RESEARCH PROGRESS IN THE SPLICING AND RESTORATION OF ARTIFACT FRAGMENTS BASED ON POINT CLOUD

Jianghong Zhao[1,2,3], Lisha Yin[1,3*], Jia Yang[1,3], Xinnan Hua[1,3], Ziling Liu[1,3], Xin Wang[1,3]

1. School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, Beijing 102616, China;
2. Key Laboratory for Urban Spatial Information of the Ministry of Natural Resources, Beijing 102616, China;
3. Beijing Key Laboratory for Architectural Heritage Fine Reconstruction & Health Monitoring, Beijing 102616, China;

KEY WORDS: Artifact fragments, 3D point cloud, Feature extraction, Fragment splicing.

ABSTRACT:

Due to environmental reasons, most of the artifacts are fragmented, and the surface information of the artifacts is also blurred. The traditional method of repairing artifacts mainly relies on archaeologists to manually repair them, using fragment features to compare each fragment one by one, this method will cause secondary damage to the fragments. Based on computer technology, virtual restoration of artifacts fragments can obtain the latest unearthed data of artifacts quickly, preserve digital information of artifacts, achieve permanent preservation, and provide prior knowledge for subsequent artifacts restoration. Point cloud data is widely used in artifacts virtual restoration technology due to its good depth of information. This paper takes ceramics, bronzes, Terra-cotta Warriors, and other individual artifacts fragments as the main research object, and the point cloud data obtained by 3D laser scanner as the main research data. It comprehensively classifies and summarizes the work of computer artifacts splicing in recent years.

0 INTRODUCTION

Cultural heritage is an important carrier of a long history and an important medium for inheriting culture. It has an undeniable significance in the cultural development of a country(Tsigkas G., 2020). Although the protection technology of artifacts has been greatly improved, it still faces many limitations and problems: 1) Due to environmental reasons, the artifacts have suffered varying degrees of corrosion damage; 2) At the site of artifacts excavation, the main recording methods include taking photos, manually recording, drawing, and registering, that are resulting in single content; 3) The lack of information on unearthed artifacts is severe, and traditional manual restoration not only takes time, but also causes secondary damage to the artifacts(Miguel Á., 2015); 4) Traditional restoration techniques can only maintain the current status of artifacts as much as possible, and cannot avoid damage to the artifacts(Nemoto T., 2023). Computer technology is not limited by time and space in virtual restoration, providing dynamic demonstrations for artifact splicing. Digital artifacts can efficiently and permanently store cultural artifact information, ensuring that artifacts remain in their original state and providing a reference for subsequent restoration research(Einaghy H., 2022).

At present, there are few reviews on the virtual restoration of artifacts. In 2021, Geng G.H. et al (Geng G.H., Feng L., Li K., Zhou M.Q., Wang X.F., 2021.) summarized four splicing algorithms and three classification algorithms for fragments of Terra-cotta Warriors. The essence of splicing artifact fragments is the splicing of point clouds, so this article refers to other literature on point cloud registration in recent years. In 2022, Yang J.Q. etc (Yang J.Q., 2022.) summarized two aspects: coarse registration and fine registration based on multi-view point clouds. However, for artifacts, there is almost no overlap between each fragment except for the fractured part, making it impossible to use multi-view for registration. In the same year, Li J.W. etc.(Li J.W., 2022,) summarized from two aspects: non-learning based and learning based. In the point cloud splicing method based on non-learning, they elaborated the splicing method that is based on the feature in detail from three aspects: feature detection, feature description method, and feature splicing. However, the point cloud object is wide, and it does not have a significant reference for the splicing of damaged artifact fragments. Based on the broken artifacts such as ceramics, bronzes, and Terracotta Warriors, this paper takes the point cloud data obtained by a 3D laser scanner as the research object and summarizes in detail the splicing methods of artifacts in recent years.

The original way of artifacts restoration is mainly through two-dimensional images, which has great significance for calligraphy, painting, knitted fabrics, and other artifacts(Zhu Y.L., 2017; Ostertag C., 2020; Abitbol R., 2021; Zhang M., 2017; Lima-Hernandez R., 2021; Zhao R.C., 1994), but has certain limitations for Terracotta Warriors, ceramics and other artifacts with a certain thickness. Lu H.R. etc(Lu H.R., 2015.) used the Leap motion device to obtain hand movement status and achieved the splicing of artifacts fragments through human-computer interaction. Artifacts can be restored by selecting different methods based on different characteristics. The overall technical process is shown in Figure 1.

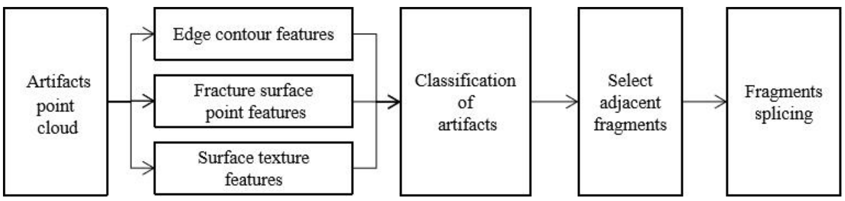


Figure 1. The process for automatic splicing of artifact fragments

* Corresponding author

1. FEATURE EXTRACTION OF CULTURAL ARTIFACT FRAGMENTS

There is almost no overlap between the fragments of the unearthed artifacts, except for the fractured parts. Therefore, when extracting features from fracture parts, the following issues need to be considered: 1) For artifacts of damage severely, can the extracted features accurately describe the fracture parts; 2) Whether the extracted fragment features meet the automatic splicing requirements; 3) If the feature extraction method applied to various cultural fragments of different materials. This chapter divided feature extraction into three categories: fragment feature contour lines extraction, fracture surface feature points extraction, and surface feature textures extraction.

