PROYECTO

PHOENIX-CH:

Pointcloud Healing and Object Estimation through cross-attentIon eXploration

CIENCIAS DE LA COMPUTACIÓN
UNIVERSIDAD DE CHILE

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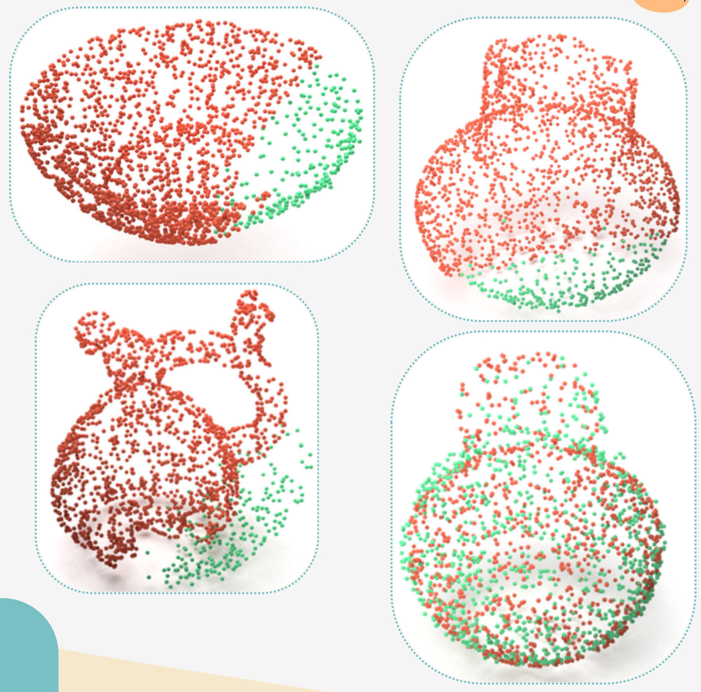


1. CONTEXT & RELATED WORKS

Archaeology seeks to understand human history through ancient artifacts, but these objects often suffer from deterioration or incompleteness. Digital models obtained through scanning frequently exhibit defects, such as missing geometry due to occlusion.

To address these challenges, some researchers have explored reconstruction using implicit representations [3, 4], altough these methods often require watertight meshes. Alternatively, [1, 2] focused on directly working with point clouds to repair objects. Notably, [2] and [3] specifically explored generating only the missing geometry rather than reconstructing the entire object, something really useful for repairing archaeological objects.

2. OBJECTIVE

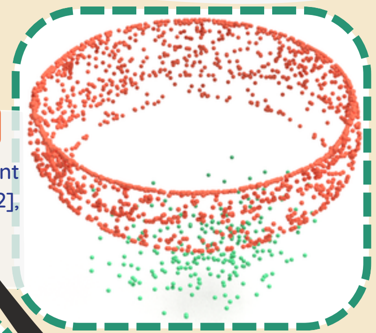
Explore and develop some AI models to restore incomplete point clouds of archaeological artifacts, combining the strengths of implicit representations and point-cloud-based approaches. We use PointAttN [1], and two custom variations.

3. Feature Extractor (FE)

Processes the point cloud of the damaged object and generates a high-dimensional embedding [1]. By leveraging transformer-based architectures, this module captures the relationships between points, even in incomplete geometries.

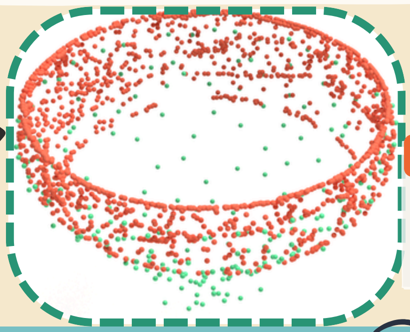
Seed Generator (SG)

Using the embeddings, reconstructs a low-resolution point cloud [1]. This "coarse" output is then concatenated with the input point cloud and sampled to produce "seeds," which serve as the foundation for the next stage in the reconstruction process.



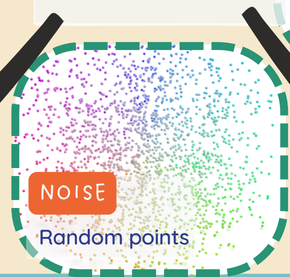
COARSE MODIFIED

Predicted missing point cloud. Inspired by [2], [3].



