Abstract

With the development of 3D modeling and fabrication, 3D shape retrieval has become a hot topic. In recent years, several strategies have been put forth to address this retrieval issue. However, it is difficult for them to handle cross-modal 3D shape retrieval because of the natural differences between modalities. In this paper, we propose an innovative concept, namely, geometric words, which is regarded as the basic element to represent any 3D or 2D entity by combination, and assisted by which, we can simultaneously handle cross-domain or cross-modal retrieval problems. First, to construct the knowledge graph, we utilize the geometric word as the node, and then use the category of the 3D shape as well as the attribute of the geometry to bridge the nodes. Second, based on the knowledge graph, we provide a unique way for learning each entity’s embedding. Finally, we propose an effective similarity measure to handle the cross-domain and cross-modal 3D shape retrieval. Specifically, every 3D or 2D entity could locate its geometric terms in the 3D knowledge graph, which serve as a link between cross-domain and cross-modal data. Thus, our approach can achieve the cross-domain and cross-modal 3D shape retrieval at the same time. We evaluated our proposed method on the ModelNet40 dataset and ShapeNetCore55 dataset for both the 3D shape retrieval task and cross-domain 3D shape retrieval task. The classic cross-modal dataset (MI3DOR) is utilized to evaluate cross-modal 3D shape retrieval. Experimental results and comparisons with state-of-the-art methods illustrate the superiority of our approach.

Keywords: 3D shape retrieval, Cross-domain 3D shape retrieval, Cross-modal 3D shape retrieval, 3D shape knowledge graph.

1. Introduction

3D shapes are widely employed in our daily life thanks to the advancement of digitalization methods and computer vision, including computer-aided design, medical diagnostics, bioinformatics, 3D printing, medical imaging, and digital entertainment. In recent years, there has been a desire for quick generation and simple access to vast quantities of 3D shapes, particularly for applications in virtual and augmented reality. It is reasonable to utilize some references to obtain similar 3D shapes and accelerate secondary development. These references can be 3D shapes \[1,2\], 2D images \[3\], sketch images \[4\] and text information \[5\]. Numerous methods have been put out in recent years to deal with this issue.

The MVCNN\[6\] extracts a series of rendered views on 2D pictures and combines information from several perspectives of a 3D shape into a single, compact shape descriptor. PointNet++ \[7\] iteratively implements the representations in a hierarchical neural network using density occupancy grid representations for the input data to create a representation of three-dimensional forms. A multiloop-view convolutional neural network architecture for 3D shape
retrieval was suggested by Gao et al. [8]. It may be seen of as a modified MVCNN that takes into account the natural hierarchical links between views. Some researchers, however, concentrate more on the merging of multimodal information for 3D shape representation. You et al. [9] suggested a combined convolutional network that successfully integrates point cloud and multiview model information in order to train an end-to-end deep network for 3D shape representation for shape recovery and classification.

These conventional methods concentrate on the descriptive layout of 3D shapes and use them to find related 3D shapes. However, consumers may now quickly obtain photographs thanks to the advancement of computer vision and smartphones. Some academics concentrate on the issue of retrieving cross-modal 3D shapes from 2D photos. Dai et al. [10] recommended a unique deep correlated holistic metric learning (DCHML) strategy to lessen the distinction between sketch images and 3D shapes. The proposed DCHML simultaneously trains two deep neural networks (one for each domain), learning two deep nonlinear transformations to map data from both domains into a new feature space. Joint distribution adaptation (JDA), a brand-new transfer learning strategy, was put out by Long et al. [11]. It jointly adjusts the conditional distribution and the marginal distribution as part of a principled dimensionality reduction strategy to provide a new feature representation that is effective and robust to significant distributional variations.

A coherent structure that minimizes the transition across domains statistically and geometrically has been proposed by Zhang et al. [12]. In order to simultaneously decrease the geometric shift and the propagation shift, two combined projections are trained that project the information from the source domain and the target domain into low-dimensional subspaces. All of these techniques, however, concentrate on cross-modal feature learning and global structural information descriptor creation. Both of these depend on parameter learning, extensive training datasets, and model design. All of these techniques have trouble retrieving several cross-domain and cross-modal 3D models at once. These techniques cannot thus be seen as union methods.

1.1. Motivation

There are three clear problems with traditional 3D shape retrieval techniques.: 1) they depend on large-scale 3D shape datasets to train the network parameters; 2) they are inappropriate for cross-domain and cross-modal retrieval problems. One modality has difficulty achieving better results when it is applied to other datasets. 3) All of these methods cannot handle cross-domain and cross-modal 3D model retrieval at the same time.

In this paper, we propose a novel idea. If we can find an intermediate variable, which can be used to represent the 2D shape and the 3D shape information, this variable can also be used to bridge the gap between two different domains and different modalities. Naturally, this variable can be used to represent the shape information and help to guide feature learning. Thus, we need to think about how to find this intermediate variable.

In Fig. 1, one 3D shape can be represented by a set of rendered images. Meanwhile, these rendered images can be broken down into a set consisting of geometric information. For example, the “cup” can be reduced to a cylinder. The “table” can be reduced to a square plane and a cylinder. If a 3D shape can be seen as a document, the rendered images can be seen as its sentences, and the geometric information can be considered as the “geometric words”. The “geometric words” can be seen as the basic shape element. Any shape can be represented by unlimited
geometric words by combination. Here, we need to note that the “geometric word” is not the traditional concept of geometric primitives. Geometric primitives often mean standard shape information, such as cylinders, squares and triangles. However, “geometric word” has a broader definition, which can be used to represent any shape. Based on the idea of "geometric words," we can avoid relying on a huge number of 3D shapes for training by merely creating enough geometric words to describe shapes. This method may be used to tackle cross-domain information retrieval issues since every 3D shape can be represented by an infinite number of geometric words. Meanwhile, geometric information can also be extracted from 2D images, which can bridge the gap between 2D images and 3D shapes. Thus, it is reasonable to handle cross-modal 3D shape retrieval. However, we also have to face the following problems: 1) how to find and define the “geometric word”, which can be seen as a complete set for shape representation; and 2) how to handle shape retrieval and cross-modal shape retrieval based on these “geometric words”.