1.1 Fragment feature contour lines extraction

In the process of edge contour extraction, the extracted edge contours must be able to accurately describe the geometric shape of the fragments. In two-dimensional images, contour edge extraction methods include Grid Partitioning(Yang F.T., 2020), Depth Image(Dong Q.Q., 2023), Gaussian Mapping Clustering(Su Y.L., 2019), and so on. For 3D point clouds, the density of the point cloud distribution around the sampling points can be used to determine whether they are edge points. Liu E. etc (Liu E., 2020) projected the point cloud onto a two-dimensional plane, if the K-neighborhood projection points of the sample points were evenly distributed around them, then the sample points are non-edge points, otherwise, the sample points are edge feature points. But this method can cause blurring in the extraction of critical points On this basis, Chen Y.R. etc(Chen Y.R., 2012) added a constraint that is the resultant force of neighborhood points on sampling points. The resultant force generated by the neighboring points of non edge points approaches zero. The surrounding points of the edge points are distributed on one side, and the resultant force by the surrounding points on the sampling points tends to a larger value.

When normalizing vectors and calculating the resultant force, the main basis is the Euclidean distance between the sampling point and the neighboring points. However, the point cloud distribution obtained by the 3D laser scanner is scattered, and there cannot be a uniform situation completely. So for two sampling points that belong to edge points, different classification results may be obtained due to different densities of surrounding points. In response to the above issues, Han Y.C. etc (Han Y.C., 2018) added an edge coefficient F after calculating the resultant force on the sampling points. The distribution density and distance of surrounding points do not affect on the edge coefficient, to eliminate the influence of distance neighboring points, when searching for sampling points, the concept of search range is introduced to avoid falling into a dead cycle, but it also results in weak automaticity of this method. To further distinguish between edge points and critical points, Zhou Q. etc (Zhou Q., 2021) added weight coefficients before calculating the resultant force. The weight coefficients are inversely proportional to distance.

When obtaining two-dimensional contour lines by point cloud projection, the three-dimensional features of the point clouds are ignored. The projection distortion during the point cloud projection process can lead to feature extraction errors. Wen Y. etc (Wen Y., 2020) extracted the contour lines of the fracture surface by determining the angle between the normal vectors of two adjacent triangles. But the surface of artifacts is complex, and it is difficult to obtain the angle. Therefore, Li K. etc (Li K., 2015) used the Region Grow to segment the primary fracture surface from the triangular surface of the fragments, using the Adjacency Growth to obtain the secondary fracture surface for the primary fracture surface. The secondary fracture surface was scanned using a group of planes parallel to the normal vector of the fracture surface, and the curvature extremum points of the scan point sets were calculated to fit the contour lines of the fracture surface. Liu J. etc (Liu J., 2014) adopted a calculation method based on adjacency points to obtain the contour lines of the fracture surface. Li Q. etc (Li Q., 2019) used multi-scale curvature to distinguish edge points and non-edge points, segment the fracture surface according to the roughness degree of surfaces, and use Boundary Tracking for the fracture surface to obtain more orderly and accurate edge points. To avoid incorrect extraction due to uneven point clouds while extracting contour lines, Wang S.R. etc (Wang S.R., 2021) used Delaunay Neighborhoods instead of Spherical Neighborhoods when selecting neighborhoods, used Fuzzy Region Growth to extract feature points belonging to multiple planes, and finally used the Twin Long Circles to generate feature lines. For cultural artifact fragments with high hardness, to accurately extract sharp points, Wang X.H., etc (Wang X.H., 2020) gives a feature weight to each point, which is defined by the mean curvature of the k neighborhood of the sampling point. Tan X.G., etc (Tan X.G., 2019) considered the upper and lower neighborhood points while extracting contour points, and obtains two support regions composed of three points to extract information about sharp points. After obtaining the contour line of the fracture surface, Wen Y., etc (Wen Y., 2020) obtained the thickness features of the fragments using the upper and lower edges of the fracture surface and provided constraints for fragment splicing.

Due to the damage of artifacts edge features, relying on a single contour line feature may result in mismatching. Therefore, some scholars have considered extending a single contour line feature to its neighborhood range to improve matching accuracy. The Line Support Region in a 2D image is a set of pixel regions, within this region, the vertical lines angle are along the gradient direction of all pixels within a certain threshold (Burns J.B., 1986). Lin Y.B., etc(Lin Y.B., 2015) extended it to the point cloud environment, the line segment is defined as the set of intersection points of two half-planes, and the point region near the line segment is defined as the 3D Line Support Region. General Adaptive Neighborhoods (GAN) (Johan D., 2006; Johan D., 2006) was originally used in image processing, providing an intrinsic multi-scale representation, and generating a space adaptive analysis of neighborhood region based on local structure and features (Debayle J., 2016). Zhang Y.H., etc (Zhang Y.H., 2018) introduced GAN to artifact fragment point cloud splicing by defining a set of adaptive neighborhoods for each point on the fracture edge lines, transforming fragment edge lines matching into feature points GAN matching, and using Oriented Local Alphabetic Pattern (OLAP) to represent adaptive neighborhood of feature points to instead of differential geometry calculations in the matching process. To reduce the computational effort, Zhang H.C., etc (Zhang H.C., 2011) used the curvature of points to retrieve the feature contour lines to obtain the contour line segment of the feature point and represent the feature points with a two-dimensional feature descriptor consisting of curvature and deflection rate.

