Sensors and Materials, Vol. 34, No. 12 (2022) 4551–4568
MYU Tokyo

S & M 3128

Processing of Multitemporal 3D Point Cloud Data for Use in Reconstructing Historical Geographic Scenarios

Yang Lin,[1,2,3*] Hu Yang,[1] Wu Weihong,[4] Sheng Yehua,[1,2] and Jia Xin[3]

[1]Key Lab. of Virtual Geographical Environment, Ministry of Education, Nanjing Normal University, Nanjing 210023, China
[2]Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing 210023, China
[3]Institute of Environment Archaeology, Nanjing Normal University, Nanjing 210023, China
[4]College of History, Anhui University, Hefei 230039, China

(Received September 16, 2022; accepted December 12, 2022)

Keywords: multitemporal point clouds, point cloud data processing, historical geographic scenario, 3D reconstruction

Developing methods of reconstructing historical geographic scenarios is a significant research topic in the field of geographic information science. To reconstruct an archaeological geographic scenario, we adopted 3D laser scanning technology to acquire hierarchical excavation data in accordance with the field archaeology criterion. This technology originated from the laser sensor and it can perform accurate, fast, and noncontact data acquisition in the field of archaeology. The processing of the scanning data is closely related to the accuracy and efficiency of the reconstruction. Our research focused on the methods of multitemporal point cloud data registration, object-oriented target segmentation, and relic feature extraction based on the nearest neighbor search method. In this study, archaeological excavation data acquired in 2015 at the Lingjiatan site in Hanshan Country, Anhui Province, was taken as the research object. The experiment revealed that the proposed methods can realize the efficient and automatic data collection and geometric feature extraction of relics with high feasibility and reliability. The proposed methods are expected to increase the application of multitemporal point cloud data processing and provide basic modeling methods and data for reconstructing historical geographic scenarios.

1. Introduction

Reconstructing a historical geographic scenario is an important part of research related to the construction of a virtual geographic environment. A geographic scene recovered on the basis of limited archaeological data and knowledge can reflect the lives of ancient people and serve as a basis for historic research to help understand their living environment. However, compared with a geographic scene, constructing a historical geographic scene is much more difficult becuase of the lack of real-time, integrated, and precise geographical data.

*Corresponding author: e-mail: yanglin@njnu.edu.cn
https://doi.org/10.18494/SAM4128

ISSN 0914-4935

As the basic and primary method of obtaining first-hand data for use in historical geographic scene reconstruction, field archaeology is characterized by irreversibility, dynamic layer excavation, and multitemporal data recording. Thus, it is necessary to promptly, accurately, and completely record the relics and remains found during the various stages of an archaeological excavation. The recorded data are the basis for the reconstruction of the historical geographic scene. However, the slow data acquisition and sometimes low accuracy of traditional manual 2D mapping methods are common problems in field archaeology that lead to difficulties in integrally and quickly displaying and building a 3D model of an actual site. Similarly, using only single-period field archaeology data leads to an incomplete 3D reconstruction. Therefore, continuous data collection during an archaeological excavation is required to meet the basic requirements of standard archaeological field investigation rules and for recording all the different types of remains.

In recent years, 3D laser scanning technology, which originated from the laser sensor, has been increasingly developed as a spatial data acquisition method. This scanning technology allows researchers to efficiently, quickly, and accurately obtain 3D point cloud data of a measured object surface. Phased scanning can record the actual conditions of an archaeological excavation scene. A unified spatial reference and further data processing of the point clouds acquired in the different stages of an excavation are the primary foundation for the 3D reconstruction of historical geographic scenes. However, multiple scanning (especially of a large site) can produce a large number of point clouds, which decrease the efficiency of scene reconstruction. There is much redundant data in the original data sampling and modeling of an archaeological site. The redundant data, except for the sampling points around the outlines and edges of relics, are of little use in feature extraction and scene modeling. Thus, it is necessary to adapt or design corresponding methods and algorithms to extract the features of relics in order to reduce the point data.

However, because of the distinctiveness of archaeological excavations and the irregular shapes of relics, developing a method for automatically extracting the features of relics using multitemporal point clouds is the main challenge and our goal. The process of feature extraction related to point data includes multitemporal 3D laser scanning for data collection during the archaeological excavation, point cloud data registration, segmentation, and feature extraction. The results of this study provide reliable data support for the subsequent 3D reconstruction of historical geographic scenes and for improving the efficiency and accuracy of archaeological mapping. The methods developed in this study may also be applicable to research involving the use of multitemporal point clouds in other related fields.

Owing to recent technological developments, 3D laser scanning technology is being increasingly used in various fields. It is widely used in cultural relic protection, urban building measurements, deformation monitoring, large-scale structure modeling, bridge reconstruction, and other fields. In this method, the static state of a scanned object at a specific time is recorded as 3D laser point cloud data. If 3D point clouds are collected at different times, they can record the changes in the scanned object over a period of time, creating a multitemporal point cloud dataset. Multitemporal point clouds are an important data source for analyzing the temporal and spatial changes of scanned objects. Such analysis is very useful in monitoring the deformation of buildings, in the detection of changes in terrain and landscapes, and for the 3D visualization and modeling of large scenes. For example, laser scanning technology was used to precisely examine the sky pillar of the Buddha Pavilion in the Summer Palace in Beijing, China.(1) Alessandro *et al.* of the University of Geneva carried out 3D scanning research on the Hagia Sophia. They monitored and analyzed the deformation of the large and complex ancient buildings of this cathedral.(2) Allen *et al.* carried out comprehensive 3D reconstruction and deformation detection of St. Pierre's Cathedral using a ground 3D laser scanner.(3) In addition, 3D terrain change detection has been applied to analyze glacier degradation and movement(4) and debris flows,(5,6) as well as for landslide detection(7) and earthquake disaster assessment.(8) Regarding the detection of 3D changes in urban buildings, Zhang employed 3D change detection technology to study buildings using light detection and ranging (LiDAR) point cloud data collected using multiple cameras over time. Zhang detected changes in building microstructures based on texture and local geometric feature extraction.(9) Airborne LiDAR data acquired at different times have been used to detect short-term changes in buildings, with studies focusing on the analyses of the detection accuracy regarding the changes in the buildings.(10) The surface roughness has been used to distinguish buildings and vegetation in a digital surface model at different times and to assist in determining the type of change that occurred through geometric analyses.(11) Fast parallel approaches and an alternative registration approach have been employed to automatically and rapidly match planes extracted from pairwise temporally spaced mobile laser scanning and airborne laser scanning datas*ets al*ong the Napa fault in California, USA.(12) The snowpack distribution was determined using terrestrial laser scanning with a high spatial resolution (0.25 m) on 23 survey dates during three snow seasons in a small study area (1000 m^2) in the central Pyrenees in Europe.(13) A scaled demonstrator was developed for the acquisition of a 3D tunnel model profile with a laser scanning system consisting of a camera and a circular laser that scanned the surface of the entire tunnel.(14) Günther *et al.* analyzed a time series of repeated terrestrial laser scans to quantify land surface subsidence in a tundra upland area in the Teshekpuk Lake Special Management Area on Alaska's North Slope.(15)