In this paper, based on the concept of a “geometric word”, we propose a novel 3D shape knowledge graph and graph embedding method to address cross-domain and cross-modal 3D shape retrieval problems. First, we apply OpenGL to develop a toolbox to extract a set of rendered images of 3D shape. Then, we employ an image segmentation method to extract a set of part shapes. Meanwhile, the classic unsupervised classifier, K-means, is utilized to find the geometric words based on these part shapes. Prior to this point, we have obtained a set of rendered images and related part shapes. Second, we build the 3D shape knowledge graph according to the relationship among the 3D shape, rendered image, part shapes and geometric words. Third, a unique graph embedding strategy is proposed to learn the embedding of 3D shapes, rendered images, part shapes and geometric words by fully considering the structural information among them. Finally, an effective similarity measure method is proposed to handle the 3D shape retrieval problem. In particular, our method efficiently solves the cross-domain and cross-modal 3D form retrieval issue at once and makes use of little data to build the 3D shape knowledge network.

1.2. Contributions

The contributions of this paper are summarized as follows.

- We propose a novel 3D shape knowledge graph that can handle the cross-domain and cross-modal 3D shape retrieval problem. To the best of our knowledge, we are the first to introduce the knowledge graph concept to handle the 3D shape retrieval problem. Moreover, we are the first to propose an approach that can simultaneously solve the two problems.

- We propose a brand-new graph embedding strategy for the representation of entities in the 3D shape knowledge graph, which can effectively handle representation learning under supervised and unsupervised conditions.

- We propose a novel similarity metric between query shape/image and target 3D shape based on the knowledge graph embeddings. It can effectively consider the geometric structure information and category information of 3D shapes for more accurate retrieval results.

In what follows, we outline the remainder of our document. We present the associated work in Section 2. Section 3 presents the proposed solution. We show important experimental results in Section 4. A review of the results is also given in this section. Here, we will use our approach to address various problems of 3D shape retrieval and demonstrate the efficiency of our approach. Finally, in Section 5, we discuss possible future work.

2. Related Work

In recent years, the number of different 3D shape recognition methods has exploded. We will introduce some classic 3D shape retrieval and cross-modal 3D shape retrieval methods published recently in this section.

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1. https://github.com/tjuliangqi/opengl_render_img_in_a_specific_view
2.1. 3D Shape Retrieval

3D shape retrieval has been applied in various areas with the development of 3D data processing technology. To convolve a 3D shape in a manner similar to any other tensor, several works have focused on voxelized shapes. These techniques are constrained by their resolution because of the sparseness of the data and the high cost of 3D convolution computing. For 3D object identification and retrieval, Garro et al. suggested tree-based shape representations based on specific graph kernels and the scale space of the autodiffusion function (ADF), which are simple and effective representations of structural information. They ignore geometric information with practical significance. When handling classification and retrieval issues, Wang et al. suggested the EdgeConv module, which is appropriate for point representations of structural information. They ignore geometric information with practical significance. When handling classification and retrieval issues, Wang et al. suggested the EdgeConv module, which is appropriate for point representations of structural information. They ignore geometric information with practical significance.

In recent years, graph structures have been applied to handle the representation of 3D models. A graph neural network is utilized to handle feature learning. Wang et al. proposed the local spectral graph convolution to jointly consider the information of the points and their neighboring points. Te et al. used spectral graph theory to develop a regularized graph convolutional neural network, which maps the point cloud into the graph structure and defines the calculation on this structure by utilizing Chebyshev polynomial approximation.

In order to solve classification and retrieval issues, Wang et al. presented EdgeConv that is appropriate for point clouds tasks incorporated with CNN. Shi et al. presented Point-GNN in order to lessen translation variance, and they also created a box merging and scoring process in order to precisely aggregate detections from various vertices. An edge-oriented graph convolutional network was suggested by Zhang et al. to take use of multi-dimension edge information for relationship modeling explanation and investigating the processes of interaction between nodes and edges.

These methods focus on how to use the structure information to improve the performance of 3D shape features. Obviously, these graph structures ignore the cross-modal relation information and the local information of 3D shapes.

Both of these methods created the corresponding networks for learning the 3D form representation using the widespread deep learning methodology. These methods depend on the vast amount of training data instead of the geometric structural data. Utilizing it to solve the cross-domain 3D form retrieval challenge is challenging.

2.2. Cross-modal 3D Model Retrieval

Image-based retrieval is a contemporary technique that is absolutely capable of becoming a strong competitor. A new paradigm for image-based 3D shape recovery was proposed by Mu et al. The image in issue was initially represented as a Euclidean point, and all the displayed views of a 3D shape were then represented as a Symmetric Positive Definite (SPD) matrix, or, put another way, a point on a Riemannian manifold. The recovery of the image-based 3D shape is finally simplified to the learning of Riemannian metrics from Euclidean metrics. Using a 3D shape similarity measure, Li et al. constructed the embedding space; then, they used a convolutional neural network (CNN) to “purify” images by eliminating distracting elements. Joint embedding enables the retrieval of cross-view images, image-based shape retrieval, and shape-based image retrieval. There are few works that can be found in the community of image retrieval, and limited information can be referenced. Given a random noise sampled from fixed distribution, it is possible to use the common Generative Adversarial Network to generate an image with reasonable content and to handle the transformation of the function. We will explain these works in detail next. The definition of SeqViews2SeqLabels is worth learning during the process of feature extraction. To learn the global characteristics
of the 3D shape, the SeqViews2SeqLabels model is proposed. The spatial and content knowledge of all sequence views is maintained by the aggregate sequence view. At the same time, by modifying the weight of special views, the discriminative capacity of the SeqViews2SeqLabels model is enhanced.

From these approaches, we can find that all of the methods can be seen as cross-domain feature learning. They seek the feature learning of multiple modalities data on the embedding space. Obviously, they also ignore geometric information with practical significance.

Figure 2. The framework of our approach, which includes three parts: knowledge graph construction (entity and edge extraction), graph embedding and similarity measure. K-means is used to generate geometric descriptions for knowledge graph. The graph embedding strategy is utilized to address the embedding generation of entities for model retrieval.