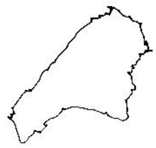
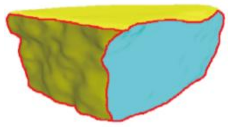
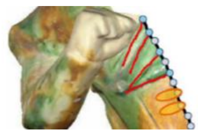
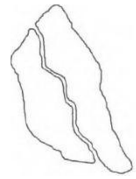
The classification of edge contour feature	Extracting 2D contour lines from points cloud projection	Extracting 3D contour lines from fragmented point clouds	Extracting support regions from contour lines	Extracting feature line segments from contour lines
Schematic diagram				
Reference	Liu E., 2020; Chen ; Y.R., 2012; Han Y.C., 2018; Zhou Q., 2021; Wang X.H., 2020	Wen Y., 2020; Li K., 2015; Liu J., 2014; Li Q., 2019; Wang S.R., 2021; Tan X.G., 2019	Lin Y.B., 2015; Zhang Y.H., 2018	Zhang H.C., 2011
Advantage	Has good descriptive ability for thin-walled fragments.	Gets contour lines that have stronger description.	Adding constraints during the splicing process.	Reduce computational complexity.
Disadvantage	Projection distortion may occur during the point cloud projection process.	Not suitable for severely damaged artifact fragments.	Make computational more complex.	Low accuracy

Table 1. Comparison of edge contour feature extraction methods

1.2 Fracture surface feature points extraction

For fragments with a certain thickness, Differential Invariants can be used for fracture surface matching, but the calculation of higher-order derivatives leads to amplifying the effect of noise (Manay S., 2004). Integral Invariant are immutability of rotate translation, and have good stability in volume integral descriptors, spherical region descriptors, and distance descriptors compared to differential invariant, and are more robust to noise (Pottmann H., 2009). The Integral Invariant are expressed as the volume of the sphere outside the surface Ω. The two-dimensional representation is shown in Figure 2.

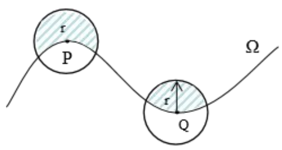


Figure 2. Two-dimensional representation of Integral Invariant

Li Q.H., etc(Li Q.H., 2012) used Integral Invariant for a point p on a surface to define the degree of concavity to determine if it is a feature point, the feature descriptor of the fracture surface is Ω(p1,p2,......, pk), subsequently using the feature descriptor to obtain adjacency fragments. Zhao S.L., etc (Zhao S.L., 2012) were classified into feature points and non-feature points using Two-size Integral Invariant. After calculating the integral invariant for the fracture surface points, Zhou P.B., etc (Zhou P.B., 2019) calculated the curvature at each point on the fracture plane and the normal angle to two adjacent points, considering both to define the feature parameter of the feature point at fracture surface, which are proportional to whether the point is a feature point or not. Gao H.J., etc (Gao H.J., Geng G.H., Wang P., 2019.) constructed the FPFH descriptor for the feature points, describing the relationship between the normal feature point and the normal adjacency point. Geng G.H., etc (Geng G.H., Yao W.M., 2021) gave larger weight to feature points located on contour lines to further select feature points. However, constructing feature descriptors based on fracture surface feature points is subject to some errors, resulting in distortion of the descriptors. Therefore, Liu X.N., etc (Liu X.N., 2020) constructed a 4×4 template with a growth point within each module, with 8 gradient directions present at each growth point, centered on the feature points. A convolution kernel is used to convolve each growth point, and finally, the feature descriptor of feature point Q is a 4×4×8 gradient vector.

Although, extraction of feature points from the fracture surface enables the matching, the features extracted are essentially a description of a single point and cannot meet the subsequent matching requirements if the artifact is damaged severely. Both curvature and Integral Invariant are simple to calculate but poorly expressed. Therefore, Zhao F.Q., etc (Zhao F.Q., 2022) uses Voronoi to extend feature points into feature point regions where the feature regions of each feature point do not overlap. Starting from the physical meaning of the Laplace Operator, Sun J., etc （Sun J., 2009）defined Heat Kernel Signature (HKS) for spatial points on 3D objects, which represents time discretely. This descriptor not only provides a more concise description of feature points but also represents all the information about the intrinsic geometry of 3D objects with a high degree of stability. Zhang Y., etc (Zhang Y., 2019) extracted the HKS descriptor for points with high curvature on the fracture surface. The HKS is introduced into the frequency domain information to construct a scale-invariant Si-HKS descriptor while retaining the characteristics of HKS by Bronstein M., etc (Bronstein M., 2019), but the dimension of the Si-HKS descriptor is too high, resulting in too much computation. Therefore, Gao, H.J.; etc (Gao, H.J.; Geng G.H.; Zeng, S., 2020.) used the Bag Of Words (BOW) to construct a more low-dimensional SiHKS-BOW descriptor. Zeng H., etc (Zeng H., 2018) based on Local Multilevel Pattern (LMP) encoding method defined the LMP-HKS descriptor as time-invariant. Yuan, J., etc (Yuan, J., 2018) extracted feature points of the fracture surface by using the Significance Index Function and the topological features of the fracture surface are extracted by extending the feature points into its topological region. Topological features have a holistic description of the fracture surface with a high degree of stability.

The classification of surface feature	Point feature	Point feature area	Fracture surface feature
Feature extraction	**Integral Invariant** (Li Q.H., 2012;Zhao S.L., 2012;Zhou P.B., 2019) **ISS** (Gao H.J., 2019)	**Voronoi** (Zhao F.Q., 2022) **HKS** (Zhang Y., 2019; Bronstein M.M., 2010; Gao H.J., 2020; Zeng H., 2018)	**Principal curvatures** (Yuan J., 2018)
Feature descriptors	**Concave-convex degree** (Li Q.H., 2012; Zhao S.L., 2012) **Feature parameter descriptor** (Zhou P.B., 2019) **FPFH** (Gao H.J., 2019; Geng G.H., 2021) **SURF** (Liu X.N., 2020)	**Region vector descriptor** (Zhao F.Q., 2022) **HKS descriptor** (Zhang Y., 2019; Bronstein M.M., 2010; Gao H.J., 2020; Zeng H., 2018)	**Feature grid** (Yuan J., 2018)
Advantage	Low computational complexity	Highly descriptive	Considering the global information on the fracture surface
Disadvantage	Poor descriptive, ignoring global features	Computational complexity	Easy to accumulate errors

Table 2. Fracture surface feature extraction methods

1.3 Surface feature textures extraction

The surface texture features of the fragments are an important basis for the splicing of artifacts. Figure 3 shows the splicing result of Terracotta Warriors fragments with surface texture.