Most previous studies were focused on the detection of changes in terrain and buildings, i.e., research objects that have remained relatively static. Therefore, a method for deep fusion processing of multiphase point cloud datasets is lacking, such as integrated modeling of multi-phase point cloud datasets, feature recognition by comparing different sets of phase point cloud data, and obtaining deep-level details. Regarding the 3D reconstruction of historical and geographic scenes, the focus of this study, archaeological excavation is an active and constantly changing process, and the analysis of the related data involves the fusion of multitemporal point cloud datasets acquired at an archaeological excavation site. This includes multitemporal laser point cloud data registration, target segmentation, and extraction of the features of archaeological objects. The results of this study expand the range of applications and the research depth of multitemporal point cloud data analysis.

2. Materials and Methods

2.1 Experimental data

The Lingjiatan archaeological site, located in Lingjiatan Village, Tongzha Town, Hanshan County, Anhui Province (Fig. 1), has a history of about 6000 years. Lingjiatan is the largest and most complete Neolithic site found in the Chaohu Basin in the lower reaches of the Yangtze River. This site has major significance in studying the evolution of ancient Chinese civilizations and the integration of different cultures. Thus, it plays an important role in Chinese archaeology.(16–20)

From 28 April to 14 June 2015, after six initial archaeological excavations had been carried out by Anhui Provincial Institute of Cultural Relics and Archaeology in the previous 10 years, a rescue excavation was performed in the southern residential area of Jiazhuang Village. This excavation is important for studying the layout of ancient sites and for documenting the lifestyle of the ancient people that lived in this area. In this study, three exploratory ditches were selected as the research objects [Fig. 2(a)], with a total excavation area of more than 200 m^2 in the southwestern corner of the site. The strata in these three ditches were in good condition and included precious burnt soil layers and other relics. The authors of this paper participated in the excavation. A 3D laser scanner (FARO Focus 3D 120, Faro Technologies, Inc., Lake Mary, FL, USA) was employed to scan the ditches layer by layer in accordance with standard archaeological excavation criteria [Fig. 2(b)]. The 3D laser scanner used (FARO FOCUS 3D 120) can quickly and precisely collect vast amounts of high-density spatial data about a hierarchical excavation site. The scanner has a maximum measurement range of 150 m, a field of view of up to 305° × 360°, a scanning speed of 976000 points/s, a distance accuracy of ±2 mm within a 25 m measurement range, a minimum angle step width of 0.009° in the horizon and vertical directions, and a built-in high-resolution camera (>70 million dpi).

A total of 14 excavation phases were scanned to obtain 3D laser point cloud datasets, including most of the strata and abundant remains (e.g., ash pits, tombs, and wells) from the

Fig. 1. (Color online) Location of the Lingjiatan site.

(a) (b)

Fig. 2. (Color online) (a) Scanning area and (b) using a Faro scanner.

contemporary age to the Tang and Song dynasties to the Neolithic period. In this study, feature extraction methods for immovable relics in general (rather than for specific types of relics) were developed for use in reconstructing historical geographic scenarios.

2.2 Research methods

In this study, a 3D laser scanner was usually used to collect multistage archaeological point cloud datasets as part of the field archaeological excavation process. With the goal of determining the characteristics of archaeological objects, we developed a multitemporal point cloud data processing method, including data registration, data segmentation, and an improved radius search method for relic feature extraction. The results of this study provide reliable data support for the subsequent 3D modeling of the site's historical scenes.

2.2.1 Multitemporal point cloud data registration

Because of the size of most archaeological excavation scenes and the limited scanning perspective of the terrestrial laser scanners employed in previous studies, in general, it is difficult to obtain a complete point cloud dataset for an object at one station. Therefore, it is important to determine how to conduct multistation scanning to complete the collection of 3D data for a scene during every phase of the excavation. In addition, to obtain an integral 3D relic model, multiphase point cloud data collection during the different phases of the excavation is also required. Therefore, the registration operation developed in this study includes two parts: single- and multiphase multiview data registration.

Because of the complexity of the archaeological excavation site analyzed in this study and the remains themselves (caused by the manual excavation and the manufacturing level of the ancient remains), it was difficult to completely register the geometric characteristics of the scanned objects. Therefore, the matching of corresponding points was adopted in the single-phase multi-view registration. A spherical target (i.e., the connection point of the adjacent station) was used to calculate the normal vector of the target and the coordinates of the geometric center point, which were used as the feature points of the point cloud registration. Subsequently, the coordinate transformation parameters of the adjacent stations were calculated to unify the coordinates of the single-phase multistation data.(21)

Existing multiperiod data registration methods mainly include feature-based registration, registration based on a point set, and iterative closest point (ICP) registration.(22) Among them, the registration accuracy and efficiency based on specific features depend on the quality and time cost of the extracted features, which makes it unsuitable for use when the nature of the archaeological remains is not obvious. The registration method based on point sets requires a high consistency between the two sets of points. It is unsuitable for multitemporal and multi-station (i.e., the scene changes greatly) point cloud registration related to ongoing field archaeology investigations. However, the ICP-based registration method is based directly on the original data. This method does not require a high degree of matching of the features and point sets. Therefore, in this study, we adopted an ICP algorithm for the registration of the multi-temporal point cloud data.

To improve the matching efficiency and accuracy of the multitemporal point cloud data, we developed a mechanism for updating the coordinate transformation matrix, which was used to transform all the point clouds. Using this mechanism, all the other point clouds were converted into the coordinate system of the first point set, and the optimal transformation between each successive and overlapping point cloud was calculated. Finally, these transformations were accumulated to all of the point clouds. The multitemporal point cloud registration method based on the optimal transformation is summarized in Fig. 3.

