ARTIFICIAL INTELLIGENCE FOR THE AUTOMATIC REASSEMBLY AND VIRTUAL RECONSTRUCTION OF ARCHAEOLOGICAL POTTERY FRAGMENTS: A CRITICAL REVIEW OF METHODS, BENCHMARKS AND PROSPECTS FOR CENTRAL ASIAN ARCHAEOLOGY

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https://doi.org/10.5281/zenodo.24142230

Abstract: Archaeological pottery is usually recovered as thousands of broken, partly eroded sherds, and its manual reassembly is slow and requires physical handling of fragile material. This review examines how digitization and artificial intelligence (AI) are changing that task. Based on a structured, source-verified survey of peer-reviewed papers, conference proceedings and preprints, it traces the pipeline from 3D scanning through fracture-surface segmentation to pairwise and multi-fragment matching, and compares three method families: symmetry-guided geometric reassembly, learning-based pose estimation and generative completion. Results obtained on synthetic benchmarks and on small real datasets are not directly comparable: the highest reported part accuracy on the synthetic Breaking Bad benchmark is 90.2% (on a volume-constrained subset), whereas Structure-from-Sherds++ reached 87% reassembly accuracy on 142 real fragments of ten pots, and one batch-scanning system reports more than 700 sherds digitized per day. Erosion, missing fragments, mixed assemblages and the scarcity of real training data remain the main open problems. An expert-in-the-loop workflow is proposed, and its relevance for Uzbek–Chinese field projects in the Fergana Valley is discussed.
Keywords: *archaeological ceramics; sherd reassembly; artificial intelligence; 3D scanning; virtual reconstruction; Fergana Valley.*

Аннотация: Археологическая керамика, как правило, обнаруживается в виде тысяч разбитых и частично эродированных черепков, а её ручная сборка отнимает много времени и требует физического обращения с хрупким материалом. В статье рассматривается, как цифровизация и искусственный интеллект (ИИ) меняют эту задачу. На основе структурированного обзора рецензируемых статей, материалов конференций и препринтов, источники которого проверены, прослеживается технологическая цепочка от 3D-сканирования и сегментации поверхностей излома до попарного и многофрагментного сопоставления, а также сравниваются три группы методов: геометрическая сборка на основе симметрии, оценка положения фрагментов с помощью обучаемых моделей и генеративное достраивание. Результаты, полученные на синтетических тестовых наборах и на небольших реальных выборках, напрямую несопоставимы: наивысшая заявленная точность размещения фрагментов на синтетическом наборе Breaking Bad составляет 90,2 % (на подмножестве с ограничением по объёму), тогда как метод Structure-from-Sherds++ достиг точности сборки 87 % на 142 реальных фрагментах десяти сосудов; одна из систем пакетного сканирования сообщает об оцифровке более 700 черепков в сутки. Основными нерешёнными проблемами остаются эрозия, утраченные фрагменты, смешанные комплексы и нехватка реальных обучающих данных. Предложена схема работы с обязательным участием эксперта, обсуждается её значимость для узбекско-китайских полевых проектов в Ферганской долине.
Ключевые слова: *археологическая керамика; сборка черепков; искусственный интеллект; 3D-сканирование; виртуальная реконструкция; Ферганская долина.*

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Annotatsiya: Arxeologik sopol buyumlar odatda minglab singan va qisman yemirilgan parchalar holida topiladi, ularni qo‘lda birlashtirish esa ko‘p vaqt talab qiladi va mo‘rt materialni jismonan ushlashni taqozo etadi. Ushbu maqolada raqamlashtirish va sun’iy intellekt (SI) bu vazifani qanday o‘zgartirayotgani ko‘rib chiqiladi. Manbalari tekshirilgan tuzilmaviy sharh (taqrizdan o‘tgan maqolalar, konferensiya materiallari va preprintlar) asosida 3D skanerlashdan sinish yuzalarini segmentatsiya qilish hamda juft va ko‘p bo‘lakli moslashtirishgacha bo‘lgan texnologik zanjir kuzatiladi va uch guruh usul taqqoslanadi: simmetriyaga asoslangan geometrik birlashtirish, o‘rgatiladigan modellar yordamida bo‘laklar vaziyatini baholash va generativ to‘ldirish. Sintetik test to‘plamlarida va kichik real tanlanmalarda olingan natijalarni bevosita solishtirib bo‘lmaydi: Breaking Bad sintetik to‘plamida bo‘laklarni to‘g‘ri joylashtirishning eng yuqori e’lon qilingan aniqligi 90,2 % (hajm bo‘yicha cheklangan qism to‘plamda), Structure-from-Sherds++ usuli esa o‘nta idishning 142 ta real bo‘lagida 87 % aniqlikka erishgan; paketli skanerlash tizimlaridan biri sutkasiga 700 dan ortiq parcha raqamlashtirilishini bildiradi. Asosiy hal etilmagan muammolar: yemirilish, yo‘qolgan bo‘laklar, aralash majmualar va real o‘quv ma’lumotlarining yetishmasligi. Mutaxassisni jarayonga majburiy jalb etuvchi ish sxemasi taklif etiladi va uning Farg‘ona vodiysidagi o‘zbek–xitoy dala loyihalari uchun ahamiyati muhokama qilinadi.