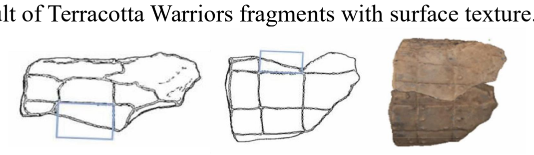


Figure 3. Feature point enhancement

For artifact fragments with rich and widely distributed texture information, Wang, Y., etc (Wang, Y., 2018) proposed a method of first enhancing and then extracting the sharp features of bronze shallow reliefs using feature point projection distance. Wang, P., etc (Wang, P., 2018) calculates the curvature of surface points on terracotta fragments to extract valley ridge points and obtain the surface texture of valley ridge lines. Subsequently, analysis of regular textures to obtain cell textures and broken textures, and matching rules were developed. Wang, P., etc (Wang, P., 2019) generated surface texture lines using Splatting Lines to complete the restoration of the artifacts. However, this method can only be used for fragments with distinct and regular texture features and is too limited to be widely used. To consider the fact that broken textures are mostly located at the edge contours of fragments, Yuan J., etc (Yuan J., 2018) constructed the distance fields from feature points on broken textures to edge lines and from feature points on fracture surfaces to edge lines respectively and completes the description of artifact fragments through the two distance fields.

When using surface texture for stitching, Wang P etc (Wang, P., 2018; Wang, P., 2019) based on regular texture to achieve splicing, and only regular texture on the armor parts of the terracotta warriors, for the rest of the parts, cannot be applied, Yang J etc (Yuan J., 2018) is the combination of texture information and fracture surface information. The use of surface textures can achieve artifact fragment stitching, but has greater requirements for artifact textures and are not universally applicable.

2. CLASSIFICATION OF ARTIFACT FRAGMENTS

To ensure accurate stitching results, all objects to be matched need to be retrieved one by one, and fragments will be classified first to improve retrieval efficiency. Currently, classification methods for heritage fragments include supervised and unsupervised. If the fragment information is known, the labels can be defined manually before classification, and the classification work is done through supervised learning. Zhao S.Z., etc (Zhao S.Z., 2019) extracted point features, texture features, and geometric features of terracotta fragments and uses a Hierarchical Semantic Network to classify terracotta fragments into five categories: head, arms, upper torso, lower torso, feet, and pedals. Li Y. and Gao, H.J. etc (Li Y., 2020; Gao, H.J., 2020) used Point-Net to achieve the classification of different parts of the terracotta fragments.

However, most of the artifacts have a single unique texture and a big difference, and there is a lack of training samples using supervised classification. Moreover, the features of artifacts are severely damaged and highly unknown, and it is difficult to manually add classification labels before classification, so we can only rely on feature similarity for classification. In terms of images, Wei Y., etc (Wei Y., 2017) used a Scale-invariant Feature Transformation (SIFT) to extract fragment surface texture information and construct a Bag-of-Words for fragment images, by combining the above all using SVM for training to achieve terracotta fragment classification. Zhang H.C., etc (Zhang H.C., 2011) classified fragments into eight categories: concave, convex, ridge, flat, valley, narrow saddle, saddle, and flat saddle based on Gaussian Curvature and Mean Curvature. Wang, P. etc (Wang, P., 2018) analyzed the extracted texture information and classified textures based on intact and broken edges. Lu Z.J., etc (Lu Z.J., 2020) established a local reference system for the 3D point cloud for rotational projection to obtain a 2D image with depth information, and the rotational projection features were extracted, the Integral Invariant as locally significant features to complete the classification of different parts of the terracotta warriors using a combination of multiple features.

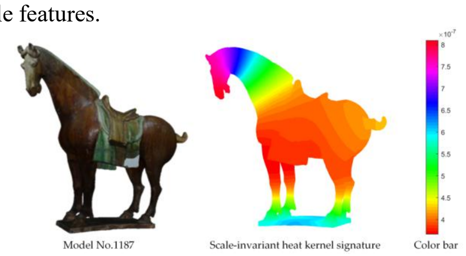


Figure 4. A 3D shape and its heat kernel signature.

As shown in Figure 4, Gao, H.J. etc (Gao, H.J.; Geng G.H.;

Zeng, S., 2020.; Gao H.J., Geng G.H., Yang W. 2018.) were clustering analysis to HKS descriptors and experimented on a variety of artifacts such as horse and human figurines, and the results showed that it could meet the classification requirements by showing different features according to different parts.

Supervised Learning	Hierarchical semantic network	Zhao S.Z., 2019	Classify different parts of Terracotta Warriors	There are significant limitations to artifacts fragments
	Point-Net	Li Y., 2020 Gao H.J., 2020		
Unsupervised Learning	2D depth Image SIFT	Lu Z.J., 2020 Wei Y., 2017	Classify different parts of Terracotta Warriors	Fuzzy classification results
	Gaussian curvature and Mean curvature	Zhang H.C., 2011	Concave, convex, ridge, flat, valley, narrow saddle, saddle, flat saddle	Fuzzy classification results and a large classification range
	Surface texture	Wang P., 2019	Complete texture, broken texture	Can only be applied to texture-rich and rule
	HKS	Gao H.J., 2018 Gao H.J., 2020	Roughly classify different parts of artifacts	The classification of buffer zones in different parts is blurred