Although the calculation of an ICP algorithm is simple and intuitive, the registration accuracy is acceptable, and the efficiency of the algorithm largely depends on the initial transformation estimation. The initial transformation estimation is related to the accuracy requirements of the archaeological application (e.g., 3D visualization, mapping, and spatial analysis), which determine the related parameters of the registration algorithm (e.g., the iterations and threshold). In addition, the estimation can be obtained by calculating the registration accuracy of the corresponding pairs of points in the overlay regions (the common scanning area of the adjacent

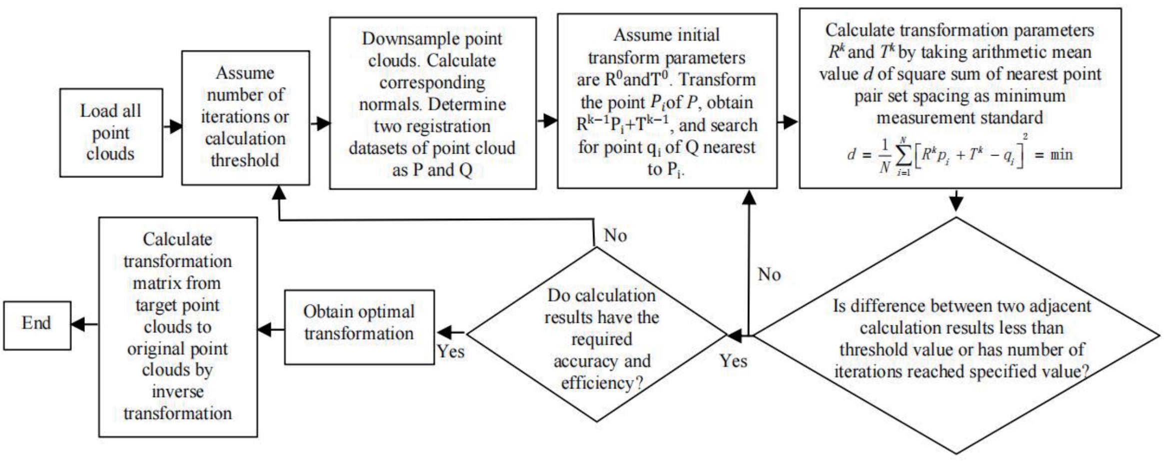


Fig. 3. Flowchart of the registration method.

scanning stations), which helps to adjust the parameters. Therefore, before an ICP algorithm is used for registration, a rough registration based on the fixed targets should be completed during the acquisition of the multi-temporal data to ensure the sufficient convergence speed and registration accuracy of the next ICP algorithm program.

2.2.2 Clustering and segmentation of archaeological excavation point cloud data

First, the original laser point cloud data should be segmented to realize the modeling and management of the various remains in a historical geographic scenario. Point cloud data segmentation is designed to extract the different objects in the point cloud dataset based on the spatial and geometric features to enable the adoption of different methods and separate processing for the various types of point clouds. The effective segmentation of a point cloud dataset is the premise and foundation of the subsequent 3D modeling and feature extraction.

In this study, both relic and nonrelic objects were segmented and recognized through data processing. In accordance with the operation methods used in an archaeological excavation, the nonrelic objects mainly include the four profiles of the excavation unit (the four profiles were excavated as vertical panels to expose and record the cultural strata), which are similar to the plane. Therefore, in this study, we developed a data segmentation method for archaeological point clouds that combines plane and clustering segmentation. The specific method is as follows. First, the normal vectors of the point clouds were calculated; all of the planes were extracted by the random sample consensus (RANSAC) method;(23) and the plane inliers were obtained. Then, a Euclidean aggregation algorithm [based on the Point Cloud Library (PCL)](24) was used to cluster and segment the other point cloud data. The specific process is shown in Fig. 4.

2.2.3 Geometric feature extraction of relics based on improved octree search method

Coarse classification results for archaeological objects can be obtained by the point cloud segmentation discussed above. To develop a fine 3D model of an archaeological scenario, it is essential to obtain the geometric features of the various remains. Therefore, with the goal of developing a multitemporal point cloud dataset for the relics scanned layer by layer based on the criteria for archaeological excavation, an improved octree search algorithm was developed to extract the geometric features of the remains. The traditional excavation and recording methods used in field archaeology are as follows. Archaeologists start to excavate layer by layer from the top to the bottom of the strata. Once a relic is discovered, they stop to measure and map the 2D

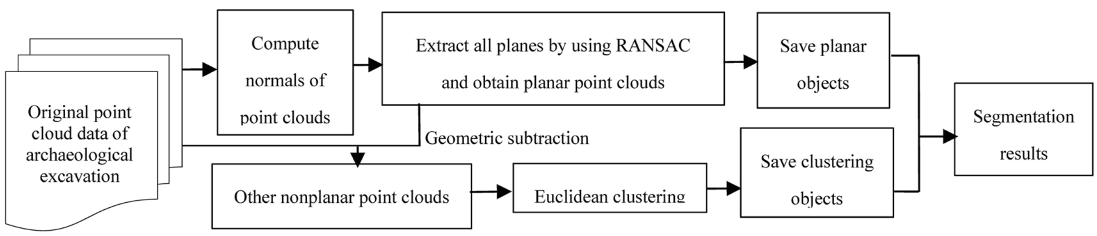


Fig. 4. Schematic diagram of the data segmentation process.

contour line of its exposed surface. Then, they continue to excavate it until its internal formation is completely exposed. This is followed by the collection of some common data (e.g., the depth and width) and mapping. The same process is conducted for any relic found. The multitemporal point clouds are acquired before and after the relics are excavated. Thus, datasets including the volumes and contour lines of relics can be obtained by applying geometric operations to the point cloud data collected in two adjacent periods, before and after the excavation. This process provides real and accurate 3D data for the subsequent archaeological scene modeling.

It is necessary to establish a spatial index for the point cloud data to improve the efficiency of data querying and searching. The common spatial indexes generally have a top-down and hierarchical structure, such as the binary space partitioning (BSP) tree, K-dimensional (K-D) tree, region (R) tree, quad tree, and octree. The octree is a widely used tree data structure and is usually used to manage sparse 3D data. It can be used to detect and search the changes among multiple unordered point clouds. The corresponding common search methods include the neighbor within voxel search, k-nearest neighbor (KNN) search, and neighbor within a radius search. Among them, the KNN search algorithm is simple, but it has low calculation efficiency for large-scale sample data. The search points and results of the neighbor within a voxel search depend on the resolution of the octree. The neighbor within a radius search method is simple and flexible and is often used to search within a single dataset. To achieve a comparative search of two datasets, in this study, we improved the conventional neighbor within a radius search method and designed two pointers for two datasets. Dataset A (pre-excavation data) and dataset B (postexcavation data) were set as the search points, and an octree was established for each dataset. Traversing each point in one dataset and searching for the corresponding point in the other dataset within the radius threshold ensures that the homologous points in the two datasets belong to the extracted relics.

