A REVIEW OF POINT CLOUD SEGMENTATION OF ARCHITECTURAL CULTURAL HERITAGE

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ABSTRACT:

With the continuous development of laser scanning technology, the model reconstruction and information management system of architectural cultural heritage are gradually taking shape. Among them, point cloud segmentation of architectural cultural heritage is important for Historic Building Information Model (HBIM), disease extraction and analysis, heritage restoration and other research. This paper mainly focuses on the systematic analysis and summary of the point cloud segmentation of architectural cultural heritage, introduces related concepts, and summarizes the segmentation methods from three aspects: traditional methods, machine learning based on artificial features, and deep learning. In addition, this paper summarizes the evaluation metrics and public datasets of semantic segmentation commonly used today, and further elucidates the relevant applications after segmentation. Finally, this paper analyzes and prospects the main problems and future development trends. This review aims to provide a useful reference for relevant researchers in the field of architectural cultural heritage protection.

0. INTRODUCTION

Architectural cultural heritage is a high degree of unity of national art and thought, with historical and cultural value. However, under the influence of climate change, natural disasters and man-made disasters, architectural cultural heritage inevitably faces the risk of destruction and extinction, and it is urgent to carry out relevant conservation and restoration work in a timely manner.

With the emergence and popularization of 3D optical instruments, digital photogrammetry and 3D laser scanning overcome the damage caused by direct measurement to architectural heritage, and can generate real 3D models in terms of geometric and radiation accuracy. It has become a key technology for data collection and digitization of architectural heritage. However, the collected point cloud data is scattered and disorganized., and cannot directly provide the geometric and semantic information of the building. Therefore, it is necessary to interpret the point cloud scene and segment the required components to provide the basis for the production of related vector maps (Qi Y.Z et al., 2023), HBIM (Macher et al., 2017), monitoring and restoration of architectural heritage (Niu and Tian, 2022).

Traditional methods for point cloud segmentation include region growing, feature clustering, model fitting, and edge detection (Lu J et al., 2003). With the continuous development of artificial intelligence (AI), methods based on machine learning and deep learning enable fine segmentation of point clouds by assigning semantic labels to them, which has led to significant progress in automated point cloud segmentation. Many reviews have been published for point cloud segmentation (Xie Y et al., 2020; Zhang J et al., 2019), but there are only few related reviews in the field of architectural cultural heritage. Among them, literature(Isa S,2018)reviewed the processing of point clouds of cultural heritage buildings from the perspectives of data structure and filtering; literature (Sapirstein, 2019)focused on the study of algorithms for automated reconstruction and visualization of damaged ancient inscriptions; literature (Liu X.W et al., 2023) summarized the 3D digitization of Chinese ancient buildings; literature (Yang S et al., 2022) analyzed the research hotspots, landmark literature, national cooperation and interdisciplinary models of cultural heritage point clouds through CiteSpace software, and revealed some trends. However, the focus of research in this literature is not on point cloud segmentation of architectural cultural heritage, and the only review that comprehensively presents this topic is in the literature (Yang S et al., 2023).

This paper summarizes the methodological theory, key technologies, advantages and disadvantages of current existing methods by summarizing representative or cutting-edge literature in related fields around the problem of point cloud segmentation of architectural cultural heritage. Finally, this paper discusses the open challenges and new trends in the field of architectural cultural heritage in the future.

1. CULTURAL HERITAGE INTRODUCTION

Cultural heritage refers to the material and intangible cultural assets with historical, cultural and artistic values inherited by a country or a country's people, reflecting the vitality and creativity of the nation. Current cultural heritage is divided into two categories: tangible cultural heritage and intangible cultural heritage. Among them, intangible cultural heritage is a variety of traditional artistic expressions and cultural sites that exist in

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intangible form, have been presented for generations, and are closely linked to human life, such as performing arts, social customs, and traditional handicrafts (Zhang B.F, 2019).

