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The Application and Challenges of 3D Model Retrieval Technology in the Information Age

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Abstract

In recent years, with the continuous development of computer vision, 3D model retrieval technology has also made certain progress. This paper mainly describes some application scenarios of 3D model retrieval technology and demonstrates the important role it plays in current and future development.At the same time, in the face of generative artificial intelligence and the continuous demand for retrieval technology, this paper also presents the challenges currently faced by 3D model retrieval technology and the future research trends.

Keywords

3D Model Retrieval, Application scenarios, Technical challenges

1. Introduction

With the continuous development of 3D data acquisition technology, 3D graphic modeling methods and graphic hardware technology, more and more 3D object model libraries have emerged. Therefore, the development of 3D related technologies has been quite rapid and can now basically be compared with text and image-related technologies.With the sharp increase in the number of 3D models, retrieving the desired model from a large number of 3D models has become an urgent need in daily life.In recent years, due to the rapid development of deep learning, researchers have mainly conducted studies from two aspects: model-based and view-based methods, based on the different formats of the input 3D models. Among them, model-based methods are further divided into voxel-based and point cloud-based methods.

Elements in three-dimensional space are called voxels and are represented by the distribution of corresponding binary variables. The voxel-based method learns 3D features from voxels. This method has a good generalization ability while keeping the geometric structure information of the object unchanged. However, due to the relatively sparse voxels, it consumes memory and has a large amount of computation, which is more limited for large-scale applications. Wu, Song, Khosla, Yu et al. (2015) first introduced deep learning into the field of 3D model retrieval and proposed a deep learning model called 3DShapeNets, which learns semantic features and global features at different levels from voxelized 3D shapes. To accelerate learning from voxels using deep learning models, Wang, Liu, Guo, Sun et al. (2017) proposed a new convolutional neural network based on the Octree data structure (Octree-based CNN, O-CNN), which takes the normal vectors of the leaf nodes of the octree as input and performs 3D-CNN operations to extract global features.

A point cloud is a collection of points of an object that have coordinate information and intensity information in a three-dimensional coordinate system. Qi, Su, Mo, and Guibas (2017) proposed the classic PointNet network, which takes the cooperation of point clouds as input, studies point cloud features through shared MLP, and to solve the problem of point cloud disorder, uses Max pooling to obtain global features. To address the issue that the PoinNet network cannot learn local features, Qi, Yi, Su, and Guibas (2017) further proposed the PointNet++ network. This network imitates the local connection operation in CNN and adds a hierarchical network on the basis of PointNet to perform regional learning on the data and then aggregate it into global features. To address the issue of uneven sampling density, the author proposed a method of adaptively combining features from multiple scales, which endows the network with excellent robustness.

The view-based approach turns 3D problems into 2D ones by rendering 3D data into 2D views, and thus can be solved by using convolutional neural networks (CNNS). Therefore, it has demonstrated better performance in many tasks. Su, Maji, and Kalogerakis (2015) proposed the Multi-view Convolutional neural Network (Multi-View CNN, MVCNN), which automatically learns and combines the features of multiple views through a CNN architecture with a pooling layer to generate a single and concise 3D shape descriptor, and its performance far exceeds that of traditional methods. In addition to using convolutional Neural networks, Han, Shang, Liu, Vong et al. (2019) and Ma, Guo, Yang, and An (2019) respectively used Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) to learn view sequence information. Further obtain the connections between views. In recent years, researchers have conducted studies on multimodal 3D model retrieval to learn features under different representations.

This article will focus on introducing the application scenarios of 3D model retrieval, as well as the current challenges and research trends faced by this technology.