The specific feature extraction method is as follows. On the basis of the above-described point cloud segmentation results, two-point cloud datasets were obtained: when the contour of a relic is exposed but the relic has not yet been excavated, and after the interior of the relic has been cleaned. Then, these two datasets were overlapped and searched. Finally, the non-overlapping area was defined as the point cloud data for the exposed surface and the body of the relic. The detailed process is shown in Fig. 5.

First, two types of point cloud datasets were searched by comparing them with each other. One was preexcavation dataset A (including the exposed surfaces of the relic and nonrelic data), and the other was postexcavation dataset B (including the bottom surfaces of the relic and nonrelic data). Then, the upper surface (c) and bottom surface (d) of the relic were obtained, and they were added to form the modeled relic body (e).

The feature extraction of the exposed line was as follows. Based on the extracted data for the upper and bottom surfaces of the remains, the neighbors within the radius search method were used to search for the nearest neighbor points in the two datasets. Then, the junction points were obtained, which were the exposed line data for the relic (f). Through a comparison of several experimental results, we found that the boundary points obtained by searching from the upper to the bottom surface data provide a better approximation of the real exposed contour of the relic. This method is based on the two feature datasets and has proven to be flexible, making it easy to

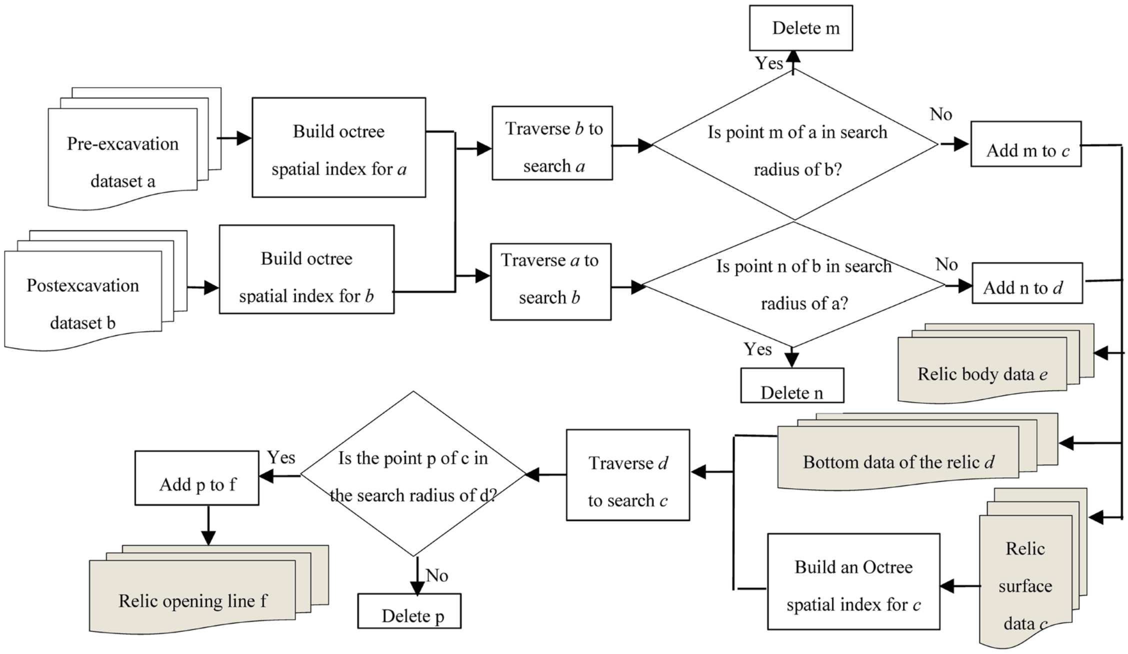


Fig. 5. (Color online) Schematic diagram of the feature extraction of relics.

obtain the boundary points of a relic.

In the feature extraction of a nonrelic, the point cloud data for the same nonrelic could vary with the distribution of the survey stations and the registration data collected via scanning during two adjacent phases (i.e., before and after a relic is excavated). Therefore, it is necessary to set an appropriate threshold to avoid an inaccurate search result for the point cloud.

3. Results

As discussed in Sect. 2, we used the adjacent multiphase point cloud datasets for two square excavation units, TW48S01 and TW48S02, in the archaeological excavation of the Lingjiatan site in 2015 as the experimental data. The experiment was conducted using an Intel i7 CPU with a memory capacity of 16 GB, a hard disk of 240 GB, and the Windows 10 operating system.

3.1 Multitemporal point cloud data registration

The experiments were completed using a PCL and an ICP algorithm (Fig. 6) written as a C++ program. The detailed implementation process was as follows. Figure 6(a) shows the interface of the registration experiment (original and target point cloud datasets), and Figs. 6(b) and 6(c) present the results of the registration (blue areas are the pre-excavation data and yellow areas are the postexcavation data). The result of the registration is satisfactory (Fig. 6).

Figures 7 and 8 show the registration results for the single-phase multiview point cloud dataset and the multitemporal point cloud datasets, respectively, for excavation units TW48S01