The physical cultural heritage includes immovable cultural relics such as ancient relics, building buildings, cultural sites, stone carvings and murals, and movable cultural relics such as artworks, documents and manuscripts, as well as historical and cultural cities. Architectural cultural heritage is a part of the tangible cultural heritage, mainly in the form of buildings or groups of buildings, which embody the characteristics of a specific historical period and regional culture, such as palaces, castles, churches, temples, monuments, etc. (Liu Q, 2009). Most of the studies targeting architectural cultural heritage are disease extraction (Alkadri et al., 2022), heritage restoration (Hou M et al., 2018), deformation monitoring (Domej et al., 2022), and digitization and documentation (Dzieglewski, 2015). In this paper, we mainly focus on point cloud segmentation of various historical buildings, cultural sites, and ancient building complexes to summarize.

2. ARCHITECTURAL HERITAGE POINT CLOUD SEGMENTATION

Traditional point cloud segmentation methods determine whether the point cloud belongs to the same group by selecting the initial seed point or the starting point and setting a certain standard. The common criteria include density, normal vector, curvature, etc. Machine learning and deep learning-based approaches achieve semantic segmentation of point clouds by feature extraction and training classifiers or segmentation networks with labeled point clouds. This section summarizes the current research status of point cloud segmentation in the field of architectural cultural heritage from three aspects: traditional segmentation methods, artificial feature-based machine learning, and deep learning-based, followed by a summary of publicly available datasets and related subsequent applications in this field.

2.1 Traditional segmentation methods

2.1.1 Edge detection-based methods

Edge detection-based methods generally detect the intensity change of edge points by curvature, facet normal and gradient etc. to get the boundary of different segmented regions.

According to the characteristics of different surface boundaries out of the point cloud normal vector and curvature changes, Xu et al. (Xu L et al., 2016) extracted the boundary points in the building point cloud through octree subdivision to realize the ancient building point cloud segmentation. Elkhrachy (Elkhrachy, 2017) computes the surface normals of the point cloud, determines the edge points by comparing the pinch threshold of the normal vectors, and then segments the feature planes from the historical building point cloud by fitting the building boundaries.

The edge detection-based method can quickly identify significant regional boundary points, but the segmentation accuracy is easily affected by noise and point cloud densities, and it is easy to identify poorly for gentle excessive boundaries.

2.1.2 Model-fitting based methods

The model fitting-based method focuses on fitting basic geometries such as planes, balls, and cylinders from the point cloud for classification. The main methods for model fitting are Hough transform and random sample consensus (RANSAC) (Gu Y et al., 2017). Hough transform is mostly used to detect planes and spheres, and RANSAC can detect straight lines, circles, etc.

One of the most effective methods in the Hough transform is the 3D random Hough transform (RHT). Maltezos et al. (Maltezos and Ioannidis, 2018) proposed the "Adaptive Point Random Hough Transform" (APRHT) and a multiscale framework based on detail 1 (LoD 1) and detail 2 (LoD 2). The planar detection was performed by lod1, and the sparse point cloud was extracted by a subsampling process. Secondary plane detection is performed according to lod2, and the corresponding exact plane parameters were calculated. Zhan et al. (Zhan Q.M et al., 2011) projected the point cloud of the wall and platform base of the ancient building after segmentation and recognition onto the XOY plane in the unit of the block, and used Hough transform and least square method to extract line segments and circles respectively.

Zhang et al. (Zhang R.J et al., 2020) used the RANSAC method to segment the point cloud of column members and the enclosing box method to segment the members such as beams and squared elements based on the information of the geometric structure and dimensions of ancient buildings. Huang et al. (Huang and Zhu, 2020) used a secondary spatial indexing method of global octree and local K-D tree to spatially partition the point cloud model data, and then used the improved RANSAC algorithm combined with linear least squares fitting algorithm to extract the geometric feature surfaces of ancient buildings. Macher et al. (Macher et al., 2014), on the other hand, segmented the point clouds in the geometric primitives based on the RANSAC algorithm, and then the segmented geometric primitives are applied to surface modeling or boundary extraction, especially for the extraction of profiles.

Model fitting methods are suitable for segmenting targets with simple, regular or known geometries and have good robustness and generalization capabilities. However, it can be relatively difficult to build a suitable model for complex heterogeneous components in architectural cultural heritage. In addition, the method is susceptible to factors such as noise and occlusion, resulting in a poor fit.

2.1.3 Regional growth-based methods

The region-based growth segmentation first selects the original seed point as the starting point and grows and spreads to the neighborhood space of the seed point according to the predefined growth rules. Then, the neighboring points with high feature similarity to the seed point are selected to join the region, and the growth process is repeated with this neighboring point as the new seed point.