Kalit so‘zlar: *arxeologik sopol; sopol parchalarini birlashtirish; sun’iy intellekt; 3D skanerlash; virtual rekonstruksiya; Farg‘ona vodiysi.*

Introduction

Pottery is among the most abundant categories of archaeological finds, but it is almost always found broken. Most ceramics recovered from sites are fractured, and the available material therefore appears mostly as fragments [8].[1] Traditional study depends on manual drawing and on physically trying fragments against each other; Karasik and Smilansky noted that slow, often inaccurate manual drawings cannot cope with the volume of information produced by large excavations [2]. Computer-assisted reassembly is not new — the “Virtual Archaeologist” system was already described in 2001 [10] — but two developments have changed the field: affordable 3D scanners and deep learning. A recent survey describes the transition “from early procedural approaches to recent deep learning approaches” and notes that reassembly of fractured objects has not yet been recognized as a distinct sub-area of geometry processing [1]. For Central Asian archaeology the question is practical. Joint Uzbek–Chinese teams work in the Fergana Valley: a Luoyang–Fergana expedition was established in 2023 between the Luoyang Institute of Archaeology and Fergana State University to excavate the Kuva settlement [12], and joint teams have worked at Mingtepa since 2012 [13]. Pottery vessels are among the funerary finds reported from Munchaktepa [11].[2] Teams that recover large ceramic assemblages need to know which digital methods are mature enough for fieldwork and which are still laboratory research. This article asks three questions. (RQ1) Which stages make up a computational pipeline for pottery reassembly, and which methods serve each stage? (RQ2) What quantitative evidence exists for the accuracy and speed of these methods on real and synthetic data? (RQ3) What limits their use in excavation practice, and how should an archaeological team integrate them? The contribution is a critical synthesis with explicit warnings about comparability, together with a verification-oriented workflow for field teams.

[1]In this article “sherd” and “fragment” are used interchangeably for a broken piece of a ceramic vessel; “reassembly” means finding the correct relative position of fragments, and “virtual reconstruction” means building the digital model of the whole vessel.

[2]The information on the Kuva, Mingtepa and Munchaktepa projects comes from press reports [11–13], not from peer-reviewed excavation reports; it is used only to document that joint Uzbek–Chinese fieldwork exists and that ceramic material is among its finds. No claim is made here that these projects have already applied the AI methods reviewed.

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2. Materials and Methods

3. The study is a narrative critical review with structured source selection, not a systematic review in the PRISMA sense. Targeted searches were carried out in November 2026 in arXiv, the CVF Open Access archive, the ACM Digital Library records, the IJCAI proceedings, publisher and repository pages, using combinations of the terms *pottery*, *sherd*, *fragment reassembly*, *3D reconstruction* and *deep learning*. A source was included if (i) it addressed digitization, matching or reassembly of fragmented archaeological or ceramic objects, or provided a benchmark for it; (ii) it reported quantitative results or a dataset; and (iii) its bibliographic data and key figures could be verified against a primary page (publisher, proceedings or preprint server). Numerical values were taken from the original papers where possible. Where a value is quoted from the comprehensive survey of Lu et al. [1] (technology comparison and benchmark tables), this is stated. No experiments were run and no new data were produced.[3] Findings from non-peer-reviewed sources are labelled.[4]

3. Results and Analysis

3.1. Pipeline and digitization

The literature converges on a five-stage pipeline (Fig. 1): excavation and collection; 3D digitization; segmentation of each fragment into original and fracture surfaces; pairwise and multi-fragment matching; and virtual reconstruction with validation [1, 3]. The digitization stage determines the data quality for everything after it. According to the comparison in [1], laser scanning reaches about 0.01–3 mm accuracy, photogrammetry up to about 0.15 mm while capturing colour and texture, structured light about 0.1 mm with high speed, and computed tomography 0.001–0.5 mm with access to internal structure (Fig. 2).