COARSE

Predicted low-resolution point cloud of repaired object

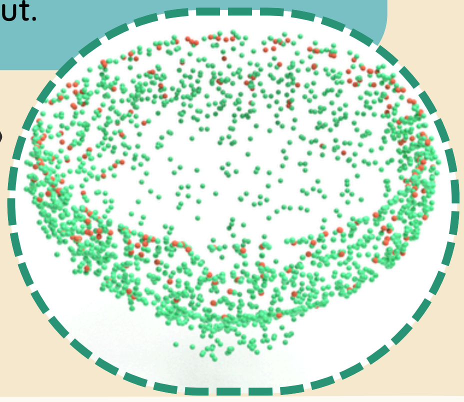


NOISE

Random points

Point Generator (PG)

Refines the seeds into a high-resolution reconstruction. It combines the seeds generated by the SG with the embeddings from the FE to significantly increase the number of points, achieving a detailed and complete point cloud of the object [1]. This module is stacked twice to iteratively improve resolution, culminating in a highly detailed final output.

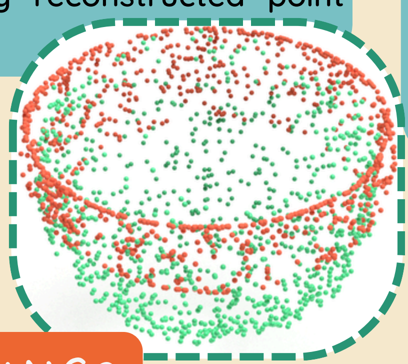


Denoiser

Transforms noise into a reconstructed object by associating noisy input with the seeds, which represent a partially repaired object. This module combines three inputs:

- Shape code
- Noise
- Deeds (sampled coarse+inputs)

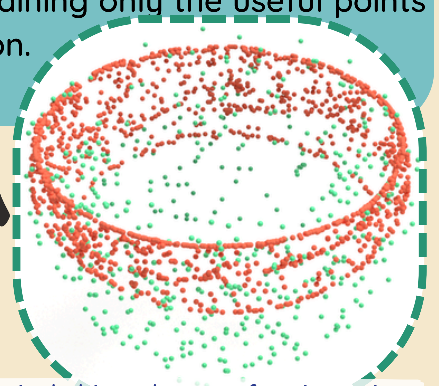
Using a cross-attention mechanism, it captures the relations between these inputs to determine and apply a transformation to the noise. The result is a high-resolution, fully reconstructed point cloud.



Primal Extractor (PE)

Filters the noise, classifying points that contribute to the object repair. Its inspired by [4]. It uses the same three inputs as the Denoiser.

By employing a cross-attention mechanism, it captures the relationships between these inputs, determining which points from the noise are worth keeping. This results in occupancy probabilities. Points with a classification probability below a threshold (e.g., 0.5) are discarded, leaving a filtered point cloud containing only the useful points for reconstruction.

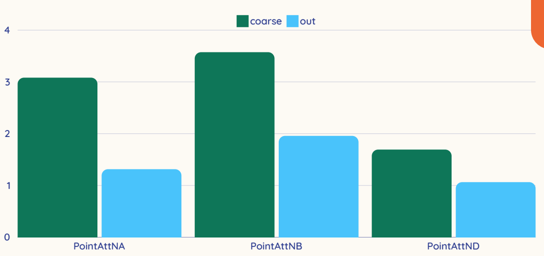


4. RESULTS

Quantitative results were evaluated on a custom validation dataset by Jaramillo, using Chamfer and Hausdorff distances between the generated point clouds and ground truths.

For qualitative analysis, several rendered visualizations of the reconstructed objects were examined to assess the quality of the repairs.

'CD' BY EXPERIMENT



CD results for 'coarse' and 'out' objects, grouped by model.

5. FINDINGS

PointAttNA demonstrated promising results in repairing archaeological objects by transforming noise into useful points for reconstruction, though challenges remain with complex geometries.
PointAttNB was functional, but point density issues limited the quality of repairs, suggesting the need for further research on improving output consistency.
PointAttN by itself showed effective repairs in simpler objects, but struggled with more intricate shapes, indicating that more diverse training data is needed for better generalization. Overall, these models represent significant progress in digital object repair, with room for improvement through enhanced data and techniques.

REFERENCES

[1] Jun Wang, Yinghan Cui, Dongyan Guo, Junxia Li, Qingshan Liu, and Chunhua Shen. Pointattn: You only need attention for point cloud completion. In AAAI Conference on Artificial Intelligence, 2022.
[2] Ivan Sipiran, Alexis Mendoza, Alexander Apaza, and Cristian Lopez. Data-driven restoration of digital archaeological pottery with point cloud analysis. International Journal of Computer Vision, 130, 09 2022.
[3] Nikolas Lamb, Sean Banerjee, and Natasha Kholgade Banerjee. Deepmend: Learning occupancy functions to represent shape for repair. In Shai Avidan, Gabriel Brostow, Moustapha Ciss´e, Giovanni Maria Farinella, and Tal Hassner, editors, Computer Vision – ECCV 2022, pages 433–450, Cham, 2022. Springer Nature Switzerland.
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