Region growth algorithms are often used in conjunction with model fitting algorithms in segmentation applications. Ma et al. (Ma C.Y et al., 2023) first denoise the point cloud, and then use the region growing algorithm to segment the point cloud with the normal smoothness θ and the number of local adjacent connection points m as constraints to obtain sparse point cloud data on different planes. Next, the RANSAC algorithm is used to fit and segment the plane point cloud. Liu (Liu J.X, 2022) used the minimum curvature region growth algorithm for coarse segmentation of the roof surface, followed by the RANSAC algorithm for segmentation of small planes and optimization of the roof surface. Zhao et al. (Zhao C et al., 2021) first calculated the point cloud normal vector and curvature, and then iteratively grew the region using the normal vector angle and drape of the point and the roof surface as constraints. Then, the RANSAC algorithm was used to extract the small roof surface and iteratively merged the roof surface based on the idea of calculating the interior points to achieve the segmentation of the point cloud roof surface.

The region-growing method can effectively segment regularly shaped point cloud data, adapt to different data features and preserve the integrity and continuity of the target object through parameter adjustment. The algorithm is simple and easy to implement, and has good generality. However, the segmentation results are affected by the parameter settings and initial seed points, and there are problems of missing and wrong segmentation.

2.1.4 Feature clustering-based methods

The feature clustering-based approach is mainly applied to unsupervised point cloud segmentation tasks. This method achieves segmentation by combining points with similar geometric spectral features or spatial distribution into the same uniform pattern, and is mostly used for segmentation of irregular objects.

Zhao et al. (Zhao J.H et al., 2011) established point cloud index by KD tree, then used Gaussian mapping to map the points on the surface to Gaussian spheres, and used distance density to cluster the points on Gaussian spheres to achieve segmentation of ancient architecture point clouds. Wan et al. (Wan F et al., 2021) improved the Euclidean clustering algorithm and proposed a genetic algorithm-based Euclidean clustering point cloud segmentation algorithm to segment the point cloud planes that satisfy the adaptation degree. Sampath et al. (Sampath and Shan, 2008) first partitioned the building point cloud into planar and broken line components using the eigenvalues of the covariance matrix in a small neighborhood. Then, the planar components of the point cloud were divided into small blocks containing 6-8 points and their normal vector parameters were determined. Finally, the normal vectors were clustered together to determine the principal directions of the roof planes.

The feature clustering method can achieve better results and higher efficiency in feature calculation, but the method is very sensitive to noise and heterogeneous points.

In addition to the above segmentation methods, there are other segmentation methods available. For example, Dong et al. (Dong Y et al., 2021) used a hierarchical semantic network to classify the roof point clouds of Ming and Qing dynasty official buildings. Pan et al. (Pan Y et al., 2019) proposed a segmentation method based on super voxel and global graph optimization for achieving segmentation of ancient bridge point cloud data. Each method has its own scope of application, and multiple methods are usually required to be used together in the segmentation process to take full advantage of the different methods.

2.2 Artificial feature-based machine learning segmentation methods

In the field of digital heritage, the emergence of machine learning and deep learning techniques has greatly facilitated the interpretation of digital data, the semantic structure and the identification of research objects. The artificial feature-based machine learning approach first preprocesses the data, then extracts the features, trains and evaluates the model, and then uses the trained model to classify the data.

Artificial features of point clouds can be classified into three categories: statistical features, histogram-based features, and geometric features. The statistical features include the number of point clouds in the neighborhood, density, elevation difference, elevation standard deviation, etc. Histogram-based features include Point Feature Histogram (PFH), Fast Point Feature Histogram (FPFH), Signature of Histograms of Orien Tations (SHOT), etc. Geometric features include linearity, flatness, sphericity, etc. Commonly used classifiers are Support Vector Machine (SVM), Random Forest (RF), Parsimonious Bayes, etc (Chu S.R, 2021).