Table 3. Classification of artifacts fragments

3. FINDING NEIGHBOURING FRAGMENTS

In the process of finding adjacency fragments, the essence of comparing all fragments one by one is an iterative calculation, in which the feature matching degree is obtained, and if the matching degree is greater than a certain threshold, the two fragments containing the two sets of features can be judged as adjacency fragments. During the violent retrieval process, Liu E., etc (Liu E., 2020) used Artificial Fish Swarm Algorithm (AFSF) (Yazdani, D., 2011) to dynamically change the search length and step size, improving efficiency and accuracy. Gao H.J., etc (Gao H.J., Geng G.H., Wang P., 2019.) drew on the Random Sample Consensus (RANSAC) (Fischler, M.A., 1981) idea to filter incorrect matches. For more accurate selection of sample subsets, Jia C.Q. etc (Jia C.Q., 2020) adds three improvements to this method: 1) Setting the best matching degree during the iteration; 2) After ensuring a minimum subset of three, adding only one pair of feature matching point pairs for verification based on the smallest subset, ensuring that only four pairs of feature matching points need to be computed each time; 3) The correct point pairs already computed will not appear in subsequent iterations. The improved method can further reduce the amount of computation and improve the efficiency of the algorithm. Liu X.N. etc (Liu X.N., 2020) constructed the Jaccard coefficient for artifact fragments and uses the Jaccard coefficients of two fragments to construct Jaccard Distance for finding adjacency fragments.

4. MATCHING ARTIFACT FRAGMENTS

The essence of artifact fragment matching is fragment point cloud matching. Traditional point cloud matching algorithms include ICP, NDT, 4PCS, SAC-IA, etc. (Zhou Z.X., 2023). ICP algorithms are more widely used in artifact fragment matching currently. The traditional ICP algorithm (Besl, P.J., 1992) is to find the best transformation matrix for two sets of point clouds, given a set of matching point clouds to ensure the objective function E is minimized. Wen Y., Gao H.J., and Liu X.N., etc (Wen Y., 2020; Gao H.J., 2019; Liu X.N., 2020) are all able to achieve fine splicing of artifact fragments using ICP. Li Q., etc (Li Q., 2019) added distance restrictions, normal constraints, and concavity constraints to ICP to improve the matching efficiency and enhance the matching accuracy. Zhou P.B., etc (Zhou P.B., 2019) used the feature parameters obtained in the feature extraction process as constraints in the iterative process to achieve fragment matching. Zhao F.Q. etc (Zhao F.Q., 2022) used the KD-tree algorithm to obtain the nearest corresponding point of the matching point pair during the iterative process and then used the Euclidean Distance of the corresponding point as a constraint. Zhao, F.Q., etc (Zhao, F.Q., 2018) proposed the AIF-ICP, which adds a dynamic iteration factor to the iterative process of the ICP algorithm to improve the computational efficiency. But the ICP algorithm cannot be applied to the case where the two adjacency fragments have no overlap region due to the breakage of the artifact fragments, resulting in certain limitations.

Quaternion (Horn B K P., 1987) is a super complex that can be used to represent a rotation relation in three-dimensional space, the rotation matrix can be obtained from the quaternions. Liu E., and Yuan J., et al (Liu E., 2020; Yuan J., 2018) used Dual Quaternions to obtain a transformation matrix to achieve fragments matching of ceramics and other artifacts. Yuan, J., etc (Yuan, J., 2018) used the Quaternion to obtain the rotation matrix R and translation matrix T for three sets of feature point pairs of non-commutative and used the Exhaustive Search to obtain the transformation matrix with the highest accuracy.

4PCS (Cong, B., 2022) is a point cloud coarse matching algorithm based on the RANSAC, extracting the four points that are co-planar from a set of point cloud data and finding the set of four points that are approximately congruent under the rigid body transformation in the corresponding point cloud set. Zhao F.Q., etc (Zhao F.Q., 2022) used the 4PCS to achieve coarse matching of terracotta fragments, followed by the ICP algorithm to achieve fine matching. Figure 5 shows the process of splicing together the fragments of the Terracotta Warriors.

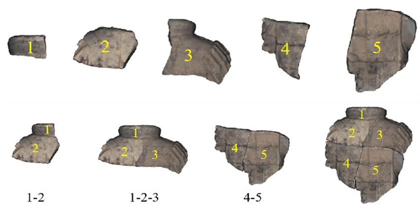


Figure 5. Fragment splicing results

5. SUMMARIZE

This paper introduces four parts: Artifact fragments feature extraction; Classification of artifact fragments; Adjacency fragment selection; Fragment splicing. Using point cloud data of single artifacts as the research object. Although this technique of splicing has been implemented, there are still many problems: 1) For heavily broken artifact fragments, the extracted features do not describe the fragment well; 2) The point cloud data of artifact fragments have edge contour features, fracture surface features, and surface texture features at the same time, and only one feature is used in the splicing process, resulting in wasted information; 3) Supervised learning-based classification methods have major limitations for artifact fragments, unsupervised learning-based classification methods require advanced consideration of fragmentation features, and the final classification results are ambiguous; 4) Accumulated errors occur when fragments are stitched together one by one, affecting alignment accuracy.

In order to cope with the problem of automatic splicing of cultural artifact fragments and to improve the efficiency and accuracy of splicing, the future development trend of splicing of cultural artifact fragments is expected to be as follows: 1) In the process of feature extraction, each fragment can be described by combining various features, such as expert a priori knowledge, historical knowledge(Cohen F., 2013; Sun, J.Z., 2017), etc. ; 2) After completing the artifact of fragments, repair the holes(Zhang Y.H., 2017; Zhang J., 2019); 4) The all fragments should be considered in the process of splicing and reducing the accumulation of errors;

Acknowledgements

This study is sponsored by the Project of the Open Research Fund of the Key Laboratory for Digital Mapping and Land Information Applications of the Ministry of Natural Resources (ZRZYBWD202102).

REFERENCE

Abitbol R., Shimshoni I., Ben-Dov J., 2021 Machine Learning Based Assembly of Fragments of Ancient Papyrus. *Journal on Computing and Cultural Heritage (JOCCH),* 14(3):1-21. doi.org/10.1145/3460961.

Besl P.J., McKay N.D., 1992. Method for registration of 3-D shapes. *Sensor fusion IV: control paradigms and data structures.* 1611:586-606. doi.org/10.1109/34.121791.

