2023 IMEKO TC-4 International Conference on
Metrology for Archaeology and Cultural Heritage
Rome, Italy, October 19-21, 2023

AI-assisted Reconstruction of Archaeological Pottery from digital 3D mesh models

Eleonora Marconi[1,2], Antonio Budano[1], Giancarlo Della Ventura[3], Federico Fina[3], Alberto Botti[4], Sandro Tassa[4], Ottavia Palacino[4], Lorenzo Conte[5], Marianna Franco[5], Francesco Pacetti[5], Caterina Coletti[6], Armida Sodo[3], Luca Tortora[1,2,3]

[1] *Laboratorio Analisi Superfici Roma Tre LASR3, via della Vasca Navale 84, Roma, 00146, Italy*
[2] *Istituto Nazionale di Fisica Nucleare INFN, Tre via della Vasca Navale 84, Roma, 00146, Italy*
[3] *Dipartimento di Scienze dell'università di Roma Tre, via della Vasca Navale 84, Roma, 00146, Italy*
[4] *ARAKNE, Via Edoardo D'Onofrio 304, Roma, 00155, Italy*
[5] *Sovrintendenza Capitolina ai Beni Culturali SCBC, Piazza Lovatelli 35 - 00186 Roma, Italy*
[6] *Piazza dei Navigatori 7, 00147 Roma*

***Abstract* – Ancient pottery in archaeological sites is typically found as broken fragments. The collection, classification, and assembling of those pieces into their original artifact may take years of hard work, especially when the fragments are irregular, intermixed with parts of different vessels, or if some key pieces are missing. This problem is traditionally handled via two main steps: (1) the Classification of Archaeological Fragments into similar groups (CAF) and (2) the Reconstruction of each group into the original Archaeological Objects (RAO). Over the years, many alternatives have been proposed to solve this problem. A seminal approach was exploiting the color and texture properties of the fragments. More recently, the use of 3D computer-aided reconstruction methods gained attention as promising tools in pattern recognition. For this reason, researchers have implemented algorithms to collect all the information necessary to reconstruct a complete vessel from suitable data collected via 3D scanners. In this work, four types of algorithms were tested to reconstruct the objects without an a priori knowledge of the final shapes. The method exploited the geometric features obtained from the 3D mesh model acquisition on artificial samples from a broken mug, used as test cases. The best algorithm satisfying the final 3D reconstruction was then applied to the study of archaeological ceramic fragments from Villa della Piscina in the Parco Archeologico of Centocelle (Rome, Italy) within the project ERCOLE. The aim of this work is at developing a tool that satisfies the criteria of accuracy, performance, robustness, transportability, cost, and careful handling of archaeological specimens.**

I. INTRODUCTION

The archaeological study of ceramics is a mainstay for understanding both the daily life of ancient communities and their social features such as religious practices and commercial exchanges [1]. During archaeological excavations, it is extremely rare to find intact ceramics such as pots, jars, and bowls. The artifacts are usually found fragmented and are therefore called "sherds". Their position and orientation in the ground can provide information about the societies from which they came [2].

The ceramic sherd reconstruction technique usually used by archaeologists consists of relieving and graphically representing the fragments. The drawing of ceramic fragments plays a fundamental role in the hypothetical reconstruction of the shape of whole objects to which such fragments originally belonged. Traditionally, only fragments that contain an original rim or base edge, referred to as "diagnostics", are considered to be useful to the archaeologist [3].

Pottery classification is based on several parameters such as the dimensions, shape, and materials used to manufacture the pot. Archaeologists use their experience and expertise to weigh these parameters and classify pottery [4]. The methodology presented in this work complements the knowledge of the archaeologists and allows obtaining a more accurate profile-based classification of pottery.