2.3. 3D Model based on Component Theory

In this paper, we proposed a “geometric word” theory inspired by our previous work[29], which can be utilized to represent any shape information. Obviously, a “geometric word” can be seen as the component of the object. Component theory has been proposed for a long time. Liu et al. [30] proposed a novel formulation that learns physical primitives by explaining both an objects appearance and its behaviors in physical events. This method proposed an interesting idea to handle segmentation problems based on tool behaviors. However, it is also suitable for more classic models. Katageri et al. [31] proposed the point decomposition network (PointDCCNet) for 3D object classification. This approach relied on the performance of the decomposition module. Our approaches are also inspired by some multi-view 3D model segmentation methods, such as [32, 33, 34], which transform 3D point clouds to 2D images and thus, the 3D analysis is reduced to a 2D CNN-based problem. Feng et al. [35] proposed a Group-view Convolutional Neural Network (GVCNN) for hierarchical correlation modeling toward discriminative 3D shape description. This approach provides multiview information to a set of groups. Each group can be seen as a component. This design can effectively remove redundant information to improve the final performance. Mo et al. [36] proposed a 3D object dataset containing numerous elaborate annotations and structured object parts. This dataset proposed a better perspective to
understand the 3D model and inspired us to propose geometric word theory. In recent years, many works have studied in fine-grained and hierarchical shape segmentation. Yi et al.[37] utilized the noisy part decomposition from the CAD model designs to learn consistent shape hierarchies. Besides, a recursive binary decomposition network[38] is proposed for shape hierarchical segmentation as well.

3. Our Approach

In this section, we provide a detailed introduction to our approach. The framework of this work is shown in Fig.2. The whole framework includes the following three steps.

- **3D shape knowledge graph construction:** We first render multiple images from different viewpoints of 3D shapes. Then, we utilize an image segmentation method [39] to segment each rendered image into a set of shape parts. These shape parts are classified into a set of geometric words. Each part of the shape can be projected into a geometric word. Based on the above processes, we define the entity and edge for 3D shape knowledge construction.

- **Graph embedding:** We propose a graph embedding strategy according to the structure of a 3D shape knowledge graph. Specifically, we define the category edge in the knowledge graph. We can control this edge to make our approach handle supervised or unsupervised problems;

- **Similarity measure:** Based on the embeddings of entities, we propose an effectiveness similarity measure method, which designs different similarity measure strategies, as shown in Fig.2. We will detail these steps in the subsection 3.4.

3.1. Data Preprocessing

Data processing is key step in our approach. The aim of this part is to find visual geometric words for 3D shape knowledge graph constructs, which includes three steps. 1) We extract the rendered views from 3D model. Here, each 3D model can generate a set of images. 2) We applied the image segmentation method to segment these rendered images. Each object will be segmented into a set of parts. Each part has a clear affiliation with the rendered image. 3) We classify these parts to find the general information. The goal of this step is to find the geometric word. Each class can be seen as one geometry word. The center point is utilized to represent the geometric word.

In the process, we focus on the 2D object segmentation method. Many classic 3D shape decomposition techniques or unsupervised 3D shape decomposition techniques [30][40][41] cannot be used to handle this problem. We do not find that there is an effective method that can provide object segmentation. Many traditional methods focus on semantic segmentation and 3D field segmentation, which is not suitable for our work. Thus, we build a new 3D shape segmentation dataset and apply the classic FCN model [39] to train the segmentation model.

The shape segmentation dataset is shown in Fig.3. The details of this dataset are shown in the supplemental files. We also published this dataset on GitHub[2]

![Figure 3. Some training examples in the object segmentation dataset](https://github.com/datar001/segmentation-dataset)
model. Here, we apply 4,940 samples as the training data, 1,900 samples as the validation data and 760 samples as the testing data. Fig. 4 shows some segmentation results.

In the training step, compared with other traditional segmentation models, the label information of each object does not need to be provided. We only provide the ground truth of segmentation. This means that the segmentation model trained by our dataset is a common segmentation model that can be utilized to segment any shape. Finally, we extract a set of shape parts for each rendered image or real image, as shown in Fig. 4. Some popular segmentation methods are selected as the comparison methods. The related experimental results are shown in Table 1.

The retrained model achieves the best performance. Based on these processes, we achieve a set of rendered images, shape parts and geometric words. Meanwhile, they have the clear relations. This information will help us to construct the 3D shape knowledge graph. Here, we need to note that the segmentation methods are only a preprocessing step. The performance of the segmentation method can influence the final retrieval and classification results. Other segmentation methods can also be used in this work. Here, we only select the best performance of the method for the next work.

### 3.2 3D Shape Knowledge Graph Construction

To construct the 3D shape knowledge graph, we need to define the entity and related edge information. If the edge/relation is not sufficient, the 3D shape is not represented by enough geometric words. Limited information is not conducive to the learning of entities. Thus, the structure of the knowledge graph is very important. We will detail this process in this section.

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**Table 1. Performance comparisons of the FCN with other classical methods on our dataset**

| Model          | Backbone       | MIoU  |
|----------------|----------------|-------|
| U-Net[42]      | VGG16          | 80.68 |
| SegNet[43]     | VGG16          | 82.84 |
| PSPNet[44]     | ResNet-103     | 86.49 |
| DeepLab v3[45] | ResNet-101     | 90.42 |
| FCN            | VGG16          | **96.09** |
First, we define the entities in the 3D shape knowledge graph $G$:

1) Model entity: This represents the 3D shape from the query data. Here, we use PointNet++ [14] to extract the feature vector for each 3D shape and integrate it to $G$. To guarantee that the descriptor of the 3D shape has the same dimension, we apply PCA [46] to reduce the dimension of the feature vector.