The selection of features directly affects the prediction results of the model, and the correct identification of geometric and radiometric features is the basis of classification. Grilli et al. (Grilli et al., 2019a) first used CloudCompare to compute features for spherical neighborhoods of different radius sizes (multiscale approach). Then, the features were examined to investigate whether the features described certain classes well at a given scale. Finally, the optimal subset of features was selected to highlight the differences between the classes of interest. In the literature (Grilli and Remondino, 2019), depending on the need and scope of the classification, the appropriate features were selected, and for different cases, clusters or RF classifiers were applied to classify heritage textures. Sabine (Sa B.N, 2022) used spectral information as a feature parameter and validated the spatial-spectral model point cloud of ancient building components using an RF classifier based on spectral feature ordering, which provided a new form of digital information acquisition and preservation for ancient buildings.

In order to improve the generalization ability of the model so that it can be applied to different scenarios, the researchers added classes such as modeling and drainage pipes to the model of (Grilli et al., 2019a) in the literature (Grilli and Remondino, 2020), and selected radiation features and geometric-covariance features. Further, the researchers tested the model on different data sets to improve the generalization of the model.

To achieve a fine-grained geometric description of architectural heritage objects, Teruggi et al. (Teruggi et al., 2022) proposed a point cloud classification method combining multi-layer multi-resolution (MLMR) and random forest (RF) to classify point clouds of different resolutions with different details. Dong et al. (Dong et al., 2022) constructed a multi-scale feature vector to segment the roof point cloud by combining geometric features with construction specifications specific to Ming and Qing dynasty ancient buildings. This method enabled point cloud classification of ancient building roofs and distinguished fine constituent elements such as kissing beasts, ridges, flat tiles and round tiles on the roof, thus describing the details of ancient buildings more accurately.

Artificial feature-based machine learning allows the selection of relevant features according to research needs, making the model more interpretable and controllable. Compared with deep learning, this method has lower computational complexity and fast training speed, which is suitable for processing small-scale data sets, and can avoid problems such as over-fitting or under-segmentation. However, manual feature extraction requires expertise and experience, and the effectiveness of feature extraction has a large impact on the performance of subsequent algorithms.

2.3 Deep learning-based segmentation methods

The models or descriptors of traditional segmentation methods cannot account for the complexity of real data. Artificial feature-based machine learning methods rely on manual feature extraction and generalization is difficult. The end-to-end deep learning-based methods can give semantic labels to each point in the scene, and at the same time can well balance the accuracy and complexity of the algorithm, providing a new idea for point cloud segmentation of architectural cultural heritage.

In 2017, Qi et al. (Qi C.R et al., 2017a) proposed a groundbreaking network-PointNet for processing directly on point cloud data. Then, in response to the poor local feature extraction ability of PointNet, PointNet++ (Qi C.R et al., 2017b) proposed a multi-level feature extraction structure based on PointNet, which can effectively extract local features and global features. The emergence of PointNet and PointNet++ changed the way of semantic segmentation of point clouds, and since then point-by-point MLP-based and graph convolution-based segmentation networks have been developed one after another. In 2019, Wang et al. (Wang Y et al., 2019) proposed a dynamic graph convolutional neural network-DGCNN. This network captures the relationship between point clouds by constructing a dynamic KNN graph and uses edge convolution EdgeConv for feature extraction, which is widely used in semantic segmentation of cultural heritage point clouds.

Grilli et al. (Grilli et al., 2019b) used RF classifier and deep learning methods based on CNN and RNN to classify heritage point clouds, respectively, and compared the advantages and disadvantages of the two methods. Haznedar et al. (Haznedar et al., 2023) combined the recovered data and laser scan data for aged and deformed scanned data in historical buildings, and used PointNet network to segment five parts, and the segmentation results were satisfactory. To overcome the problem of low segmentation accuracy due to the complexity of the training scenes, Malinverni et al. (Malinverni et al., 2019) selected four classes of arcs, columns, walls and windows and used PointNet++ networks and the "winner-take-all" (WTA) approach for segmentation.