3D systems able to automatically reconstruct objects from their fragments may find application in different fields. In archaeology, they could provide powerful support to reconstruct broken bones or shattered pottery [5]. 3D scan systems are already saving time for archaeologists, who can spend countless hours piecing together broken artifacts by hand. Moreover, they could provide archaeologists with tools to quickly make accurate measurements on fragments and reconstructed objects, allowing for improved interpretation of the observations [6]–[8]. In fact, in most cases, broken vessels and artifacts are not reassembled unless the fragments are visually similar and discovered in a context that constrained in both time and space. Using large databases of digitized fragments, automatic reconstruction systems could identify issues such as partial or incomplete reconstructions of artifacts that may have been recovered during different years of the same excavation, or even from different sites altogether [7]. In this way, reconstruction systems could not only save working time, or help build useful databases of fragments, but could also allow the reconstruction of relevant artifacts that would otherwise remain as an incoherent pile of unrelated fragments.

There are many techniques to obtain a 3D model of an object, such as photogrammetry, structured light scanner (SLS), and laser scanning [9], [10]. Structured light-based 3D acquisition systems allow digitalizing not just one point at a time, but several hundred thousand points. The process of reconstructing the shape of an object is called triangulation. When a patterned light is projected onto the surface of the object, the patterns are distorted. High-resolution cameras capture the data, which are processed by the 3D scanning software [11]. This method often provides useful information about the shape and the texture of the sherd, however, artifacts from the scanning process are possible, hindering satisfying reconstruction of the specimen. The following step consists of a jigsaw puzzle reconstruction of the fragments to obtain the original shape of the object. Many methods were investigated and developed for correctly rebuilding broken objects starting from matchings between adjacent fragments by using color surface [12], by using the morphology profile [8], similar geometry, and photometry along, or across matching fragments adjoining regions [13]

The main goal of the present research is to achieve a plausible and optimal reassembly of vascular artifact fragments using structured light scanning. Two methodological options, described by Sellán et al. [14] and Je Hyeong Hong et al. [15], were selected and compared. The approach of Sellán et al. starts by generating a synthetic dataset consisting of over one million fragmented objects derived from ten thousand original models. This dataset serves as a foundation for optimizing the task of 3D geometric shape reassembly. By employing a recently developed physically based algorithm, the dataset simulates the natural process of how geometric objects fracture into various pieces. This algorithm efficiently produces diverse fracture patterns for any given object.

For the reassembly task, three state-of-the-art deep learning methods were utilized: Global [16], [17], LSTM [18], and Dynamic Graph Analysis (DGL) [19]. Each method underwent training and testing using fractured objects from the synthetic dataset, with a maximum of 20 pieces per object. The metrics used were the root mean square error (RMSE) and the mean absolute error (MAE) between the predicted rotation and the actual rotation R, respectively. Additionally, shape chamfer distance (CD) and part accuracy (PA) metrics were used for performance evaluation.

The evaluation results and benchmarks demonstrated that graph neural networks (GNNs), such as DGL, exhibited superior reasoning abilities in determining the compatibility between fragments compared to the other two architectures (Global and LSTM). Specifically, DGL outperformed both Global and LSTM across all metrics, and its predictions of assembly results displayed a higher visual similarity to the ground truths compared to the other baseline methods.

In our work, one of the objectives will be to benchmark and assess the effectiveness of these approaches in reconstructing the selected artifacts for the ERCOLE Project. However, this evaluation assumes that the collection of sherds provided to the algorithm belongs to a single artifact. It is important to note that this assumption may not hold strong in real-world scenarios where fragments within the same excavation site may lack distinct characteristics, making it difficult to attribute them to a single artifact.

To address this limitation, we considered the method of Je Hyeong Hong et al., who proposed a procedure for the Incremental 3D reassembly of axially symmetric pots from unordered and mixed fragment collections: structure-from-sherds (SFS). Based on this approach, we reanalyzed the same set of three-dimensional scans, introducing the flexibility that the fragments may not belong to a known number of artifacts a priori. In this way, we obtain both a potential reconstruction and an assignment of the fragments to the individual artifact.

By incorporating this degree of freedom, we enhanced the robustness of our reconstruction process also accounting for situations where fragments cannot be easily attributed to a single artifact within an excavation site.

In this work, we tested these different approaches for the pottery fragments from the Villa della Piscina archeological site to obtain not only a database of digitalized fragments but also the possibility to draw a 3D jigsaw reconstruction of the original vessel pottery.