2) Image entity: This represents the rendered images from the 3D shape. Meanwhile, it can also represent the real images if we utilize the knowledge graph to handle cross-modal 3D shape retrieval. Here, we apply two kinds of methods to extract these rendered images, as shown in Fig. 5. For the first case (C1), we utilize the NPC [47] to position the 3D shape so that it is oriented upright along a fixed axis (e.g., the z-axis). Then the cameras are deployed at the fixed angle $\theta$ around the fixed axis indicated before, while evaluated 30 degrees from the ground plane. The cameras should face directly to the centrum of the shape. We set $\theta$ with different values, and thus generated {20; 16; 12; 10; 8; 6; 4; 2; 1} views for each object. For the second case (C2), since we are unsure of which perspective would contribute the most to the depiction of the 3D object, we do not demand that the shapes be continuously upright. Additionally, we sample multiple views from the 3D space. To create representations, 20 virtual cameras are set up at the shape’s 20 vertices of a dodecahedron. In three-dimensional space, a dodecahedron’s vertices may be spread equally throughout. The centrum of the object is where all cameras are aimed. These two kinds of virtual view extractions have been applied in many applications. We will discuss the influence of these two view sampling methods in the experiment section.

3) Part entity: Based on these rendered images or real images, each image can be segmented into a set of parts by using the trained model [39] on our dataset. These parts are considered the part entities to represent the attributes of each 3D shape in this knowledge graph. However, the rendered images and real images have a clear distinction. The rendered image often has no background. The segmentation model can provide better segmentation results. The real image often has a complex background that will influence the final segmentation results. Thus, for real images only, we first applied the salient object detection method [48] to segment the background and the object. This operation will obviously reduce the interference of the background and provide better segmentation results.

4) Geometric word entity: This entity is the key point in the 3D shape knowledge graph, which bridges the gap between different domains or different modalities. This entity is generated by the part entity. The part entities are from different rendered images or the real images. Some images represent the same object. Thus, these part entities have the same geometric information. More shapes or real images from different categories must have more similar parts. Similar part entities can be defined as geometric words. In this paper, we utilize the pretrained CNN [49] to
generate descriptors. Then, an unsupervised classifier (K-means) is used to predict the label of each part. We define the label as the geometric word entity in $G$ and the center of which is then abstracted as the descriptor of the geometric word entity. Thus, the geometric word entity can be seen as a special part entity. Each part entity only belongs to one geometric word entity, but each geometric word entity often links several part entities.

Edges in our knowledge graph $G$ are of three kinds:

1) Lash edge: it links the 3D shape with the related rendered images, rendered image with the segmented parts, and the real image with the segmented parts. It is a kind of subordination that is utilized to represent the geometric structural information and visual information of the 3D shape in $G$. Here, each 3D model will be extracted from multiple rendered images, and each image can also be extracted from multiple segmented parts. Thus, one rendered image link to one 3D model. One 3D model links to many rendered image. Meanwhile, one part is linked to one image, and one image can be linked to multiple parts.

2) Geometric edge: each part entity can be classified into a clear geometric word by the classification method. Thus, this edge links the part entity with the related geometric word entity to represent the geometric structure of the 3D shape or the real image. The part entities come from different image entities. The similar part entities could be mapped into the same geometric word entity. Thus, one geometric word could be linked by multiple part entities. One part entity only has one related geometric word entity.

3) Category edge: it links a 3D shape entity with another 3D shape entity if they have the same label and links the image with another image if they have the same label. This edge can be seen as the a priori knowledge. If we delete these edges, our approach can be seen as an unsupervised approach. In the experiment, we will discuss the performance of this edge.

In general, our knowledge graph $G$ stores the geometric structure and the categorical information of the 3D shape. Each edge saves clear knowledge information. For example, “table, rectangle, lash” indicates that the table includes the part entities come from different image entities. The similar part entities could be mapped into the same geometric word entity. Thus, one geometric word could be linked by multiple part entities. One part entity only has one related geometric word entity.

3.3. Graph Embedding

Based on the above operations, we obtain the 3D shape knowledge graph. To handle the cross-domain and cross-modal 3D shape retrieval problem, we first need to generate the embedding for each node based on the structure of the 3D shape knowledge graph. In this paper, we propose a novel graph embedding method. This section goes into further information on this method.

3.3.1. Problem Definition

The 3D shape knowledge graph only saves the geometric structure of the 3D shape and directly shows the correlation between the visual information and the 3D shape. However, it does not handle the weak correlation between a real image and the 3D shape in (Euclidean) space. Therefore, using a graph embedding technique to create dense embedding features for sparse data makes sense.

In this paper, we propose a novel graph convolution network to generate the embeddings of nodes, which can effectively utilize the structure of the 3D shape knowledge graph, especially the geometric word information, to increase the consistency of feature vectors between two similar 3D shapes and build connections between an image and 3D shape.

We define the knowledge graph as an undirected weighted graph $G = (V, E)$, where $V$ represents the nodes, and $E$ represents the edges. Here, we define $N$ as the number of nodes in graph $G$. We split the node set $V$ into five parts: $V = \{V^M, V^I, V^P, V^G\}$, where $V^M$ represents the model entity set, $V^I$ is the rendered image entity set, $V^P$ is the real-image entity set, $V^P$ is the part shape entity set, and $V^G$ is the geometric word entity set. Our problem can be formally stated as follows: with an undirected weighted $G = (V, E)$ and the node feature matrix $X \in \mathbb{R}^{N \times K}$, representing the input of each node as an $N$-dimensional feature vector, $K$ is the number of entities in $G$. Our goal is to learn the embedding for all nodes in graph $G$. ($X^* \in \mathbb{R}^{E \times K}$) is the node embedding in graph $G$, where each node has an $E$-dimensional embedding. The final optimization objective can be written as:

$$\min_{v_i, v_j \in V} -log p(1|v_i, v_j) + log p(0|v_i, v_j), s.t. v_i \neq v_j,$$  (1)
where \( p(1|v_i, v_j) \) represents that \( v_i \) and \( v_j \) have the direct edge in graph \( G \). \( p(0|v_i, v_j) \) indicates that \( v_i \) and \( v_j \) do not have edges in graph \( G \). The goal of this objective function is to reduce the direct distance between two similar nodes. If we have the specific category information of the 3D shape or the 2D image, it will add the category edge between each other. The edge will narrow the distance between two entity embeddings. Meanwhile, if one 3D shape and 2D image have the same geometric word entity, they will have a pathway that includes multiple edges. In the processing of graph embedding, this information will also reduce the differences between two entities. The final embeddings of entities will also affect this condition.