Deep learning-based segmentation methods require large amounts of labeled data for training and testing, but there is a lack of large-scale publicly available labeled point cloud datasets in the architectural heritage domain, and the cost of acquiring these data is also high. To solve this problem, the researchers train the model with synthetic data. Morbidoni et al. (Morbidoni et al., 2020) used synthetic point cloud data to train an improved DGCNN-RadDGCNN network model and successfully applied it to real TLS point cloud segmentation, and achieved good accuracy, but there was still a lack of segmentation in similar categories. Meanwhile, Pierdicca et al. (Pierdicca et al., 2019) proposed a method to automatically generate point cloud synthetic datasets to compensate for the lack of data in semantic segmentation networks. Gunes et al. (Gunes et al., 2022) used parametric definitions of historic building elements to generate a semi-automatic synthetic dataset, the Historic Dome Dataset (HDD). Based on the similarity of Chinese ancient architectural styles, Ji et al. (Ji Y et al., 2021) used 3DMAX model to train sampling points and extracted complex roof point clouds from real ancient buildings. Although synthetic point clouds are more regular and complete than real scanned point clouds, they are able to save the cost of manually labeling training data, have structural similarity to real scanned point clouds, and are important for improving the generalization ability of neural networks. In addition to reduce the number of labels that need to be labeled and improve the application of deep learning methods to practical problems, Cao et al. (Cao and Scaioni, 2021) proposed a cultural heritage point cloud segmentation network 3DLEB-Net with limited labeled data and tested it on the Architectural Cultural Heritage (ArCH) dataset (Matrone et al.,2020). The results showed that the experiment exceeded or reached the recent state-of-the-art methods with only 10% of the training dataset, providing experience in weakly supervised or unsupervised learning in the field of cultural heritage.

In 2020, after the release of the large architectural cultural heritage (ArCH) point cloud dataset, researches on the ArCH dataset have emerged in an endless stream. Pierdicca et al. (Pierdicca et al., 2020) proposed to apply DGCNN to the task of point cloud segmentation on ArCH dataset. The segmentation was further improved by adding radiometric (HSV value) and normal features to DGCNN-Mod. Their work showed the potential offered by DL techniques for segmentation tasks. Matrone et al. (Matrone et al., 2020) compared the role of machine learning and deep learning in the classification of large cultural relics, summarized the advantages and disadvantages of ML and DL methods, and proposed a semantic segmentation framework DGCNN-Mod+3Dfeat that combined the advantages of the two methods.

In point cloud segmentation, there are some categories with obvious similar geometric features are easy to be confused, which increases the difficulty of algorithm recognition. Cui (Cui Z, 2021) chose the improved PointNet network for the initial segmentation of the total columns, frontal square and other components of ancient buildings. Then, the DI shape distribution function based on information statistics was applied to match the extracted components with the standard model, so as to determine the specific categories of components and achieve fine classification.

Method	Principle	Advantage	Disadvantage
Edge detection	The boundary of different segmentation regions is obtained by detecting the intensity change of edge points.	The identification of significant regional boundary points is accurate.	Vulnerable to noise and point cloud density, the gentle transition boundary is easy to identify unclear.
Model fitting	The mathematical model of set form is used as prior knowledge (plane, cylinder, sphere).	It is suitable for segmenting simple and regular basic geometric shapes.	It is not suitable for complex artificial or natural objects.
Region growing	Select seed points and merge points with similar properties around them.	The regular plane segmentation effect is good.	Affected by parameter settings and initial seed points
Feature cluster	The points of the same feature attribute are clustered into one class	The algorithm is stable and suitable for objects with obvious segmentation types.	It is not suitable for large-scale complex scenes, and it is difficult to distinguish objects with small feature differences.
Machine learning	The classifier is trained by manually extracting features.	The segmentation accuracy is high under applicable conditions.	It relies on feature descriptors, is not suitable for large and complex scenes, and has poor generalization ability.
Deep learning	Deep neural network is constructed to learn, extract and distinguish features,	Segmentation accuracy is better, generalization ability is	It requires a large amount of data for training, a large amount of

so as to realize semantic segmentation of point cloud.	stronger, end-to-end segmentation.	calculation, and high GPU performance requirements.