Fig. 1. Computational pipeline for reassembly and virtual reconstruction of pottery (author's schematic, synthesized from [1, 3, 5]).

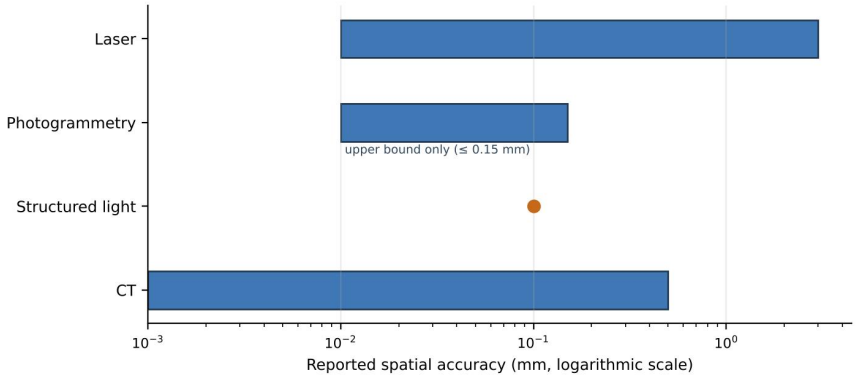


Fig. 2. Reported spatial accuracy of four scanning technologies (re-plotted from Table 1 in Lu et al. [1]). Photogrammetry is given in [1] only as an upper bound (≤ 0.15 mm).

Scale has been the main obstacle. Karasik and Smilansky scanned about 1,000 potsherds from several sites and periods, computed their axes of symmetry automatically and produced mean profiles, arguing that 3D scanning can be a standard tool for pottery analysis [2]. Brown et al. built a low-cost system that a single non-expert operator could use to digitize at least 10 fragments per hour; it was used on wall-painting fragments from Akrotiri, where 283 real fragments had been scanned by August 2008 [4]. Wang et al. proposed the FIRES batch system, which photographs fragments in batches, pairs the front and back scans by contour matching and registers them with a Bilateral Boundary ICP algorithm;

[3]Figures 1 and 4 are the author's schematic illustrations. Figures 2 and 3 are re-plotted by the author from published tables in [1]. No new experimental data were produced for this article.

[4]Sources [9] (Pinho et al.) is explicitly marked by the publisher as a "not peer-reviewed version"; [6] is an arXiv preprint. Results from preprints are used here only as indications of the state of the art.

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they report a throughput of more than 700 fragments per day on a 123-fragment dataset and field deployment at an excavation site in Armenia [5].[5]

3.2. Symmetry-guided and geometric reassembly

Wheel-made vessels are approximately axially symmetric, and this is the strongest prior available to the pottery specialist (Fig. 3). If all fragments of one vessel share the same rotation axis, the search space for placing two fragments shrinks from six degrees of freedom to one, which both reduces computation and improves noise resistance [1]. Karasik and Smilansky's software identifies the rotation axis of wheel-produced ceramics automatically [2]. More general geometric methods do not require symmetry: Huang et al. combine graph-cut segmentation of fracture surfaces, feature-based global registration for pairwise matching and simultaneous constrained local registration of several fragments with a non-penetrating ICP algorithm [3].