### 3.3.2. Graph Neural Network

As discussed, graph neural networks (GNNs) have recently emerged as a powerful approach for representation learning on graphs. Thus, we emphasize applying the GCN for 3D shape knowledge graph embedding. The goal of our work is to handle cross-domain or cross-modal 3D shape retrieval. The GCN should focus on the representation learning of the shape entity and the image entity. Here, different entities have different representations and different neighbors. However, the image or the 3D shape should have the same geometric entities in the 3D shape knowledge graph if they represent the same object. Thus, we should utilize the geometric entities to generate the embeddings of image entities and shape entities.

The classic GCN structure is used to update the node embeddings, which is defined as follows:

\[
y^{(l+1)} = \text{Relu}(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} y^{(l)} W (l)),
\]

where \( y^{(l+1)} \in \mathbb{R}^{N \times F} \) represents the output entity feature matrix of graph \( G \) in the \( l \)-th domain-shared layer, \( N \) is the number of graph entities, and \( \tilde{A} = A + I_N \in \mathbb{R}^{N \times N} \) is the adjacency matrix of graph \( G \) with added self-connections. \( A \) is the original adjacency matrix, which is obtained by taking the union of edges. \( W(l) \) is a weight matrix of the \( l \)-th GCN layer. After the graph embedding process, we fuse all the entity embeddings to generate the embeddings \( y^{(l+1)} \).

\[
\tilde{D}(i, j) = \sum_j \tilde{A}(i, j).
\]  

To learn the embeddings of an entity, we train the neural network by modeling the graph structure. We use the embeddings to generate the linkage between two entities, i.e., the probability that there exists an edge between \( v_i \) and \( v_j \) in Eq.[1]. Therefore, we formulate embedding learning as a binary classification problem by using the embeddings of two entities.

The probability that there exists an edge between node \( v_i \) and node \( v_j \) in graph \( G \) is defined in Eq.[4] and the probability that there exists no edge between node \( v_i \) and node \( v_j \) in graph \( G \) is defined in Eq.[5]

\[
p(1|v_i, v_j) = \sigma(y_i^T \tilde{y}_j),
\]

\[
p(0|v_i, v_j) = \sigma(-y_i^T \tilde{y}_j),
\]

where \( y_i \) is the embedding vector of \( v_i \), and \( \tilde{y}_j \) is the embedding vector of \( v_j \). \( \sigma(.) \) is the sigmoid function.

Therefore, the optimization objective function Eq.[1] can be written as:

\[
\min \sum_{v_i \neq v_j \in V} -\log p(1|v_i, v_j) + \log p(0|v_i, v_j)
\]

\[
= \min \sum_{v_i \neq v_j} \log p(1|v_i, v_j) + \sum_{v_i \neq v_k} \log p(0|v_i, v_k)
\]

\[
= \min \sum_{v_i \neq v_j} \log \sigma(y_i^T \tilde{y}_j) + \sum_{v_i \neq v_k} \log \sigma(y_i^T \tilde{y}_k),
\]

where \( S_p \) is the set of entities in graph \( G \) that has a clear pathway to node \( v_i \), and \( S_a \) is the set of nodes that does not have a pathway to node \( v_i \). Thus, the final objective function is defined as:

\[
L = \min \sum_{v_i \in S_p} \log \sigma(y_i^T \tilde{y}_j) + \sum_{v_i \in S_a} \log \sigma(y_i^T \tilde{y}_k).
\]
Algorithm 1 Graph Convolutional Network

Input: Graph $G = (V, E)$, the node feature matrix $X \in \mathbb{R}^{N \times M}$, and the initialized parameter $W$.

Output: The learned parameter $W$ and the embeddings $Y$.

1: Initialize parameters $W$,
2: for $(v_i, v_j) \in S$ do
3: Sample a set of samples $S$.
4: Compute Gradients: $\frac{\partial L(W)}{\partial W}$.
5: Update $W' = W - \frac{1}{b} \frac{\partial L(W)}{\partial W}$.
6: return The final embeddings: $Y$.

3.3.3. Optimization

In our model, we need to find the optimized parameter $W$. The classic backpropagation algorithm is utilized to optimize this parameter. Thus, the optimization objective is defined as follows:

$$W^* = \arg \min_W L(W) = \arg \min_W - \sum_{v_j \in S_p} \log \sigma(\hat{y}_j) + \sum_{v_k \in S_n} \log \sigma(\hat{y}_k).$$

(8)

The goal of this objective function is to find the solution that is optimal for each entity representation. $W$ is trained by the optimizer according to the gradient: $W' = W - \frac{1}{b} \frac{\partial L(W)}{\partial W}$. Here, we summarize the learning procedure of our approach in Algorithm 1. We first input the graph $G$, the input feature $X$ and the initialization parameter $W$. Then, we sample the training samples $S$. $v_i$ and $v_j$ are sampled from $S$. We use the existing pathways to train the model, compute the gradients and update the parameters of the specific graph convolutional layers. Finally, we return a set of embeddings for each entity.

3.4. Similarity Measure

Based on previous processing, we have constructed a 3D shape knowledge graph and generated entity embeddings. The next issue is how to manage the similarity measure between the candidate shapes and the query shape/image according to these embeddings. In this section, we will detail our solution.

Given a query shape $Q$, the query image $I$ and a large 3D shape dataset $M$, the purpose of 3D shape retrieval is to construct a similarity measure function to calculate the similarity between query shape $Q$, query picture $I$ and
candidate shape $M \in \mathcal{M}$. In this work, we first build the 3D shape knowledge graph on the dataset $\mathcal{M}$, query shape $Q$ and query image $I$. Then, the GCN model is utilized to generate the related embeddings for each entity. Finally, we measure the similarity between $Q/I$ and $M$ according to these embeddings.