Table 1. Comparison of point cloud segmentation methods

The comparison shows that traditional segmentation methods mainly rely on geometric constraints and statistical rules to artificially design the features of objects, and divide the point cloud data into regions with uniform geometric and radiation characteristics (Elkhrachy, 2017). However, it is susceptible to noise and outliers in the data set, resulting in over-segmentation or under-segmentation. The machine learning method based on artificial features is suitable for point cloud segmentation of small scenes. It requires professional knowledge and experience to extract features. The generalization ability is poor and it is not suitable for complex scenes. In contrast, the segmentation method based on deep learning has the advantages of not requiring manual extraction of features, being able to automatically learn feature representation, and achieving better segmentation results for objects with complex geometric shapes and partial occlusion. However, this method has high model complexity, poor interpretability and is sensitive to hyperparameters, which requires a large amount of labeled data for training. Each method has its own advantages and disadvantages (as shown in Table 1). In practical applications, we should choose one or more methods to segment according to the actual needs to achieve the best segmentation effect.

2.4 Common evaluation indicators

2.4.1 Common classification evaluation indexes

It is usually chosen to calculate the precision, recall and F1 score (for each point by comparing the labels predicted by the classifier with the same manual annotation) for each class, as well as the overall precision.

$$Precision=\frac{TP}{TP+FP}\ , \tag{1}$$

$$Recall=\frac{TP}{TP+FN}\ , \tag{2}$$

$$F1\ score=2*\frac{Recall*Precision}{Recall+Precision}\ , \tag{3}$$

$$Overall\ accuracy=\frac{number\ of\ correct\ predicition}{total\ number\ of\ predicition}\ , \tag{4}$$

where TP (true positives) = the number of true positives and predicted positives
FP (false positives) = the number of true positives and predicted positives
FN (false negatives) = the number of true positives and predicted negatives
TN (true negatives) = the number of true positives and predicted negatives.

2.4.2 Common semantic segmentation evaluation indexes

Typical point cloud semantic segmentation accuracy evaluation metrics include: mean accuracy (mAcc), overall accuracy (OA), and mean intersection over union (mIoU).

$$mAcc=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i+TN_i}{TP_i+FP_i+FN_i+TN_i}\ , \tag{5}$$

$$OA=\frac{\sum_{i=1}^{N}TP_i}{\sum_{i=1}^{N}(TP_i+FP_i)}\ , \tag{6}$$

$$mIoU=\frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i+FP_i+FN_i}\ , \tag{7}$$

where N = the number of categories

2.5 Architectural heritage point cloud related data sets

2.5.1 WHU-TLS

WHU-TLS (Yang B.S, 2021) is a dataset based on terrestrial laser scanning (TLS) acquisition, published by Wuhan University, and is widely used for urban development tracking, forest structure assessment, etc. This dataset contains a small ancient building dataset (e.g., Figure 1), which can be used for 3D modeling of ancient buildings and digital preservation of cultural heritage, but is not serving for semantic segmentation studies.

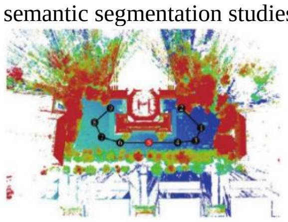

Figure 1. WHU-TLS ancient building dataset (Yang B.S, 2021)

2.5.2 Architectural Cultural Heritage (ArCH)

ArCH dataset is the first point cloud semantic segmentation data benchmark for historic architectural heritage. The ArCH dataset consists of 17 labeled point clouds and 10 unlabeled point clouds. Seventeen of the point cloud scenes (Figure2 shows some of the ArCH scenes) have been accurately labeled into 10 categories, including vaults, columns, floors, windows, doors, walls, line corners, stairs, arches, roofs and other categories of historic buildings, 15 scenes are available for training and 2 scenes are available for testing.

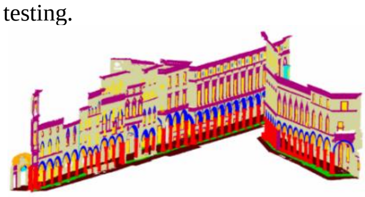

Figure 2. ArCH partial scene (Matrone et al.,2020)

2.6 Related applications after point cloud segmentation

Point cloud segmentation allows to obtain geometric primitives and related semantic information of related components, which have different applications in supporting scan-to-BIM processes, monitoring and repair purposes, maintenance building planning, damage detection and quantification, etc.