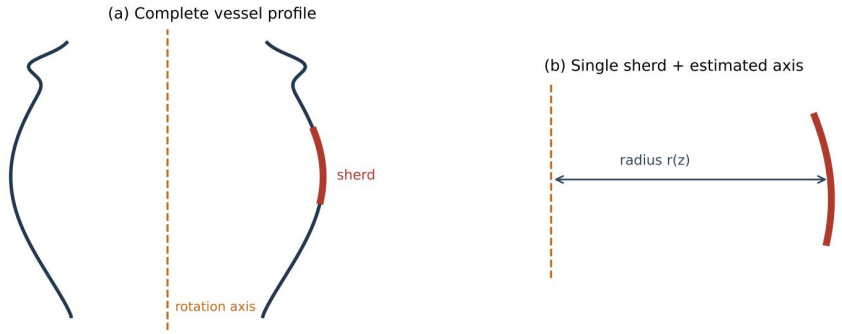


Fig. 3. Axial symmetry as a prior: (a) profile of a complete vessel with its rotation axis; (b) a single sherd whose radius r(z) relative to the estimated axis constrains its position (author's schematic).

Structure-from-Sherds++ (SfS++) transfers the logic of Structure-from-Motion to pottery: sherds are registered one at a time and beam search keeps several hypotheses alive, so that false matches between featureless fracture surfaces do not destroy the result [6]. On a dataset of 142 real fragments from 10 pots the authors report 87% reassembly accuracy, also for mixed collections of several vessels [6]. This is the most relevant published evidence for the real-world case of unsorted sherds, but it comes from one small dataset and an arXiv preprint.[6]

3.3. Learning-based reassembly and benchmarks

Deep-learning methods treat reassembly as a 3D puzzle and regress the pose of each fragment. Their development was driven by the Breaking Bad dataset, which contains over one million fractured objects simulated from ten thousand base models and was designed as a benchmark for reassembly [7]. Its meshes come from PartNet and Thingi10k and are divided into "everyday", "artifact" and "other" subsets [7]. Table 1 compares the main datasets listed in [1]. Only two of them — FIRES and RePAIR — contain real archaeological material with a ground truth or expert annotation, and both are small compared with the synthetic benchmark.

[5]Lu et al. [1] quote the FIRES throughput both as 730 fragments per day and as more than 700 fragments within 10 hours. This article uses the wording of the authors' own project page, "more than 700 fragments per day", and the field deployment is described there as lasting two and a half months in summer 2022 at an excavation site in Armenia.

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Table 1. Selected public datasets for fractured-object reassembly (after Table 3 in Lu et al. [1])

Dataset	Objects / groups	Pieces per object	Total pieces	Data origin	Type of breakage
Breaking Bad [7]	10,474	2–100	8,442,044	Shape collections	Synthetic
Fantastic Breaks	150	2	300	Household objects	Real
FIRES [5]	15	7–18	123	Pottery	Real
RePAIR	18	2–44	1,070	Frescoes	Real

Figure 4 shows the part accuracy of ten published methods on the "everyday" subset of Breaking Bad.[7] Early baselines (Global, LSTM, DGL) place about one fragment in five correctly; Transformer, diffusion and equivariant models raise this to roughly 50–70%, and the highest value, 90.2%, is reported for FragmentDiff on a volume-constrained subset [1].[8] The same survey stresses that this progress was achieved on synthetic data, and that the gap between synthetic training data and real fragments with erosion, weathering and missing pieces is a central open challenge [1].

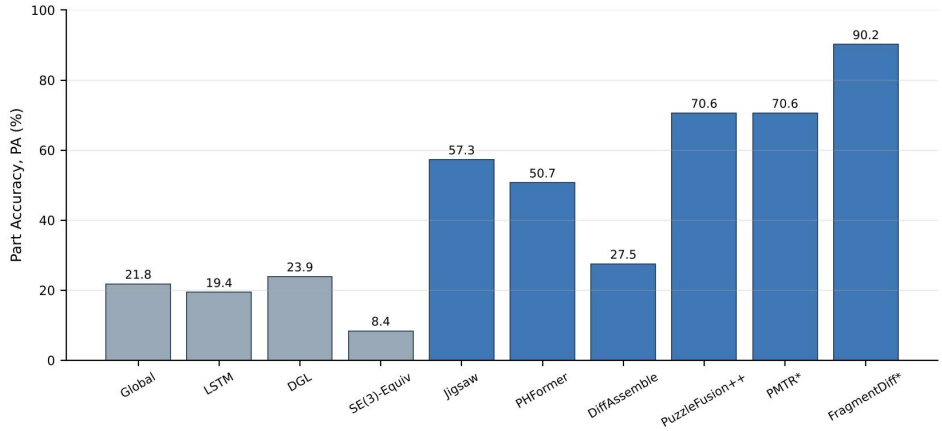


Fig. 4. Part accuracy (%) of published methods on the Breaking Bad "everyday" subset (re-plotted from Table 4 in [1]). Grey: earlier or weaker baselines; blue: recent Transformer, diffusion and equivariant models. * See note 3.