For each query shape $Q$, the directly related entities include image entities, part entities and geometric entities, as shown in Fig[1]. These entities can be represented by a set of embeddings, as shown in Fig[6]. Here, we utilize $I_Q$ to represent the image entity set, $P_Q$ to represent the part entity set and $G_Q$ to represent the geometric word entity set. Each entity will be represented by an embedding. Here, $f$ is utilized to represent the embedding of each entity. Thus, for the query shape $Q$, the image entity set can be represented as $I_Q = \{f_1^Q, f_2^Q, ..., f_n^Q\}$, the part entity set can be represented as $P_Q = \{f_1^P, f_2^P, ..., f_m^P\}$, and the geometric word entity set is represented as $G_Q = \{f_1^G, f_2^G, ..., f_k^G\}$. Each candidate shape $M$ can also be represented by the related entity set, part entity and geometric entity. Here, we utilize $I_M$, $P_M$ and $G_M$ to represent the three kinds of entity sets. Meanwhile, $I_M = \{f_1^M, f_2^M, ..., f_n^M\}$, $P_M = \{f_1^P, f_2^P, ..., f_m^P\}$ and $G_M = \{f_1^G, f_2^G, ..., f_k^G\}$ are utilized to represent the embeddings of candidate shapes. The goal is to measure the similarity between $Q$ and $M$. We first define the similarity between two different entities by Eq[9]

$$S_s(e_i, e_j) = \frac{1}{2}(1 + \cos(f_i, f_j)),$$

where $f_i$ and $f_j$ are the embedding features of entities $e_i$ and $e_j$. Here, the classic cosine distance is utilized to measure the similarity between two different entities. The cosine distance has the range $[-1, +1]$. Eq[9] is utilized for normalization.

Then, according to different entities, the similarity between query shape $Q$ and candidate shape $M$ is defined as:

$$S(Q, M) = \alpha S_M(f_Q, f_M) + \beta S_I(I_Q, I_M) + \gamma S_P(P_Q, P_M) + \lambda S_G(G_Q, G_M),$$

s.t. $\alpha + \beta + \gamma + \lambda = 1,$

where $f_Q$ and $f_M$ are the embeddings of the query shape entity and the candidate shape entity, respectively. $S_M(f_Q, f_M) = S_s(f_Q, f_M)$. Meanwhile,

$$S_I(I_Q, I_M) = \max_{i=1}^n \max_{j=1}^m S(f_i^Q, f_j^M),$$

where $n$ and $m$ are the number of image entities in $I_Q$ and $I_M$, respectively.

$$S_G(G_Q, G_M) = \text{sigmoid}(\log(M_n \cap Q_n)).$$

(12)

For $S_P(G_Q, G_M)$, we apply the bipartite graph matching method [5] to measure the similarity between the two shapes' part entity sets. However, the results of graph matching are a set of matching pairs. The matching score is the sum of the matching pairs. Here, we normalize the results by combining averages. $\alpha$, $\beta$, $\gamma$ and $\lambda$ are the weights of these four similarity measures, which are used to balance the contributions of different entities in the final similarity measure.

In other words, for each query image $I$, the directly related entities include part entities and geometric word entities. These entities can be represented by a set of embeddings. Here, $P_I$ and $G_I$ are utilized to represent the part entity set, and the geometric word entity set, respectively. We also utilize $P_I = \{f_1^P, f_2^P, ..., f_m^P\}$ and $G_I = \{f_1^G, f_2^G, ..., f_k^G\}$ to represent the embeddings of these two kinds of entities. The final similarity between the query image and candidate 3D shape is as follows:

$$S(I, M) = \beta' S_I(f_I, I_Q) + \gamma' S_P(P_I, P_M) + \lambda' S_G(G_I, G_M),$$

s.t. $\beta' + \gamma' + \lambda' = 1,$

where $f_I$ is the query image embeddings. $I_Q$ is the candidate 3D shape view embeddings set.

$$S_I(I, I_M) = \max_{j=1}^m S(f_I, f_j).$$

(14)

where $m$ is the number of views extracted from the candidate 3D shape $M$. $S_G(G_Q, G_M)$ is computed by Eq[12]. For $S_P(P_Q, P_M)$, we applied a computational approach similar to shape retrieval. $\beta'$, $\gamma'$, and $\lambda'$ are the weights of these
three similarity measures in Eq. 13, which are also used to balance the contributions of different entities in the final similarity measure.

Based on this similarity measure between $Q$, $I$ and $M$, we can handle the shape retrieval problem and cross-modal 3D shape retrieval without massive training and parameter debugging issues. We only focus on how to enlarge the size of the geometric words in the 3D shape knowledge graph.

4. Experiment and Discussion

In this section, we conduct experiments to demonstrate the performance of our approach. Section 4.3 shows the retrieval results on the popular ModelNet40 dataset to demonstrate the performance of our approach on the classic 3D shape retrieval problem. Section 4.4 shows the performance of our approach on the cross-domain retrieval problem. We applied models of the ModelNet40 testing dataset as the queries to retrieve a similar 3D shape from the Shapenet-Core-55 dataset [13]. Section 4.5 shows the performance of our approach on the cross-modal retrieval problem. Here, a 2D image is used as the query to retrieve similar 3D shapes from datasets. Section 4.6 will detail these experiments.

4.1. Dataset

To assess the efficacy of our proposed method, we made considerable use of a well-known dataset entitled ModelNet40 [13], which contains 12,311 CAD models divided into 40 categories. ModelNet40’s training and testing subsets are made up of 9,843 and 2,468 models, respectively. This dataset is utilized to find the best parameters of our model.

To demonstrate our approach on the cross-domain information retrieval task, we use the ShapeNet-Core-55 dataset. This dataset has been used for the Shape Retrieval Contest (SHREC) 2018 competition track to evaluate the performance of 3D shape retrieval methods.

Our method for cross-modal 3D shape retrieval is also shown using the MI3DOR dataset from SHREC 2018. This dataset, which includes 21,000 2D monocular photos of 21 categories and 7,690 3D shapes, is a public benchmark for 3D shape retrieval using monocular images that was provided by [52]. The benchmark is split into two sets: a training set that comprises 3,842 3D shapes and 10,500 2D images, and a testing set that uses the remaining data.

