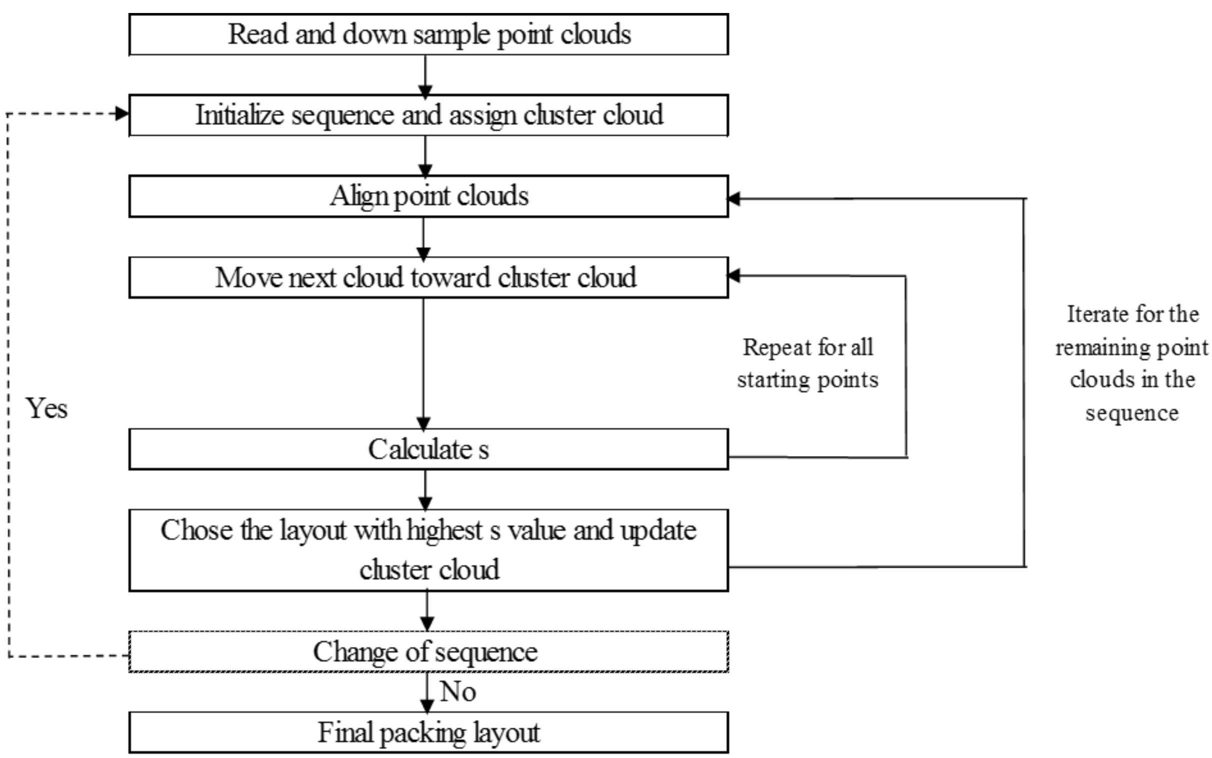

Figure 3. Flowchart of packing algorithm

In the program, a and b can be adjusted to easily change the distance between items in the final packing result.

OPTIMIZATION ASSUMPTION

The area of contact surface between objects reflects how well they fit together. If the area of contact is larger, the objects are more attached to each other and the final overall volume is smaller. Essentially, the aim is to nest the objects. For point clouds, the number of points that are in contact is counted. Based on this assumption, a criterion is proposed to judge how good the relative placement between two point clouds is. Let s define the number of points that are in contact between two point clouds. The algorithm chooses the layout with maximum s value. Consider the point cloud A and point cloud B. Let s_{AB} be the number of points that are in contact between these point clouds. For each point in point cloud A, calculate d_i, and count the points of which $a < d_i < b$. The algorithm calculates s for the different placement and chooses the layout with the highest s_{AB} value.