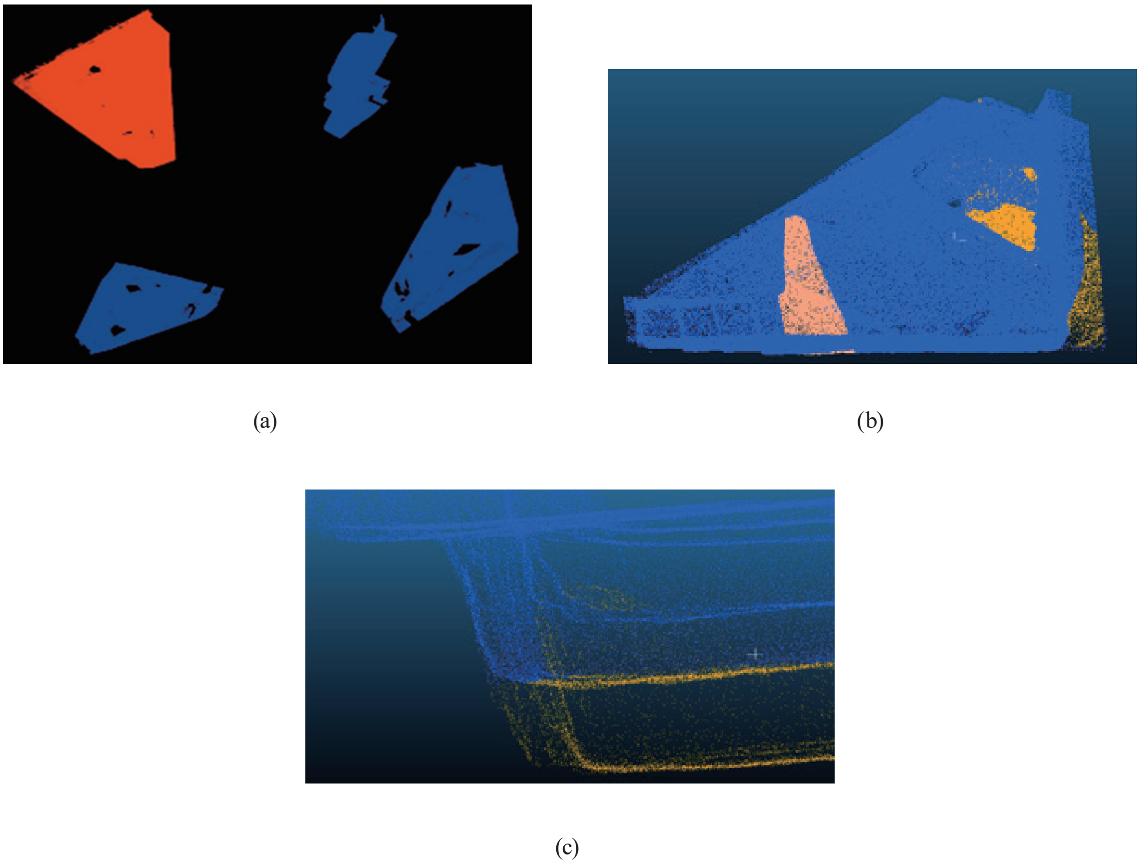
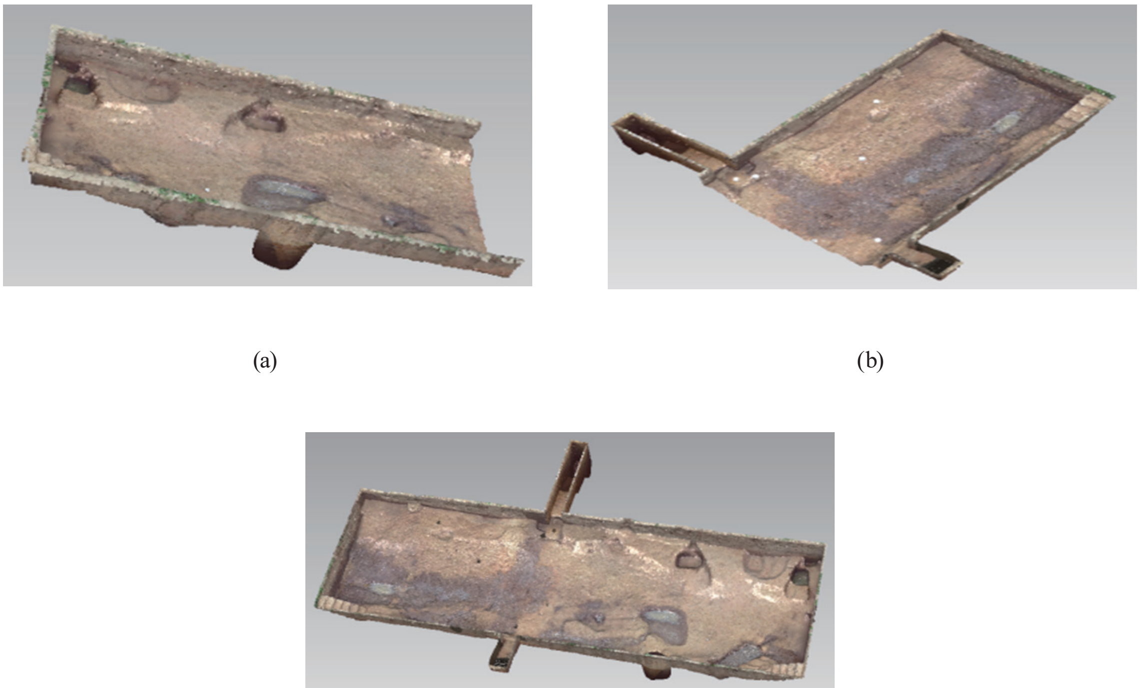


Fig. 6. (Color online) Results of the multitemporal cloud data registration of relics: (a) interface of registration and (b) vertical, and (c) side views of the experimental results.

and TW48S02. After all the archaeological point cloud data were processed using the above method, the multitemporal and multiview point cloud data were registered in the same coordinate system.

In terms of the registration accuracy, the coordinate difference M_p [Eq. (1)] between the corresponding points (20 pairs of points were chosen) for the first and last (the station most impacted by the transformation accuracy) scanning stations was calculated to be 3.3 mm. Assuming that the error contributions of the scanning resolution, the choice of corresponding points, and the registration processing are the same, the mean registration error is $\frac{\sqrt{3}}{3} \times M_p$, about 1.9 mm, which is similar to the original average accuracy (about 1 mm) of the scanner (within a range of 10 m). That is, the registration results do not significantly decrease the accuracy of the original scanning data. The registration results also meet the needs of archaeological fieldwork (see the introduction to field archaeology provided above).

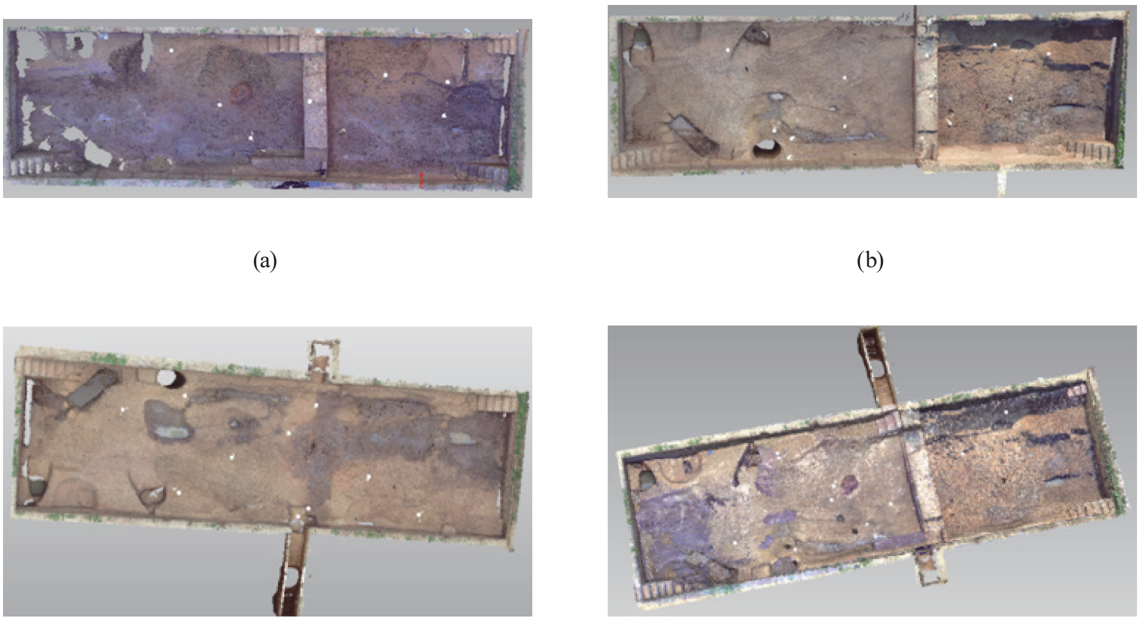
$$M_p = \sqrt{\frac{\sum_{i=1}^{n}\left(\Delta x^2 + \Delta y^2 + \Delta z^2\right)}{n-1}}. \; n\text{: number of pairs of corresponding points.} \tag{1}$$