2. Application Scenarios of 3D model Retrieval

2.1 Applications in Industrial Design

In the field of industrial design and manufacturing, 3D model retrieval technology has become an important link in the innovation of product development processes.When engineers are faced with a complex physical sample, such as an automotive part or a consumer electronics shell, and need to reverse engineer or make design improvements, they first need to obtain a large amount of point cloud data on the surface of the sample through a 3D scanning device. In traditional design, relying on engineers for model reconstruction and comparison is inefficient and prone to errors.3D model retrieval technology can efficiently input the obtained point clouds or rough models into professional retrieval systems. The system, based on the shape features and topological structures extracted by deep learning, performs rapid similarity matching in a vast enterprise-level model library.This process can precisely identify highly similar mature models or standard parts in the historical design library. Engineers can directly make parametric modifications and optimizations based on this without having to start modeling from scratch.3D model retrieval technology significantly shortens the design iteration cycle, reduces labor costs, and avoids repetitive design errors. It is a key enabling technology for modern intelligent manufacturing and knowledge engineering.

2.2 Applications in Biomedicine

In the field of biomedical engineering, 3D model retrieval technology is playing an increasingly important role.For instance, in orthopedic implants, the degree of match between the implant and the individual affects the surgical outcome and the patient's recovery and adaptation.Currently, three-dimensional reconstruction of patients' bones can be carried out based on medical images, and the reconstructed three-dimensional models can be quickly and effectively matched with the massive data in the implant database.The 3D model retrieval system can form depth features based on the key marks, volume and curvature in the key areas of the retrieved model, and at the same time combine semantic information to achieve the most suitable matching, thereby providing more refined surgery and treatment for patients.In addition, in the field of dental implants, based on the three-dimensional models of the alveolar bone of different patients, the optimal implant size and Angle for each patient can be precisely matched in the existing dental implant database.The current 3D model retrieval technology can plan different solutions based on different needs in medicine. It not only effectively assists the development of current medicine but also brings more convenient and effective cure methods to countless patients.

2.3 The Field of Cultural Heritage Protection and Digital Twin

In the field of cultural heritage protection and digital twins, 3D model retrieval technology provides powerful technical support and information retrieval functions for cultural relic restoration, cultural relic query, virtual system display of cultural relics, and other historical research.At present, many cultural relics in archaeological excavations are only partial fragments, which is not conducive to the research of archaeologists.To better apply technology to historical research, experts can first extract high-precision three-dimensional models of cultural relic fragments. The three-dimensional model retrieval technology acquires the edge morphology, texture, and material features of the model. Through the three-dimensional model retrieval system for retrieval, a fragment model that is spliced with the fragment can be obtained, thereby enabling a complete restoration of the cultural relic.In addition, 3D model retrieval technology can be applied to digital museums. Users and visitors can search for the sketches or names of cultural relics, thereby precisely displaying the virtual models of the relics, providing visitors with an immersive experience and offering convenience to the staff in their work.The application of 3D model retrieval technology in the field of cultural relics research not only facilitates the restoration of cultural relics and the display of virtual cultural relics, but also contributes to the historical research and cultural dissemination .Meanwhile, by building digital twins, systematic management and analysis of cultural relics can be carried out, providing a carrier for the permanent preservation of cultural relics and a shared platform for cultural research.

2.4 The Field of Home Service

In the field of home services, currently, people's decoration and design of their houses tend to be more inclined towards full-house customization. If users need to constantly change their furniture choices, designers have to select furniture with similar styles one by one from the furniture database to ensure the similarity of decoration styles. This process consumes a lot of labor and time costs.Applying 3D model retrieval technology to the home service field, a 3D model database of furniture is constructed. When retrieving the current furniture models, the system can form deep features based on the size, color, texture and style of the furniture models, and select similar furniture from a large number of furniture databases. This not only ensures the consistency of the decoration style but also meets the different needs of users. Applying 3D model retrieval technology to the home service field not only enables the construction of virtualized customization to meet customers' demands, but also helps to enhance the work efficiency of designers.