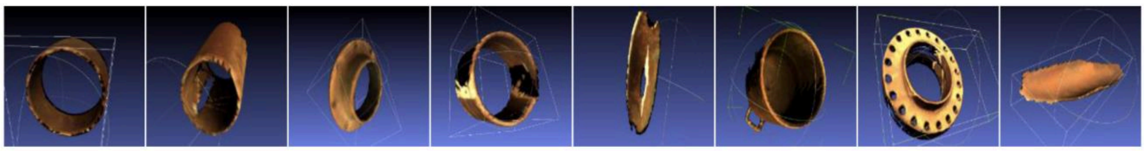

Figure 4. Eight scanned instances

Table 1. Experiment results for 8 instances

Number	Number of points/object	Packing sequence change	Bounding box Volume	Calculation time (s)
1	1000	---	0.67945	71.739
2	5000	---	0.68647	120.019
3	5000	12 times	0.64929	1411.438

ALGORITHM OUTLINE

The packing algorithm can be described as follows:

1. Read point clouds of each object, and down-sample the number of points to speed up computation. The distances between points are calculated in the proposed algorithm, which leads to the fact that the efficiency of the program highly depends on the number of points in each point cloud.
2. Determine the initial sequence of packing by sorting the point clouds in ascending order of their volume. Choose the first two point clouds to start.
3. Calculate the principle components for each point cloud using principal component analysis (PCA). Align two point clouds based on their first principle component such that corresponding principle components are pointing in the same direction.
4. Fix the position of point cloud A, and move point cloud B to a different initial starting placement. However, trying unlimited starting points is both unrealistic and inefficient. The solution is to limit the number of starting points while allowing rotation of both point clouds along the axis of their first principle component respectively. The rotation degree can be adjusted according to need. The number of starting positions of the second point cloud can be controlled through parameter φ as shown in figure 2.

5. Move point cloud B from the starting position to point cloud A by step distance combined with the previously mentioned collision detection method. The process stops when two point clouds are as close to each other as measurement error might allow without collision. Calculate s_{AB}.
6. Repeat step 4 and 5 with different starting positions for point cloud B.
7. Choose the placement with the highest s_{AB} value as the preferred layout of the two point clouds.
8. Consider the former packed point clouds as a whole, defined herein as a cluster cloud, and run the packing algorithm with the next point cloud in the sequence.
9. The iteration stops when all point clouds are allocated.
10. Change the packing sequence by randomly swapping two objects or reversing the sequence between two randomly picked objects.
11. Repeat from step 3. The algorithm stops when all the iterations finish and the layout of minimum volume is chosen.

Algorithm flowchart is presented in figure 3.

EXPERIMENT RESULTS

The packing program was written in MATLAB on the Windows platform. To evaluate the performance of the proposed algorithm, experiments were conducted using a computer with 2.80 GHz i7 CPU and 8 GB of memory.

Eight pieces of waste from a structural laboratory were scanned using 3D scanner Structure Sensor as shown in figure 4. They represented typical decommissioning objects. To shorten the processing time in the experiment, each point cloud is allowed 4 rotations (0°, 90°, 180°, 270°) around the axis of their first principle component when approaching each other, and φ is set to 45°. A Kd-tree is used to organize points in point clouds in order to improve runtime efficiency.

As the calculation time depends on the number of points input in the algorithm, the same experiment was conducted two times with a scan of each object down-sampled to 1000 points/object and 5000 points/object in experiment 1 and experiment 2 respectively. Apart from the number of points, another important factor is the packing sequence. Packing experiment 2 was carried out with 12 changes of packing sequence. The sequence is changed by randomly switching two objects' order, randomly selecting one object and insert it into the sequence or by reversing the order between two objects.

The packing results are shown in figure 5 and table 1. It can be seen from figure 5 that the collision detection method for point clouds works well in the context of packing. Comparison between figure 5a and 5b shows that a more preferable packing order can be found by changing the sequence, which leads to a smaller packing volume. It is not surprising to see from table 1 that reducing the size of the point clouds can shorten the calculation time. Further experiments will expand on these preliminary results.

CONCLUSION

The point cloud is a popular representation in many industries, such as robotics, which allows for high precision and rapid geometry acquisition for objects without existing synthetic models. However, there is no paper in the literature about packing using point clouds. This paper describes a novel collision detection method and packing algorithm for 3D irregular objects using scanned point cloud data. The proposed collision detection method considers every point in