(a) (b)

(c)

Fig. 7. (Color online) Registration results of the single-phase multiview point cloud data for excavation units TW48S01 and TW48S02: Point clouds at scanning stations (a) 1 and (b) 2, and (c) registration results.



(a) (b)

(c) (d)

Fig. 8. (Color online) Registration results of the multitemporal point cloud data for excavation units TW48S01 and TW48S02. Point clouds of phases (a) 1, (b) 2, and (c) 3, and (d) registration results of the multiphase point clouds.

3.2 Point cloud data segmentation

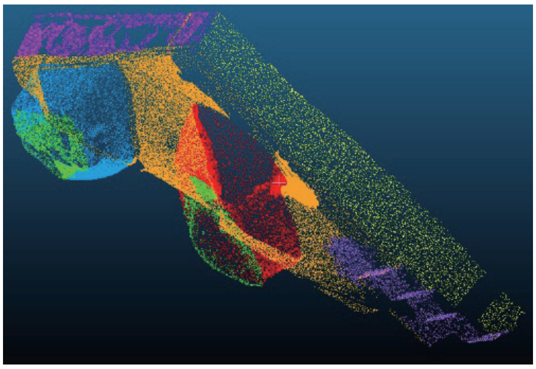
As discussed in Sect. 2.2.2, we employed both plane and clustering segmentation models to complete the segmentation of the archaeological point cloud dataset. The radius of the clustering search is the key to the segmentation results. An improper search radius will result in over- or under-segmentation. In this study, with the goal of determining the density and data volume of the experimental point clouds, the K-D tree was used to extract the point cloud features. Two suitable thresholds were tested and established, i.e., the radius of the cluster search and the number of point clusters, to limit the search for clusters and improve the accuracy of the segmentation results. The fourth-phase point clouds of excavation unit TW48S01 were taken as the experimental data, and the experimental results are shown in Fig. 9. As can be seen from Fig. 9(b), the segmentation results are as follows: tomb No. 2 (M2, red), tomb No. 1 (M1, blue), stairway (cyan), fourth excavation stratum (brown), northern profile (yellow), and western profile (purple). The two green areas are the bottoms of M1 and M2. The results of the segmentation are satisfactory.

3.3 Extraction of relic features

The above-described method was used for extracting relic features of tomb No. 2 (M2) in excavation unit TW48S01 as an example. The conventional octree radius search algorithm was improved to realize the extraction of three relic features: the exposed surface and exposed line of a relic and a relic entity. The experimental results are shown in Fig. 10.

Figures 10(a) and 10(b) show the bottom point cloud data for the exploration unit before and after excavation, respectively. The yellow area in Fig. 10(c) is the non-overlapping area obtained by superimposing the data for the two phases, namely, the tomb area. Figure 10(d) shows the extracted tomb M2 (surface point cloud dataset). The pink and yellow points in Fig. 10(d) show the exposed surface and the body of M2, respectively. Figure 10(e) shows the boundary points of M2 obtained using the nearest neighbor search between the exposed surface and the body shown

(a)



(b)

Fig. 9. (Color online) Fourth-phase point clouds of archaeological excavation unit TW48S01: (a) before segmentation and (b) after segmentation.