Burns J.B., Hanson A.R., Riseman E.M., 1986. Extracting straight lines. *IEEE Computer Society.* 425-455. doi.org/10.1109/TPAMI.1986.4767808.

Bronstein M., Kokkinos I., Scale-invariant heat kernel signatures for non-rigid shape recognition. 2010. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition,* San Francisco, CA, USA, 1704-1711, doi.org/10.1109/CVPR.2010.5539838.

Chen Y.R., Wang Y.B., Peng Z.J., Jiang J.S., 2012. An improved algorithm for extracting boundary feature points from scattered point clouds. *Computer Engineering and Applications.* 48(23):177-180+190.
doi.org/10.3778/j.issn.1002-8331.2012.23.040

Cohen F., Liu Z.X., Ezgi T., 2013. Virtual reconstruction of archeological vessels using expert priors and intrinsic di fferential geometry information. *Computers & Graphics,* 37 (1-2):41-53. doi.org/10.1016/j.cag.2012.11.001.

Cong, B., Li Q.Y., Liu R.F., Wang F., Zhu, D.Y., Yang, J.B., 2022. Research on a Point Cloud Registration Method of Mobile Laser Scanning and Terrestrial Laser Scanning. *KSCE Journal of Civil Engineering,* 26(12):5275-5290. doi.org/10.1007/s12205-022-0366-0.

Debayle J., Presles B., 2016. Rigid image registration by general adaptive neighborhood matching. *Pattern Recognition,* 55:45-57. doi.org/10.1016/j.patcog.2016.01.024.

Dong Q.Q., Wu H., Qian W.H., 2023. RGB-D saliency object detection based on cross-refinement and circular attention. J*ournal of System Simulation.* (4):1-17. doi.org/10.16182/j.issn1004731x.joss.22-1372.

Einaghy H., Dorst L., 2022. Pairwise Alignment of Archae ological Fragments Through Morphological Characterization of Fracture Surfaces. *Int J Comput Vis.* 130:2184–2204. d oi.org/10.1007/s11263-022-01635-3

Fischler M.A., Bolles R.C., 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM,* 24(6):381-395. doi.org/10.1145/358669.358692.

Gao H.J., Geng G.H., Yang W. 2018. Sex determination o f 3D skull based on a novel unsupervised learning method. *Computational and mathematical methods in medicine,* 20 18:4567267. doi.org/10.1155/2018/4567267.

Gao H.J., Geng G.H., Wang P., 2019. 3D archaeological fragment reassembly based on feature descriptors of key points. *Journal of Computer-Aided Design & Computer Graphics.* 31(03):393-399. doi.org/10.3788/LOP55.081012.

Gao H.J.; Geng G.H.; Zeng S., 2020. Approach for 3D cu ltural relic classification based on a low-dimensional descri ptor and unsupervised learning. *Entropy,* 22(11):1290. doi.o rg/10.3390/e22111290.

Gao H.J., Geng G.H., 2020. Classification of 3D Terracott a Warrior Fragments Based on Deep Learning and Templat e Guidance, *IEEE Access,* 8:4086-4098, doi.org/10.1109/AC CESS.2019.2962791.

Geng G.H., Feng L., Li K., Zhou M.Q., Wang X.F., 2021. A literature review on the digitization and virtual restoration of artifacts in the Mausoleum of Emperor Qinshihuang. *Journal of Northwest University(Natural Science Edition).* 51(05):710-721. doi.org/10.16152/j.cnki.xdxbzr.2021-05-001.

Geng G.H., Yao W.M., Zhou M.Q., Liu J., Xu X.L., Cao X., Liu Y.Y., Li K., 2021. Automatic reassembly for artifa ct fragments via adjusting the weight of the contour curve. *Journal of Northwest University(Natural Science Edition).* 51(03):397-403. doi.org/10.16152/j.cnki.xdxbzr.2021-03-008.

Han Y.C., Hou H., Bai Y.D., Zhu X.F., 2018. A closed point cloud edge extraction algorithm based on edge coefficients. *Laser & Optoelectronics Progress.* 55(11):161-166. doi.org/10.3788/LOP55.111003.

Horn, B.K.P., 1987. Closed-form solution of absolute orien tation using unit quaternions. *Journal of the Optical Societ y of America A*. 4(4):629-642. doi,org/10.1364/JOSAA.4.00 0629.

Jia C.Q., He L.G., Yang X.W., Han, X.C., 2020. Developi ng a reassembling algorithm for broken objects. *IEEE Acc ess,* 8(99):220320-220334. doi.org/10.1109/ACCESS.2020.30 42261.

Johan D., Jean-Charles P., 2006. General Adaptive Neighborhood Image Processing Part I: Introduction and Theoretical Aspects. *Journal of Mathematical Imaging and Vision,* 25(2):245-266. doi.org/10.1007/s10851-006-7451-8.

Johan D., Jean-Charles P., 2006. General Adaptive Neighborhood Image Processing Part II: Practical Applications Issues. Journal of Mathematical Imaging and Vision, 25(2):267-284. doi.org/10.1007/s10851-006-7452-7.

Li J.W., Zhan J.W., 2022, Review on 3D point cloud registration method. *Journal of Image and Graphics.* 27(02), 349-367. doi.org/10.11834/jig.210243.

Li K., Li J., Sun J.Z., 2015. An improved technique of extracting feature contour from thin-walled cultural artifact fragments. *Journal of Graphics.* 36(02):251-256. doi.org/10.3969/j.issn.2095-302X.2015.02.018.

Li Q., Geng G.H., Zhou M.Q., 2019. Pairwise matching for 3D fragment reassembly based on boundary curves and concave-convex patches. *IEEE Access,* 8:6153-6161. doi.org/10.1109/ACCESS.2019.2961391.

Li Q.H., Zhou M.Q., Geng G.H., 2012. Fracture surface matching algorithm based on integral invariants. *Computer Engineering.* 38(03):156-158. doi.org/10.3969/j.issn.1000-3428.2012.03.053.