[7]Part Accuracy (PA) is the share of fragments whose Chamfer distance to the ground-truth position is below a threshold (typically 0.01); see Lu et al. [1], Section 8.2. It is a stricter and different measure from the "reassembly accuracy" reported by Yoo et al. [6], so the two values must not be ranked against each other.

[8]Values re-plotted from Table 4 of Lu et al. [1] ("everyday" subset, objects with 2–20 fragments). PMTR and FragmentDiff (marked *) were trained and tested on the "volume-constrained" subset, and SE(3)-Equiv was originally tested on 2–8 fragments; the bars are therefore indicative, not strictly comparable.

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3.4. Generative completion

When fragments are missing, matching alone cannot give a complete vessel, and generative models are used to propose the missing shape. Navarro et al. built the IberianVoxel dataset from 1,001 voxelized Iberian wheel-made pottery profiles, each fragmented 16 times (16,016 models in total), and proposed a 3D autoencoder generative adversarial network that generates the "best-matching" complete vessel from known fragments [8]. A preprint by Pinho et al. likewise investigates a deep-learning approach to support reconstruction of vessels from sherds [9]. Table 2 summarizes the three method families.

Table 2. Method families for pottery reassembly: evidence and limits

Family	Representative works	Reported evidence	Main limitation
Symmetry-guided / geometric	Karasik & Smilansky [2]; Huang et al. [3]; SfS++ [6]	≈1,000 sherds processed [2]; 87% on 142 real fragments, 10 pots [6]	Needs distinctive fracture geometry; best for wheel-made vessels
Learning-based pose regression	Breaking Bad benchmark methods [1, 7]	PA up to 90.2% on synthetic subset [1]	Synthetic-to-real domain gap [1]
Generative completion	IberianVoxel [8]; Pinho et al. [9]	16,016 synthetic fragment models [8]	Completes shape, does not prove the physical join; preprint status for [9]

4. Discussion

Comparability. The numbers in Section 3 measure different things on different data: part accuracy on synthetic objects [1], reassembly accuracy on 142 real fragments [6], and scanning throughput [5]. They show that each stage is technically feasible, but they do not show that a complete automated pipeline works on an unsorted field assemblage. Claims that AI "solves" pottery reassembly are therefore not supported by the present evidence.

Hybrid methods are most promising. The survey observes that the joint segmentation-and-matching network JIGSAW combines learned point-wise features with classical RANSAC and transformation synchronization, which gives more robust pose estimation than either approach alone [1]. Likewise, the success of SfS++ comes from embedding a strong archaeological prior (axial symmetry) in an incremental search [6]. For vessel sherds, knowledge of the craft is thus part of the algorithm, not an external check.

A workflow for field teams. On this basis a verification-oriented workflow is proposed for assemblages such as those studied in the Fergana Valley [11–13]. First, scan sherds in batches by photogrammetry or structured light, whose indicative equipment cost in [1] starts at about USD 50–200 and rises to several thousand. Second, estimate the rotation axis and profile for diagnostic sherds [2]. Third, let an algorithm rank candidate joins and group sherds of the same vessel. Fourth, the archaeologist accepts or rejects each hypothesis and tests accepted joins on the physical sherds. Fifth, publish the virtual model together with the list of fragments actually used, so that the reconstruction can be audited. This workflow is a proposal derived from the literature and has not been tested by the author.

Limitations. The review covers a small, verifiable subset of a fast-moving literature and depends on a single comprehensive survey [1] for benchmark values. Preprints [6, 9] have not been peer-reviewed. The review contains no tests on Central Asian ceramics, which differ from the Iberian,

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Aegean and Levantine material on which most published methods were developed; whether the reported accuracies transfer to hand-made or heavily eroded Fergana material is an empirical question.