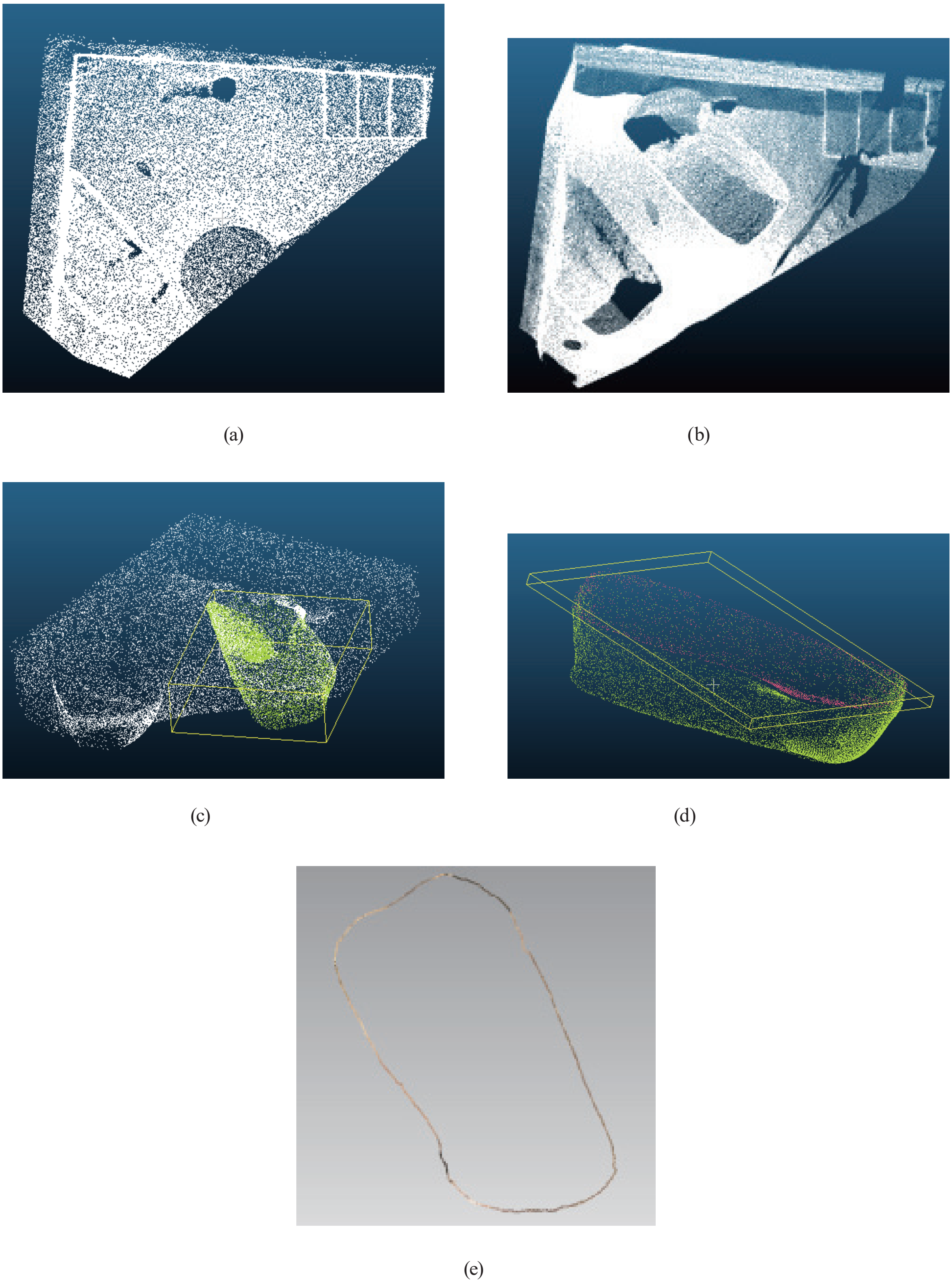


Fig. 10. (Color online) Point clouds: (a) before excavation, (b) after excavation, (c) relic point, (d) relic extraction, and (e) contour lines of the relic.

in Fig. 10(d). Figure 10(e) can also be regarded as the exposed line of M2, which can be used for archaeological mapping. Analogously, the other relics in the example area can be extracted by adjusting the parameters and thresholds of the algorithm as required, which demonstrates the flexibility of this method.

The extraction accuracy was estimated by comparing the available manual mapping results for the same excavation region. The feature extraction was based on the registered data and rigorous algorithms. Thus, the extraction accuracy was determined to be similar to the registration accuracy, about 1.9 mm (see Sect. 3.1). In contrast, for a traditional 2D manual map, taking a common 1:50 scale manually drawn map as an example, the precision of the object space was determined to be 5 mm (excluding the error related to the manual measurement and mapping). Thus, the data/mapping accuracy based on the extraction feature proposed in this paper is much higher than that of the traditional manual method.

The results of the extraction of a relic's features based on the improved radius search method can be flexibly integrated into a 3D model of a later site scene. The method employed in this study can also effectively improve the traditional method of mapping and recording archaeological remains. In addition, compared with the method of manually cutting the relic data model through software interaction, the extraction process based on point cloud data is more accurate, has reliable data quality, and is highly automated.

4. Discussion

Although the proposed methods focus on the processing of field archaeology data, their eventual purpose is to solve the key problems in historical geographic scene reconstruction. These methods advance research using point cloud data (especially multitemporal point data) processing and are applicable to other related cases. The assessment and innovation of the proposed methods are as follows.

(1) The effect of the feature extraction is essential. In recent years, as an important type of spatial data, laser point cloud data have been improved in terms of the acquisition speed and accuracy, similarly to the point data used in field archaeology. The field archaeological point data acquired using multitemporal scanning have also produced vast amounts of redundant information (especially in overlapping regions). These abundant data decrease the efficiency of scene reconstruction. In fact, the 3D modeling of an archaeological site is mainly dependent on the extracted features of relics. Therefore, we adopted algorithms for object-oriented target segmentation and relic feature extraction based on the nearest neighbor search method to reduce the amount of data. In contrast to the traditional 2D manual mapping method, the proposed method has much higher data/mapping accuracy (see Sect. 3.3).

(2) The efficiency of the proposed algorithm. The efficiency is relative to the traditional mapping method. Our methods are based on batch processing, but the traditional mapping method performs measurements and makes maps one by one. Hence, the efficiency of the algorithm depends on the number of relics. Taking a single square excavation unit containing three relics as an example, the manual field measuring and mapping of a simple relic generally takes about 20 min (excluding the digitization time); thus, it takes about 60 min to measure

and map three relics. In comparison, the process based on point clouds and the related algorithm first completes the field laser scanning (three surveying stations, about 15 min in total) of a unit at one time, and it takes about 30 min to process a batch of internal data. Thus, the average efficiency of the proposed method is higher. Moreover, the greater the number of relics, the more obvious the increased efficiency. For remains with complex shapes (such as brick-chambered tombs), it takes several days to complete manual mapping, while the method based on laser scanning only takes half a day. The more complex the archaeological relic, the more obvious the increased efficiency of the proposed method.

(3) High universality of algorithm. By applying elaborate and rigorous geometric computation to multitemporal point clouds, we achieved automatic segmentation from coarse to fine relic points and the feature extraction of relic objects. The algorithm is consistent with field archaeology criteria and ensures the integrity of the reconstructed scene, rather than only reconstructing some excavation surfaces. The proposed methods are efficient and are applicable to other research involving the use of multitemporal point clouds in related fields (such as deformation monitoring, disaster warning, and engineering drafts).

(4) High integrity of reconstruction elements. Compared with traditional 2D archaeological maps, the features extracted using the proposed methods (i.e., the point clouds of subsurfaces, surfaces, and outlines of relics) contain more integral and more precise information, which ensures the integral nature of the geographic elements of the historical scene, with less point data and higher efficiency in future modeling.

(5) Applicability of technology. The technology developed in this study may also be applicable to other multiscale geographical environments, such as natural resources surveys, conservation of historic buildings, 3D city modeling, regular deformation monitoring of huge facilities, and early warning of natural disasters.

Future research directions may include the following aspects.

To improve the quality of the 3D reconstruction of historical geographic scenarios, we will continue to focus on the fusion of multisource data, the data processing methods for use in complex excavation sites (e.g., overlapping and broken relics), and different types of sites.

Because of the limitations of the scanner, the scanning situation, and scanned objects with complex shapes, there are usually missing and blind areas in the point clouds, resulting in complete raw data and a negative impact on the subsequent 3D scenario reconstruction. Thus, we will design a method to interpolate the missing data based on a grid model or point dataset to preserve the features of the relic.

Based on the results of the multistage data registration, segmentation, and feature extraction, future research will focus on the 3D reconstruction of historical geographic scenarios. Considering the diversity and irregular shape of archaeological relics, we will investigate the fine modeling method for remains objects and the geometric modeling of nonremains objects.