To demonstrate the performance of our approach, we conducted many experiments. However, due to space constraints, we only select some key experiments to describe in the manuscript. More experiments are shown in supplementary files.

4.2. Evaluation Metrics

In 3D shape retrieval, we perform a series of comparative experiments to test the proposed method to verify that the method we proposed is successful. Moreover, by using several typical metrics [53], including nearest neighbor (NN), first tier (FT), second tier (ST), F-measure (F), and discounted cumulative benefit (DCG), we evaluate these comparative experiments. The efficiency of our proposed method is also visually represented by the precision-recall curve.

4.3. Comparison with state-of-the-art methods on ModelNet40

To validate the efficiency of the proposed method, 3D shape retrieval experiments were conducted on the Princeton ModelNet dataset [13]. We compared various models based on different representations, including volumetric-based models [13], handcrafted descriptors for multiview data [54][18], deep learning models for multiview data [6][55], deep learning models for panorama views [20] and point cloud-based models [7][14][56].

In our study, the test data serves as the query model, while the training data is used to build the 3D form knowledge network. Finally, the experimental results of all competing methods are demonstrated in Table 2. For the 3D classification task, our approach obtains the best performance. Compared to the MVCNN with AlexNet, our approach achieves a 4.2% improvement. For the retrieval problem, our approach also achieves the best results. Meanwhile, compared with these traditional methods, our approach does not require a tedious training process.
Table 2. Experimental results on ModelNet40

| Method                  | Classification (Acc) | Retrieval (mAP) |
|-------------------------|----------------------|-----------------|
| SPH[57]                 | 68.2%                | 33.3%           |
| LFD[58]                 | 75.5%                | 40.9%           |
| 3D ShapeNets[59]        | 77.3%                | 49.2%           |
| VoxNet[60]              | 83.0%                | -               |
| VRN[61]                 | 91.3%                | -               |
| MVCNN-MultiRes[62]      | 91.4%                | -               |
| MVCNN (AlexNet)[63]     | 89.5%                | 80.2%           |
| MVCNN (AlexNet)         | 90.1%                | 70.4%           |
| MVCNN (AlexNet)         | 90.1%                | 79.5%           |
| MVCNN (GoogLeNet)       | 92.2%                | 74.1%           |
| MVCNN (GoogLeNet)       | 92.2%                | 83.0%           |
| LMVCNN-VggNet-11[63]    | 92.8%                | -               |
| LMVCNN-VggNet-11[63]    | 93.5%                | -               |
| VS-MVCNN[64]            | 90.9%                | -               |
| PointNet[7]             | 89.2%                | -               |
| PointNet++[14]          | 90.7%                | -               |
| KD-Network[65]          | 91.8%                | -               |
| PointCNN[66]            | 91.8%                | -               |
| DGCNN[67]               | 92.2%                | -               |
| PVNet[68]               | 93.2%                | 89.5%           |
| N-gram Network[69]      | 90.2%                | 89.3%           |
| Ours[29]                | 95.7%                | 91.4%           |
| Our Approach (ResNet), 12× | **96.9%** | **92.7%** |

Table 3. Comparison with state of the arts on the cross-domain dataset: ShapeNet→ModelNet.

| Methods | NN | FT | ST | F_measure | DCG | ANMRR |
|---------|----|----|----|-----------|-----|-------|
| RevGard[70] | 0.89 | 0.79 | 0.90 | 0.33 | 0.83 | 0.15 |
| JAN[71]  | 0.90 | 0.81 | 0.91 | 0.33 | 0.84 | 0.14 |
| TJM[72]  | 0.90 | 0.81 | 0.91 | 0.34 | 0.84 | 0.14 |
| JDA[73]  | 0.91 | 0.82 | 0.91 | 0.34 | 0.85 | 0.14 |
| JGSA[74] | 0.92 | 0.82 | 0.92 | 0.34 | 0.85 | 0.13 |
| Ours[29] | 0.91 | 0.83 | 0.92 | 0.34 | 0.87 | 0.13 |
| Our Approach | **0.93** | **0.84** | **0.94** | **0.36** | **0.87** | **0.12** |
4.4. Comparison Experiment on Cross-domain 3D shape Retrieval

The 3D shape knowledge graph can be effectively utilized to address the cross-domain 3D shape retrieval problem. We used models from the ModelNet40 testing dataset as the query model to get related 3D shapes from the ShapeNet-Core-55 dataset in order to illustrate the point. The experimental results are used to demonstrate the effectiveness and robustness of the 3D shape knowledge graph. The related experimental results are shown in Table 3.

Here, we implemented several standard cross-domain approaches [70, 71, 74, 72, 73] as comparative methods to transfer the feature vectors from two separate datasets into the same feature space and utilized the Euclidean distance to determine similarity. It is important to emphasize that our approach does not require training steps relative to the cross-domain approaches. Thus, our approach is easily utilized for other datasets. We proposed the 3D knowledge graph theory in [29], which only focus on the 3D shape information and ignore the rendered image and can not be used to handle the cross-modal information retrieval problem. In this paper, we redesign the structure of knowledge graph and propose the new graph embedding method, and the search method. The final experimental result also demonstrates the superiority of our approach.

4.5. Comparison Experiment on Cross-modal 3D shape Retrieval

To demonstrate the superiority of our approach on the cross-modality information retrieval problem, we also conduct experiments with our method on the newest database, SHREC 2019 Monocular Image-Based 3D Object Retrieval (MI3DOR) [52].

The participant methods on the MI3DOR database include supervised and unsupervised methods. We compare our approach with supervised methods and unsupervised methods. The related experimental results are shown in Table 4 and Table 5. From these experimental results, our approach outperforms the other comparison methods. In our opinion, the reasons are as follows.