Li Y., 2020. Research on the artifact fragment matching al gorithm based on intuitionistic fuzzy and point cloud data. *Northwest university.* doi.org/10.27405/d.cnki.gxbdu.2020.0 01194.

Lima-Hernandez R., Vergauwen M., 2021. A Generative and Entropy-Based Registration Approach for the Reassembly of Ancient Inscriptions. *Remote Sensing,* 14(1):6. doi.org/10.3390/rs14010006.

Lin Y.B., Wang C., Cheng J., 2015. Line segment extraction for large-scale unorganized point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing,* 102:172-183. doi.org/10.1016/j.isprsjprs.2014.12.027.

Liu E., Cheng X., Cheng X., 2020. Application of Three-Dimensional Laser Scanning in the Protection of Multi-Dynasty Ceramic Fragments. *IEEE Access,* 8:139771-139780. doi.org/10.1109/ACCESS.2020.3012438.

Liu J., Zhou M.Q. Geng G.H., Li J.J.N., 2014. Fragments splicing method for terra-cotta figures of Qin dynasty based on contours and fracture surfaces matching. *Computer Engineering.* 40(01):181-185+190. doi.org/10.3969/j.issn.1000-3428.2014.01.038.

Liu X.N., Di H.Z., Yang W., Lin P.Y., Wang S.X., 2020. Mosaic of artifacts fragments based on SURF feature extra ction descriptor and Jaccard distance. *Optics and Precision Engineering.* 28(04):963-972. doi.org/10.3788/OPE.2020280 4.0963.

Lu H.R., Zhang Y., Niu M.M., 2015. Three-dimensional virtual reassembling for broken artifact fragments based on Leap Motion. *Journal of System Simulation.* 27(12):3006-3011+3017. doi.org/10.16182/j.cnki.joss.2015.12.018.

Lu Z.J., Li C.H., Geng G.H., Zhou P.B., Li Y., Liu Y., 2020. Classification of cultural fragments based on adaptive weights of multi-feature descriptions. *Laser & Optoelectronics Progress.* 57(04):321-329. doi.org/10.3788/LOP57.041511.

Manay S., Hong B.W., Yezzi A.J., 2004. Integral invariant signatures. *Computer Vision-ECCV 2004: 8th European C onference on Computer Vision,* Prague, Czech Republic, 20 04. doi.org/10.1007/978-3-540-24673-2_8.

Miguel Á., 2015. Digital image analysis based on study, recording, and protection of painted rock art. Some Iberian experiences. *Digital Applications in Archaeology and Cultural Heritage.* doi.org/10.1016/j.daach.2014.11.001.

Nemoto T., Kobayashi T., Kagesawa M,. 2023. Virtual Res toration of Ancient Wooden Ships Through Non-rigid 3D Shape Assembly with Ruled-Surface FFD. *Int J Comput V.* 131:1269–1283. doi.org/10.1007/s11263-023-01759-0.

Ostertag C., Beurton-Aimar M., 2020. Matching ostraca fragments using a siamese neural network. *Pattern Recognition Letters,* (131):336-340. doi.org/10.1016/j.patrec.2020.01.012

Pottmann H., Wallner J., Huang Q.X., 2009. Integral invar iants for robust geometry processing. *Computer Aided Geo metric Design*, 26(1):37-60. doi.org/10.1016/j.cagd.2008.01.0 02.

Su Y.L., Ping L.X., 2019. Point cloud edge-extraction algorithm based on Gussian map clustering. *Laser & Optoelectronics Progress.* 56(11):223-227. doi.org/10.3788/LOP56.111506

Sun J., Ovsjanikov M., Guibas L., 2009. A concise and provably informative multi-scale signature based on heat diffusion. *Computer graphics forum.* Oxford, UK: Blackwell Publishing Ltd, 28(5):1383-1392. doi.org/10.1111/j.1467-8659.2009.01515.x.

Sun J.Z., 2017. Judgment method of adjacent fragments ba sed on evidential reasoning. *Application Research of Comp uters.* 34(02):598-602. doi.org/10.3969/j.issn.1001-3695.2017. 02.062.

Tan X.G., Su R.Y., 2019. Exact restoration simulation of archaeological excavation of bronze fragments. *Computer Simulation.* 36(04):153-156+176. doi.org/10.3969/j.issn.1006-9348.2019.04.033.

Tsigkas G., Sfikas G., Pasialis A., 2020. Markerless detection of ancient rock carvings in the wild: rock art in Vathy, Astypalaia. *Pattern Recognition Letters.* 135:337-345. doi.org/10.1016/j.patrec.2020.03.026.

Wang, P., Geng, G.H., Zhang, Y.H., 2018. Fragment splicing method based on surface texture characteristics. *Laser & Optoelectronics Progress.* 55(08):274-282. doi.org/10.3788/LOP55.081012.

Wang P., Geng G.H., Yang W., Ren J., 2019. Fragment splicing method combined with surface texture and fracture contour. *Computer Engineering.* 45(02):315-320.

doi.org/10.19678/j.issn.1000-3428.0049372.

Wang S.R., Guo B., Guo R.Z., Geng G.H., Zhou X.Y., Zhang Y.H., 2021. Fuzzy sets-based feature extraction from point clouds of pottery artifacts fragments. *Journal of Northwest University(Natural Science Edition).* 21(05):750-758. doi.org/10.16152/j.cnki.xdxbzr.2021-05-005.

Wang X.H., Chen H.W., Wu L.S.. 2020. Feature extraction of point clouds based on region clustering segmentation. *Multimedia tools and applications,* 79(17):11861-11889. doi.org/10.1007/s11042-019-08512-1.

Wang Y., Chen H.M., Li W.S., 2018. Enhancement and automatic extraction of bronze pattern features. *Journal of Image and Graphics.* 23(05):740-747. doi.org/10.11834/jig.170375.