II. DATA ACQUISITION

The EinScan SE-V2 3D Scanner developed by Shining 3D, China, was employed. The 3D scanner is composed of a projector and two web-cams with a resolution of 1.3 Mpixels, equipped with a white LED source with a working distance of 290 ~ 480 mm, and a spinning sample holder with a scan speed of < 45 s. The resolution for any single image is 0.1 mm according to the manufacturer. The acquisition setup consists of the EinScan Scanner connected to a PC and the object to be recorded located on the rotating plate. A maximum 700×700×700 mm and a minimum 30×30×30 mm scan volumes can be analyzed. A series of parallel light patterns are projected on the target object; these are modified by the morphology of the object and by processing the modified patterns the software is able to reconstruct the surface of the sample. The EinScan is a portable device that requires a host computer. The rotating table is used to index the scanned part and capture all sides in one automated process. Due to its weight (2.5 kg) and size (570×210×210 mm), it can be used as a handheld device, but the software requires a graphic memory ＞1G and a RAM memory of ＞8G.

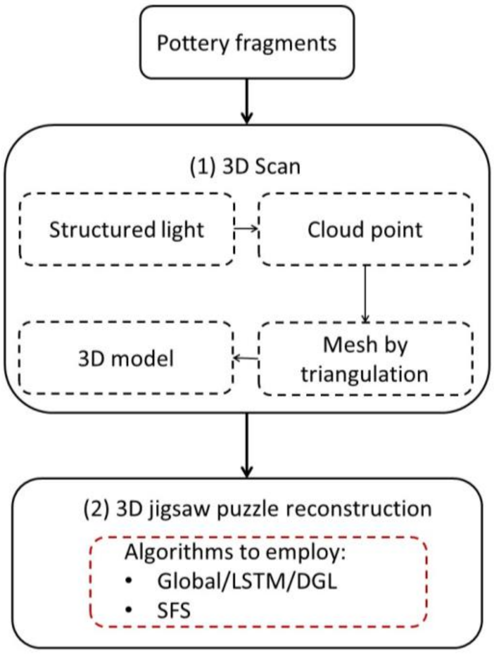

Figure 1: process diagram of 3D acquisition and jigsaw puzzle reconstruction of pottery shields.

III. RESULTS

The first step was to develop a useful tool to obtain a 3D jigsaw puzzle reconstruction of pottery fragments. The process involves (1) Acquisition of the 3D model and application of the post-processing procedure to reduce noise. (2) Identify and align the part that will match a pair of fragments by using various algorithms (Figure 1).

As a preliminary test, a commercial ceramic pot was decorated and broken into 5 pieces (Figure 2a-b). Each piece was scanned multiple times by using the EinScan SE-V2 instrument (Figure 2c) obtaining a cloud of points of the piece (Figure 2d). 3D reconstructions were obtained (Figure 3a) by meshing 3 scans set of 20-36 acquisitions through the triangulation process. The obtained 3D models had an excellent resolution, especially at the boundary of the fragment, and were processed via several algorithms in order to find the best method able to recognize fragments that originating from the same pottery and reassemble them through a jigsaw puzzle reconstruction. In Figure 4 we show as an example a 3D mesh model of a fragment from the Villa della Piscina archeological site where the techniques employed to digitalize the sherd gave very promising results.

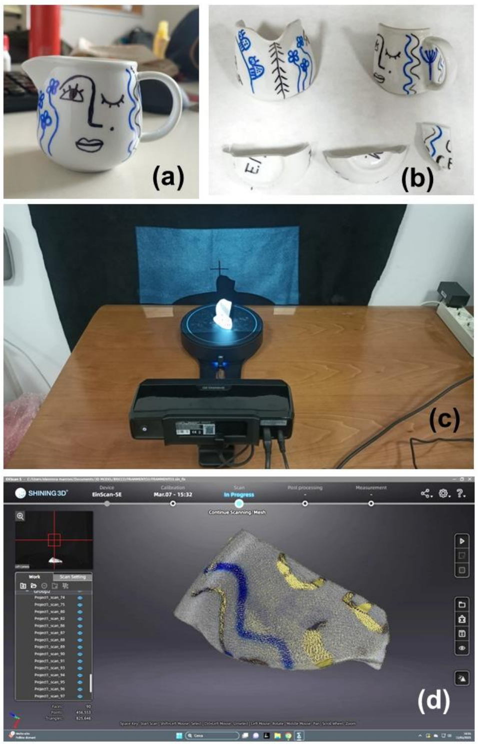

Figure 2: 3D scanner acquisition. (a) solid pottery, (b) pottery pieces, (c) 3D scanner EinScan for data acquisition, and (d) an example of the cloud of points resulting from the structured light acquisition.