- MVML implements the element-wise maximum operation to fuse the multi-view information. This procedure is effective and has been proven in numerous similar applications. However, this operation also introduces redundant information and ignores important information. It does not produce an evident improvement in the overall performance. Meanwhile, it leverages the cross-domain distance learning approach to build connections between two separate modalities. The process concentrates on the extracted features and ignores the information from raw data. Much information is overlooked in this stage, which will also impact the final performance;

- JMMD learns to complete the retrieval in an end-to-end manner. Thus, it is supposed to achieve better experimental results than that of MVML. However, the related results show the opposite condition, which is caused by that JMMD ignores optimizing the parameters during training. Meanwhile, the method emphasizes on the carving of features while neglecting the association between two separate modalities, which is critical for feature learning. Therefore, it obtains the poorest experimental results on this benchmark;

- Compared with supervised methods, our approach achieves the best results. The reasons are as follows. 1) We employed the classic CNN model to extract the view’s feature vector. Meanwhile, the GCN structure is utilized to generate the embeddings of nodes. This means that we stand on the shoulders of giants. 2) The 3D shape knowledge graph utilizes the geometric entity to build the graph between cross-modality data and the related 3D shapes. This structure provides a clear correlation in the feature learning step. The experimental data also verified our idea;

- From these experimental results, we conclude that our approach yields the best performance compared with both supervised and unsupervised tasks. Specifically, when compared to the supervised methods, our approach outperforms them by 0.6%-33.8%, 1.1%-23.8%, 1.4%-18.7%, 1.1%-7.5%, 0.9%-25%, 0.8%-23.9%, and 1.8%-31.2% in terms of NN, FT, ST, F-measure, DCG, ANMRR and AUC, respectively. Similar improvements can be obtained on unsupervised tasks, which is shown in Table 5. The above results demonstrated our method’s effectiveness for the cross-modal retrieval task.
5. Other Applications based Knowledge Graph

In this paper, shape parts are utilized to generate geometric words, which plays a key role in our approach. The shape parts are used to construct the 3D shape knowledge graph and to handle cross-domain and cross-modal 3D model retrieval. In our opinion, the 3D shape knowledge graph includes the shape geometric information, which can also be applied in other applications. In this section, we undertake new experiments to verify the effectiveness of the 3D shape knowledge graph.

5.1. Partial 3D Shape Retrieval

In this question, each query is not complete, which is part of the 3D model. A partial 3D model retrieval method is required to return a list of complete models from a database that is ranked according to model similarity with the query. Here, we proposed an effective framework to handle partial 3D model retrieval, as shown in Fig.7. We first extracted the rendered images from the partial 3D model. Then, we extracted the feature vectors based on the ResNet-34 model. These features were used to find the similar part entities from the 3D knowledge graph. Then, we applied the related information to achieve the related 3D shape as the retrieval results based on these part entities. Fig.8 shows some retrieval examples to prove the feasibility of this method.

| Method            | NN  | FT  | ST  | F   | DCG | ANMRR | AUC  |
|-------------------|-----|-----|-----|-----|-----|-------|------|
| RNF-MVCVR         | 0.97| 0.92| 0.93| 0.20| 0.93| 0.06  | 0.85 |
| SORMI             | 0.94| 0.92| 0.96| 0.18| 0.92| 0.07  | 0.81 |
| RNFETL            | 0.97| 0.91| 0.97| 0.18| 0.92| 0.07  | 0.83 |
| CLA               | 0.95| 0.88| 0.89| 0.20| 0.90| 0.10  | 0.82 |
| MLIS              | 0.94| 0.91| 0.96| 0.18| 0.91| 0.08  | 0.81 |
| ADDA-MVCNN        | 0.87| 0.86| 0.87| 0.17| 0.87| 0.13  | 0.72 |
| SRN               | 0.89| 0.86| 0.87| 0.18| 0.88| 0.12  | 0.73 |
| ALIGN             | 0.64| 0.69| 0.80| 0.13| 0.69| 0.30  | 0.55 |
| Our               | 0.98| 0.93| 0.98| 0.21| 0.94| 0.06  | 0.86 |

| Method            | NN  | FT  | ST  | F   | DCG | ANMRR | AUC  |
|-------------------|-----|-----|-----|-----|-----|-------|------|
| JMMD-AlexNet      | 0.44| 0.34| 0.49| 0.08| 0.364| 0.64  | 0.24 |
| MVML              | 0.61| 0.44| 0.59| 0.11| 0.47 | 0.54  | 0.35 |
| Our               | 0.64| 0.47| 0.62| 0.17| 0.53 | 0.49  | 0.42 |

Figure 7. Partial 3D model retrieval framework.
5.2. Text-3D Shape Retrieval

The 3D shape knowledge graph can also handle the text-to-shape retrieval. For example: “A 3D shape that contains four legs and a round surface.”. We first utilize the NLP method [76] to extract entities from this text. Then, these entities are mapped into the related geometric shape. These geometric shapes are also mapped into geometric words or part entities in the 3D knowledge graph. Finally, we selected the 3D shapes, which have a clear relationship with these geometric words and part entities, as the retrieval results. The framework is shown in the Fig. 9. Some retrieval examples are shown in Fig. 10. In this work, we selected some training samples from the Text2Shape dataset [77] to prove this idea. These samples are used to construct the 3D shape knowledge graph. Meanwhile, we also construct the mapping between geometric shape and shape description. This application also demonstrates the practical nature of our approach.
6. Conclusion

In this paper, we propose an innovative concept, namely, “geometric word”, to construct a 3D shape knowledge graph for 3D shape representation and retrieval problems, which can effectively represent and measure the relationship between two different shapes and the structural information of each 3D shape. In the 3D shape knowledge graph, “geometric word” could represent 3D shape and 2D image information, which bridges the gap between 3D shapes from different domains or the 3D shape and 2D image from different modalities. Thus, our approach can be directly utilized to handle 3D shape retrieval, cross-modal 3D shape retrieval and cross-domain 3D shape retrieval problems. To handle these retrieval problems, we propose a graph embedding strategy to further learn the descriptor based on graph structure information and an effectiveness similarity measure. The related experiments also demonstrate the superiority of our approach.

From the related experiments, we find that the construction of a knowledge graph relies on limited data. Meanwhile, a “geometric word” can be learned from several datasets. We can achieve a universal 3D shape knowledge graph similar to WordNet to represent any shape information. In future work, we will pay more attention to building a universal 3D shape knowledge graph and exploring the possibility of application in other fields.

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