Conclusion

Digitization is now fast enough to scan hundreds of sherds per day [5], axial-symmetry priors make geometric reassembly of wheel-made pottery tractable [2, 6], and learning-based models perform strongly on synthetic benchmarks [1, 7]. The decisive gap is between synthetic and real fragments. For archaeologists, the practical conclusion is to use AI as a generator of ranked hypotheses within an expert-controlled workflow, to document every algorithmic step, and to contribute real, openly licensed scan datasets from Central Asian excavations, which would reduce the data scarcity that limits the field today [1]. Joint Uzbek–Chinese projects in the Fergana Valley [11–13] are well placed to build such a dataset.

References

1. Lu, J., Han, H., Jiang, J., Liang, Y., Hua, J., Li, X., & Huang, Q. (2025). A survey on computational solutions for reconstructing complete objects by reassembling their fractured parts. *arXiv preprint* arXiv:2410.14770 (version of 28 March 2025). https://arxiv.org/abs/2410.14770
2. Karasik, A., & Smilansky, U. (2008). 3D scanning technology as a standard archaeological tool for pottery analysis: Practice and theory. *Journal of Archaeological Science, 35*(5), 1148–1168. https://doi.org/10.1016/j.jas.2007.08.008
3. Huang, Q.-X., Flöry, S., Gelfand, N., Hofer, M., & Pottmann, H. (2006). Reassembling fractured objects by geometric matching. *ACM Transactions on Graphics, 25*(3), 569–578. https://doi.org/10.1145/1141911.1141925
4. Brown, B. J., Toler-Franklin, C., Nehab, D., Burns, M., Dobkin, D., Vlachopoulos, A., Doumas, C., Rusinkiewicz, S., & Weyrich, T. (2008). A system for high-volume acquisition and matching of fresco fragments: Reassembling Theran wall paintings. *ACM Transactions on Graphics (Proc. SIGGRAPH), 27*(3). https://gfx.cs.princeton.edu/pubs/Brown_2008_ASF/fresco08_paper.pdf
5. Wang, J., Zhang, C., Wang, P., Li, X., Cobb, P. J., Theobalt, C., & Wang, W. (2023). Batch-based model registration for fast 3D sherd reconstruction. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*. https://doi.org/10.1109/ICCV51070.2023.01335. Open access: https://openaccess.thecvf.com/content/ICCV2023/html/Wang_Batch-based_Model_Registration_for_Fast_3D_Sherd_Reconstruction_ICCV_2023_paper.html
6. Yoo, S. J., Liu, S., Arshad, M. Z., et al. (2025). Structure-from-Sherds++: Robust incremental 3D reassembly of axially symmetric pots from unordered and mixed fragment collections. *arXiv preprint* arXiv:2502.13986. https://arxiv.org/abs/2502.13986
7. Sellán, S., Chen, Y.-C., Wu, Z., Garg, A., & Jacobson, A. (2022). Breaking Bad: A dataset for geometric fracture and reassembly. In *Advances in Neural Information Processing Systems (NeurIPS), Datasets and Benchmarks Track*. arXiv:2210.11463. https://doi.org/10.48550/arXiv.2210.11463
8. Navarro, P., Cintas, C., Lucena, M., Fuertes, J. M., et al. (2023). IberianVoxel: Automatic completion of Iberian ceramics for cultural heritage studies. In *Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (IJCAI-23)*. https://www.ijcai.org/proceedings/2023/647
9. Pinho, M., Mota, G., & Costa, G. (2025). A deep learning approach to assist in pottery reconstruction from its sherds [Preprint, not peer-reviewed]. *Preprints.org*, posted 17 February 2025. https://doi.org/10.20944/preprints202502.1174.v1
10. Papaioannou, G., Karabassi, E.-A., & Theoharis, T. (2001). Virtual archaeologist: Assembling the past. *IEEE Computer Graphics and Applications, 21*(2), 53–59. (Bibliographic data verified through the reference list of [3]; no open-access link verified.)

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11. Wang, R. (2025, 8 May). Unearthing the secrets of a Central Asian crossroads. *China Daily (Hong Kong edition)*. https://www.chinadailyhk.com/article/611248
12. Associated Press of Pakistan. (n.d.). Uzbekistan–China archaeologists discover ancient Kuva settlement [citing Xinhua News Agency]. Retrieved 10 November 2026, from https://www.app.com.pk/?p=1144542
13. Belt and Road archaeological cooperation fosters closer friendship among civilizations. (2024, March). Retrieved 10 November 2026, from https://kzxt.chinakongzi.org/English/CulturalHighlights/202403/t20240328_572168.htm

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