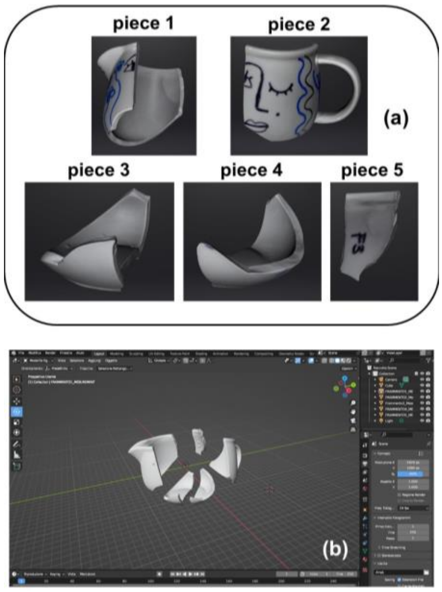

Figure 3: 3D reconstruction of the fragments (a) resulting 3D mesh, and (b) digital reconstruction of the fragments.

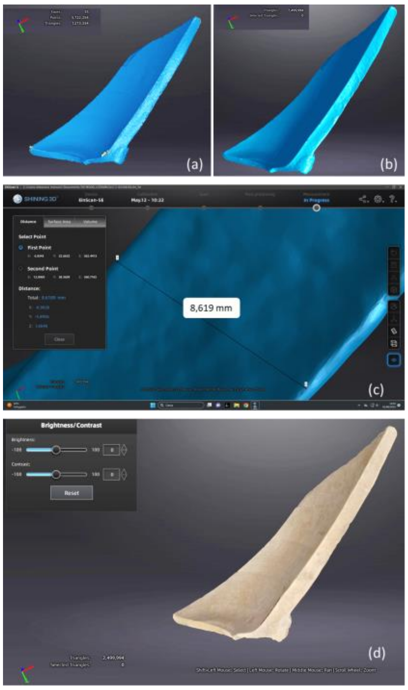

Figure 4: 3D reconstruction of a sherd generated by the EinScan scanner. (a) cloud point, (b) 3D mesh model, (c) measurements on fragments (d) textured 3D model.

IV. CONCLUSION

In this work, we collected a series of 3D images of pottery sherds by using a commercial instrument based on the structured light scanner. The 3D mesh model showed good resolution, in particular at the fragment boundaries, suitable for successive matching of the pieces into their original artifact shape. Different algorithms for their recombination, based on graph neural networks, have been tested. The final results are promising and suggest a real possibility to use these methods as a tool in archeology for solving the long-lasting problem of reconstructing ceramic objects from their fragments.

V. ACKNOWLEDGEMENTS

The authors acknowledge financial support through the ERCOLE project (Le villE del paRCO di centocelLE) funded by Regione Lazio and Ministero dell'Istruzione e del Merito (MIUR) via research grants G12666, on BURL n. 99 21.\10.2021, of LAZIO INNOVA.

REFERENCES

[1] V. Hristov and G. Agre, "A Software System for Classification of Archaeological Artefacts Represented by 2D Plans," *Cybernetics and Information Technologies*, vol. 13, no. 2, pp. 82–96, Jun. 2013, doi: 10.2478/cait-2013-0017.

[2] G. Shear, "3D Scanning for Profile Acquisition and Reconstruction of Mayan Ceramics." [Online]. Available: www.blender.org

[3] Martina Andreoli, "Laboratorio di Archeologia - esercitazioni di disegno archeologico," Università di Bolzano, 2004.

[4] S. Goel and P. Singh, "Computer Vision Aided Pottery Classification and Reconstruction," 2005.