5. Conclusions

With the goal of creating a 3D reconstruction of a historical geographic scenario and following the operation standards for field archaeology, we employed spatial point cloud data generated from a laser sensor and its technology. We adopted multitemporal point cloud data and a processing method for archaeological excavation based on 3D laser scanning technology. The archaeological excavation data for the Lingjiatan site in Anhui Province were taken as the experimental object. A method of multitemporal point cloud data registration was developed and implemented using an ICP algorithm. The focus of this study was to develop fine automatic segmentation and feature extraction methods for relic point clouds using improved octree neighbors within a radius search. Our experiment revealed that this data processing method has satisfactory feasibility, reliability, and automation. The proposed methods are expected to expand the applications of multitemporal point cloud data in archaeological research. Moreover, the results of this study provide basic modeling methods and data support for reconstructing historical geographic scenarios.

Acknowledgments

We thank LetPub (www.letpub.com) for its linguistic assistance during the preparation of this manuscript. The authors are very grateful to Anhui Institute of Archaeology for providing the opportunity to acquire the field data. Furthermore, sincere thanks are given for the comments and contributions of the anonymous reviewers and members of the editorial team.

Funding

The research in this article was supported by the National Natural Science Foundation of China (Grant No. 41631175 and No. 41471102) and National Social Science Foundation of China (Grant No. 15ZDB054).

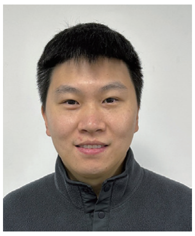
References

1 W. Zhou, Q. Li, and C. Li: Bulletin of Surveying and Mapping **4** (2012) 52.
2 E. F. Alessandro, P. George, and M.-T. Nadia: Proc. Unesco World Heritage Congress **2** (2002).
3 P. K. Allen, A. Troccoli, and B. Smith: IEEE Comput. Graphics Appl. **23** (2003) 32. https://doi.org/10.1109/MCG.2003.1242380
4 L. Fischer, H. Eisenbeiss, and A. Kaab: Permafrost Periglacial Processes **22** (2011) 140. https://doi.org/10.1002/ppp.717
5 S. B. DeLong, C. S. Pretice, and G. E. Hilley: Earth Surface Processes and Landforms **37** (2012) 262. https://doi.org/10.1002/esp.2234
6 A. Daehne and A. Corsini: Earth Surf. Processes Landforms **38** (2013) 640. https://doi.org/10.1002/esp.3351
7 G. Ventura, G. Vilardo, and C. Terranova: Remote Sens. Environ. **115** (2011) 3237. https://doi.org/10.1016/j.rse.2011.07.007
8 E. Nissen, A. K. Krishnan, and J. R. Arrowsmith: Geophys. Res. Lett. **39** (2012) 1. https://doi.org/10.1029/2012GL052460
9 L. Zhang: Ph.D. Thesis, Research on Key Technologies of 3D Change Detection Based on Multi-Time Camera LiDAR Date (WHU, Wuhan, 2014).
10 M. Rutzinger, B. Rüf, and B. Hofle: ISPRS Technical Commission VII Symposium—100 Years ISPRS—Advancing Remote Sensing Science. (IEEE, 2010) 475–480.
11 T. A. Teo and S. H. Huang: IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. **6** (2013) 2229. https://doi.org/10.1109/JSTARS.2012.2237543
12 A. Kusari, C. L. Glennie, and B. A. Brooks: 2019. IEEE Trans. Geosci. Remote Sens. **57** (2019) 3404. https://doi.org/10.1109/TGRS.2018.2884712
13 J. Revuelto, J.-I. López-Moreno, C. Azorin-Molina, E. Alonso-González, and A. Sanmiguel-Vallelado: Forests **7** (2016) 166. https://doi.org/10.3390/f7080166

14 B. V. Farahani, F. Barros, and P. J. Sousa: Tunnelling Underground Space Technol. **91** (2019) 102995. https://doi.org/10.1016/j.tust.2019.102995
15 F. Günther, G. Grosse, M. Ulrich, I. Nitze, M. Fuchs, and B. Jones: Repeat Terrestrial LiDAR for Permafrost Thaw Subsidence Change Detection in North Alaska. (IEEE, 2018) 569–570.
16 J. Zhang: Cultural Relics. **4** (1989) 1. CNKI:SUN:WENW.0.1989-04-000
17 J. Zhang: Archaeology **11** (1999) 1. CNKI:SUN:DNWH.0.1999-05-001
18 J. Zhang: Archaeology **3** (2008) 7. https://doi.org/10.1515/CHAR.2009.9.1.63
19 W. Sun: Master Thesis, The Relationship between Cultural Channels and Geographical Environmental of Anhui Neolithic Age Ruins (NJU, Nanjing, 2013).
20 Z. Shuo, X. Chen, and S. Liu: Archaeology **3** (2015) 35. CNKI:SUN:KAGU.0.2015-03-004
21 D. Zheng, D. Yue, and J. Yue: J. Geod. Geoinf. Sci. **37** (2008) 464. http://doi.org/10.3321/J.ISSN:1001-1595.2008.04.011
22 X. Zhao: Ph.D. Thesis, Research on 3D Reconstruction Method Based on Ground Laser Scanning Point Cloud Data, Wuhan University (WHU, Wuhan, 2010).
23 M. A. Fischler and R. C. Bolles: Commun. ACM. **24** (1981) 381. https://doi.org/10.1145/358669.358692
24 Point Cloud Library (PCL) · GitHub: https://github.com/PointCloudLibrary (accessed December 2022).

About the Authors

Yang Lin received her B.S. and M.S. degrees from Hohai University, China, in 2000 and 2003, respectively, and her Ph.D. degree from Nanjing Normal University, China, in 2006. From 2006 to 2017, she was an assistant professor at Nanjing Normal University, China. Since 2017, she has been a professor at Nanjing Normal University. Her research interests are in space archaeology and LiDAR data processing. (yanglin@njnu.edu.cn)



Hu Yang received his B.S. and M.S. degrees from Nanjing Normal University, China, in 2013 and 2016, respectively. His research interests are in geographic information science and space archaeology. (405767657@qq.com)

Wu Weihong received his B.S. degree from Zhongshan University, China, in 1989 and his M.S. degree from Peking University, China, in 1993. His research interests are in prehistoric archaeology. (shuozhiah@163.com)

Sheng Yehua received his B.S., M.S., and Ph.D. degrees from China University of Mining and Technology, China, in 1986, 1989, and 1997, respectively. His research interests are in geographic information science and remote sensing. (shengyehua@njnu.edu.cn)

Jia Xin received his B.S. degree from Taiyuan University of Technology University, China, in 2005 and his Ph.D. degree from Lanzhou University, China, in 2012. Since 2019, he has been an assistant professor at Nanjing Normal University, China. His research interests are in environmental changes and human activities and environmental archaeology. (jiaxin@njnu.edu.cn)