Wei Y., Zhou M.Q., Geng G.H., Zou L.B., 2017. Classific ation of terra-cotta warriors fragments based on multi-featu re and SVM. *Journal of Northwest University(Natural Scie nce Edition).* 47(04):497-504. doi.org/10.16152/j.cnki.xdxbzr. 2017-04-006.

Wen Y., Zhou M.Q., Zhang P.F., 2020. Matching method of cultural artifact fragments constrained by thickness and contour feature, *IEEE Access,* (8):25892-25904. doi.org/10.1109/ACCESS.2020.2969995.

Yang J.Q., Zhang S.K., Fan S.C., 2022. Survey on multi-view point cloud registration algorithm. *Journal of Huazhong University of Science and Technology(Natural Science Edition).* 50(11), 16-34+43. doi.org/10.13245/j.hust.221102.

Yang F.T., Yang J., 2020. Grid map division method based on line segment detection. *Transducer and Microsystem Technologies.* 39(10):142-144+148. doi.org/10.13873/J.1000-9787(2020)10-0142-03.

Yazdani, D., Nadjaran Toosi A., Meybodi, M.R., 2011. Fuzzy Adaptive Artificial Fish Swarm Algorithm. *Lecture Notes in Computer Science.* 6464. doi.org/10.1007/978-3-642-17432-2_34.

Yuan J., Zhou M.Q., Geng G.H., Zhang Y.H., 2018. Automatic reassembly of fractured fragments using Morse topological features. *Acta Automatica Sinica.* 44(08):1486-1495. doi.org/10.16383/j.aas.2017.c160778.

Yuan J., Zhou M.Q., Geng G.H., Zhang Y.H., 2018. Heritage debris splicing algorithm based on contour line two-way distance field. *Computer Engineering*. 44(06):207-212+218. doi.org/10.19678/j.issn.1000-3428.0046520.

Zeng H., Liu W.L., Yu H.P., 2018. Scale-invariant local feature extraction method for non-rigid 3d model. *Transactions of Beijing Institute of Technology.* 38(06):619-624. doi.org/10.15918/j.tbit1001-0645.2018.06.011.

Zhang H.C., Wang Y.T., Zhang F.F., 2011. Efficient matching algorithm for 3d contour curve. *Computer Engineering.* 37(08):228-230. doi.org/10.3969/j.issn.1000-3428.2011.08.079.

Zhang J., 2019. Research on hole restoration and fracture surface-based splicing of cultural artifact fragments. *Northwest university.* doi.org/10.27405/d.cnki.gxbdu.2019.000298.

Zhang M., Chen S.M., Shu Z.Y., 2017. A fast algorithm for 2D fragment assembly based on partial EMD. *The Visual Computer,* 33(12):1601-1612. doi.org/10.1007/s00371-016-1303-3.

Zhang Y., Geng G.H., Zhou M.Q., 2019. Approach of cult ural artifact fragments assembly on fractured surfaces drive n by heat kernel signature. *Journal of Shaanxi Normal Un iversity(Natural Science Edition).* 47(03):64-68+72. doi.org/ 10.15983/j.cnki.jsnu.2019.03.131.

Zhang Y.H., Li K., Chen X.H., Zhang S.L., Geng G.H., 2018. A multi-feature fusion method for reassembly of 3D cultural heritage artifacts. *Journal of Cultural Heritage,* 33:191-200. doi.org/10.1016/j.culher.2018.03.001.

Zhang Y.H., 2017. Research on feature extraction from scattered point clouds and reassembly of fragments with defective fractures. *Northwest university.*

Zhao F.Q., Geng G.H., 2022. Automatic matching algorithm of cultural artifact fragments based on feature region division. *Acta Electronica Sinica.* 50(06):1436-1443. doi.org/10.12263/DZXB.20201236.

Zhao F.Q., Zhou M.Q., Geng G.H., 2018. Terracotta warri or blocks matching algorithm based on contour curve and feature region. *Transactions of Beijing Institute of Technol ogy.* 38(03):293-299. doi.org/10.15918/j.tbit1001-0645.2018.0 3.012.

Zhao S.L., Li Q.M., Jiang H.H., 2012. Extracting feature points for scattered points based on volume integral invari ant. *Mechanical Science and Technology for Aerospace En gineering.* 31(11):1855-1859. doi.org/10.13433/j.cnki.1003-87 28.2012.11.012.

Zhao R.C., 1994. A new method for extracting and segmenting image texture features. *Acta Electronica Sinica.* (04):46-52. doi.org/10.3321/j.issn:0372-2112.1994.04.008.

Zhao S.Z., Hou M.L., Li A.Q., Yang S., Hu Y.G., Dong Y.Q., 2019. A classification technology of Terra-Cotta Warriors' fragments with multiple. *Geomatics World.* 26(05):14-21. doi.org/10.3969/j.issn.1672-1586.2019.05.002.

Zhou P.B., Zhao F.Q., Wu Z.K., 2019. Feature surface mat ching method of terracotta based on geometric features. *Tr ansactions of Beijing Institute of Technology.* 39(05):532-53 8. doi.org/10.15918/j.tbit1001-0645.2019.05.016.

Zhou Q., Zhang M., Li W., Anvarjon N., Du M.D., 2021. Edge contour extraction of ancient fragments based on point cloud data. *Journal of Shaanxi University of Science & Technology.* 39(06):174-181.doi.org/10.19481/j.cnki.issn2096-398x.2021.06. 027.

Zhou Z.X., Huang D.D., Liu Z., 2023. Point cloud registr ation algorithm based on 3D shape context features. *Journ al of Applied Optics.* 44(02):330-336. doi.org/10.5768/JAO2 02344.0202005.

Zhu Y.L., Li Z.Y., Wu T., 2017. Image restoration for regular ancient fabric texture. *Cotton Textile Technology.* 45(10):9-12. doi.org/10.3969/j.issn.1001-7415.2017.10.003.