For disease detection, disease information such as cracks and defects are extracted from the relevant components by segmenting them. The literature (Alkadri et al., 2022) identified potential cracks in components by calculating the geometric properties of point clouds to assess the surface performance of building heritage. Chen (Chen P, 2022) extracted and detected wall crack information using digital image processing techniques based on point cloud orthophotos of ancient building wall cracks and generated thematic maps of crack remnants for archiving data

In the process of obtaining point cloud data to realize Scan-to-BIM in HBIM modeling, it is necessary to process the obtained point cloud, semantically describe the unstructured point cloud, and segment the modeling object. Macher et al. (Macher et al., 2017) extracted point clouds such as ground, ceiling, and wall by performing multiple segmentations, and then reconstructed and described in IFC format and integrated into BIM software. Reference (Croce et al., 2023) used the point cloud obtained by semantic segmentation to construct a reference model composed of template geometry, and used visual programming languages (VPLs) to realize model reconstruction. Then, it was proposed that the integration of HBIM and H-GIS system might become the theme of future research. At the same time, Niu et al. (Niu and Tian, 2022) proposed that HBIM cooperates with architecture, history, archives management, visualization, 3DGIS and other technologies to realize a multi-party participation and collaborative management of digital archived management platform, which effectively solved the problem of digital archiving of historical buildings. Poux et al. (Poux et al., 2017) developed a tool through WebGL that can perform semantic extraction and visualization of historical point clouds to achieve effective communication between participants. Qi et al. (Qi Y.Z et al., 2023) obtained different components by segmenting the building plane by RANSANC algorithm, and then selected the appropriate intermediate height to slice the segmented point cloud model and project it to generate a plan. Domej et al. (Domej et al., 2022) performed numerical modeling of cultural heritage point clouds and performed stability analysis through finite element.

3. CONCLUSION

Although some achievements have been made in the research of point cloud segmentation of architectural cultural heritage, there are still some problems to be solved in the existing methods. Therefore, this paper will analyze these problems from the technical point of view, and look forward to the future development trend of point cloud segmentation of cultural heritage.

⑴There is a lack of large-scale public data benchmarks in the field of architectural cultural heritage. Although there have been many public datasets in the fields of computer vision, remote sensing, and autonomous driving, there is only one large public dataset ArCH in the field of architectural cultural heritage, lacking more public datasets of scenes and categories. Therefore, it is necessary to cooperate and produce more relevant data sets to promote the development of the digitization process of cultural heritage.

⑵The target boundary of semantic segmentation is fuzzy, which easily leads to the error of target segmentation at the boundary. In the semantic segmentation task, due to the fuzzy boundary of the target, the target segmentation error at the boundary is often caused. When dealing with adjacent or intersecting components, it is also prone to unclear segmentation contours. In order to solve these problems, boundary-aware methods can be considered to improve the effect of semantic segmentation. In addition, the segmentation results can be post-processed to further optimize the segmentation effect.

⑶The problem that small components are easy to be segmented incorrectly. Small components and decorative components in the cultural heritage point cloud are easy to be segmented wrongly in the segmentation process due to the small amount of data, which accounts for less in the whole scene. The segmentation accuracy of the point cloud of small components can be improved by improving the sampling method of the segmentation network or adding feature pyramids to the semantic segmentation network to obtain more detailed information. The technique of multi-source and multi-scale data fusion segmentation can also be used to improve the segmentation accuracy.

⑷Due to the high cost of manually labeling large-scale data, weakly supervised or unsupervised methods can be considered to reduce the difficulty of labeling. To achieve more scenes and more types of architectural heritage point cloud segmentation, more large-scale data sets need to be developed. Point-by-point data labeling is expensive and it is relatively difficult to obtain architectural cultural heritage data sets. Therefore, it is very important to explore weakly supervised or unsupervised segmentation for cultural heritage protection in future research.

This paper mainly summarizes the development of point cloud segmentation technology of architectural cultural heritage in recent years. Firstly, it introduces the relevant definition of cultural heritage and the current basic situation. Secondly, the related methods of point cloud segmentation in the field of architectural cultural heritage are introduced in detail from three aspects: traditional segmentation method, machine learning based on artificial features and deep learning, and the advantages and disadvantages and application scope of various methods are compared. Then, some commonly used point cloud data sets, evaluation indicators and related applications after segmentation are described. Finally, the problems existing in the current research are discussed and prospected. At present, the research on point cloud segmentation in architectural cultural heritage is increasing, but there are still problems to be improved, and there is still much room for improvement.

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