3. The Challenges of 3D Model Retrieval

3.1 The Challenges Brought by Generative Artificial Intelligence

In recent years, the rapid development of generative artificial intelligence such as large language models has brought huge potential to current 3D model retrieval technology, while also presenting more complex and difficult challenges. Generative artificial intelligence typically takes in data such as text and images, and the system analyzes the semantic retrieval of relevant models, and then assists in generating new three-dimensional content based on the retrieved models. Generative artificial intelligence generates 3D models based on demand, seemingly capable of replacing the structure of 3D model retrieval. However, in reality, current generative artificial intelligence still cannot fully meet the goals of retrieval systems. For instance, the generated models may seemingly conform to semantic requirements on the surface, but their textures, materials, and complex topological structures cannot replace the retrieval targets. Especially for the refined model requirements in industrial or professional fields. Therefore, it is difficult for the generative 3D model to be consistent with the current model database representation, and it is quite challenging for it to become a supplementary model to the current database.

Therefore, at present, large models have put forward higher requirements for semantic understanding and 3D generation. The system not only needs to be able to understand individual objects, but also the relationships between objects, context and implicit semantics. Accurately parsing and matching such complex intentions onto 3D models is a huge challenge.

3.2 Challenges Faced by Retrieval Efficiency

With the large-scale increase in the number of 3D models, the retrieval efficiency has become an issue that cannot be ignored, restricting the implementation and deployment of large-scale 3D model retrieval systems.In 3D model retrieval, the complexity of the model's structural representation (such as point clouds, meshes, etc.) (Qi, Su, Mo, & Guibas, 2017) and the massive data scale bring certain computational intensity to the retrieval efficiency.Firstly, the structure of a 3D model is complex, and its features must include shape, texture, and topological structure. Therefore, high-dimensional features are required to have a certain discrimination ability. As a result, both the training and testing of the model require a large amount of computing power, so high-computing-power Gpus and a certain amount of time are needed.In addition to model training, due to the large number of model databases, the storage of the model feature library is also a problem that needs to be solved.At the same time, when the number of models reaches a certain scale, the calculation of feature similarity during model retrieval requires a considerable amount of time, thereby affecting the retrieval efficiency and reducing the user experience of the system.

Therefore, in future model retrieval technologies, it is necessary to construct lightweight feature extraction networks, reduce high-dimensional discriminative features, conduct distributed computing to lower computing power consumption, and integrate generative learning to explore more effective, compact, and discriminative features.

3.3 The Challenges Faced by Retrieval Effect

Although the current 3D model retrieval technology has achieved certain results, there are still certain differences between the retrieval effect, such as retrieval accuracy rate, precision rate and recall rate, and the actual requirements. The main reason for the difference lies in the certain gap between the representation of features and the understanding of high-level semantics. The structure of 3D models is complex and usually relies on scene representation. Objects with the same structure in different scenes have different meanings. For example, study chairs and business chairs have a high degree of similarity in shape and structure, and thus are very close in feature representation. In the retrieval system, they are represented as similar objects.However, due to the differences in other high-level semantics such as its scene and texture, it is not the target object for users to retrieve.In the 3D model retrieval technology based on sketches and two-dimensional images, the input sketches or two-dimensional images have significant differences from the 3D models in the database , which leads to a decline in feature discrimination ability and thus affects the retrieval effect.In addition, many existing datasets have limited scale, insufficiently comprehensive category coverage, and non-standard label annotation, all of which restrict the current retrieval effect. Therefore, in order to enhance the retrieval effect, a more powerful cross-modal semantic understanding model is needed to conduct in-depth mining of the information and structure of 3D models (Dong, Zhu, Lin et al., 2024).

4. Conclusion

Based on the current development of 3D model retrieval technology, this paper expounds the application of 3D model retrieval technology in the fields of industrial design, biomedicine, cultural heritage protection and home services, and explains that 3D model retrieval technology plays an important role in various fields. At the same time, the challenges faced by 3D model retrieval technology in terms of generative artificial intelligence, retrieval efficiency and retrieval effect are proposed, as well as the future research directions in response to each challenge.

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