[5] M. Kampel, R. Sablatnig, H. Mara, and M. Lettner, "3D Acquisition of Archaeological Ceramics and Web-Based 3D Data Storage," in *Digital Discovery. Exploring New Frontiers in Human Heritage. CAA2006. Computer Applications and Quantitative Methods in Archaeology. Proceedings of the 34th Conference. Archaeolingua, Budapest*, 2006, pp. 549–553.

[6] H. Mara and R. Sablatnig, "A Comparison of Manual, Semiautomatic and Automatic Profile Generation for Archaeological Fragments * † ‡."

[7] A. R. Willis and D. B. Cooper, "Computational reconstruction of ancient artifacts: From ruins to relics," *IEEE Signal Process Mag*, vol. 25, no. 4, pp. 65–83, 2008, doi: 10.1109/MSP.2008.923101.

[8] A. Karasik and U. Smilansky, "Computerized morphological classification of ceramics," *J Archaeol Sci*, vol. 38, no. 10, pp. 2644–2657, Oct. 2011, doi: 10.1016/j.jas.2011.05.023.

[9] D. Akca, "3D modeling of cultural heritage objects with a structured light system," *Mediterranean Arhaeology and Archaeometry*, vol. 12, no. 1, pp. 139–152, 2012.

[10] H. Rahaman and E. Champion, "To 3D or Not 3D: Choosing a Photogrammetry Workflow for Cultural Heritage Groups," *Heritage*, vol. 2, no. 3, pp. 1835–1851, Jul. 2019, doi: 10.3390/heritage2030112.

[11] R. Wang, A. C. Law, D. Garcia, S. Yang, and Z. Kong, "Development of structured light 3D-scanner with high spatial resolution and its applications for additive manufacturing quality assurance," *The International Journal of Advanced Manufacturing Technology*, vol. 117, no. 3–4, pp. 845–862, Nov. 2021, doi: 10.1007/s00170-021-07780-2.

[12] C. Toler-Franklin, B. Brown, T. Weyrich, T. Funkhouser, and S. Rusinkiewicz, "Multi-feature matching of fresco fragments," *ACM Trans Graph*, vol. 29, no. 6, pp. 1–12, Dec. 2010, doi: 10.1145/1882261.1866207.

[13] G. Oxholm and K. Nishino, "A flexible approach to reassembling thin artifacts of unknown geometry," *J Cult Herit*, vol. 14, no. 1, pp. 51–61, Jan. 2013, doi: 10.1016/j.culher.2012.02.017.

[14] S. Sellán, Y. C. Chen, Z. Wu, A. Garg, and A. Jacobson, "Breaking Bad: A Dataset for Geometric Fracture and Reassembly," *Thirty-sixth*

Conference on Neural Information Processing Systems Datasets and Benchmarks , 2022.

[15] Je Hyeong Hong, Seong Jong Yoo, Muhammad Arshad Zeeshan, Young Min Kim, and Jinwook Kim, "Structure-From-Sherds: Incremental 3D Reassembly of Axially Symmetric Pots From Unordered and Mixed Fragment Collections," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 2021, pp. 5443–5451.

[16] J. Li, C. Niu, and K. Xu, "Learning Part Generation and Assembly for Structure-Aware Shape Synthesis," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, no. 07, pp. 11362–11369, Apr. 2020, doi: 10.1609/aaai.v34i07.6798.

[17] Nadav Schor, Oren Katzir, Hao Zhang, and Daniel Cohen-Or, "CompoNet: Learning to Generate the Unseen by Part Synthesis and Composition," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 2019, pp. 8759–8768.

[18] J. Wolper, Y. Fang, M. Li, J. Lu, M. Gao, and C. Jiang, "CD-MPM: continuum damage material point methods for dynamic fracture animation," *ACM Trans Graph*, vol. 38, no. 4, pp. 1–15, Aug. 2019, doi: 10.1145/3306346.3322949.

[19] G. , Zhan *et al.*, "Generative 3D part assembly via dynamic graph learning," *Adv Neural Inf Process Syst*, vol. 33, pp. 6315–6326, 2020.