Sketch-based 3D Shape Retrieval Using Similarity Weighting between Multi-View

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Abstract. 3D shape retrieval has always been a hot research topic in the field of computer vision, and the research goal is to perform fast and efficient retrieval to obtain 3D shapes that meet user needs. With the rapid development and popularization of touch screen devices, hand-drawn sketches have undoubtedly become the most convenient and user-friendly input form. However, the huge difference between the 3D shape and the 2D sketch is the main challenge that affects retrieval performance. In this paper, we propose a method of adding a sketch and view feature similarity comparison module during the training process to obtain the scores for the final feature descriptors under the premise of feature extraction of the 3D shape based on multi-view. Specifically, we render the 3D shape into 2D views from multiple different perspectives to represent the shape. Perform feature extraction on two types of inputs through two different networks, and design a similarity weighting module to calculate the scores of each view, so as to obtain the final descriptors. Finally, a final descriptor similarity metric network is trained based on contrastive loss. The experimental results on SHREC’13 dataset demonstrate the superiority and robustness of our method.

1. Introduction
In the field of computer vision, the subject of 3D model retrieval has always been enthusiastic by researchers. How to perform convenient and user-friendly input and obtain efficient and accurate retrieval result is the key problem. Both the model-based method and image-based method[1][2][3] are effective. Directly using the model as input or rendering the shape as multi-angle 2D views[3] could reduce the dimensional difference between the retrieval input and the shape to a certain extent, but the input mode is difficult to meet the diverse and convenient needs of users. Using the hand-drawn sketch as input solves this difficulty well.

In the sketch-based method, selecting the view that best expresses the shape as the representation of the shape is currently a more common method. However, the method based on “Best View” does not make good use of the advantages of rich shape information. MVCNN[3] was introduced by [4] to the sketch-based method to solve this problem.

In this paper, we have modified and improved on the basis of [4]. The hot and powerful ResNet[5] was used to design two independently trained Sketch-ResNet and View-ResNet for feature extraction and metric learning. We added the similarity weighting module between the feature extraction part and the metric learning to replace the view pooling module to calculate the similarity score of each view and the sketch more accurately, thereby obtaining the more representative final descriptor. Finally, the Siamese Network[6] with simple principle but excellent performance was used for metric learning, and the contrast loss function was improved. We conducted a lot of experiments on SHREC’13 dataset to verify the feasibility and superiority of the proposed method.
2. Related Work

As deep learning shines in many fields, methods based on deep learning have also been introduced to the research topic of 3D shape retrieval. Wang et al.\cite{7} referred to Siamese Network \cite{4} method and used two different CNN models to extract the features of two types of inputs. Most methods were to render the 3D model into a multi-angle 2D views to represent the shape. However, due to the different habit of observing objects and drawing level of painters, the lines of sketches are very distorted and random, which causes the difference between sketches and views of the shapes. Moreover, how to extract the most expressive information from multiple views is the key issue. In order to avoid the dilemma of choosing “Best View”, Mao et al.\cite{4} introduced MVCNN\cite{3} to extract the feature information of multi-view as the final descriptor. But the feature information fusion module for multi-view in the MVCNN\cite{3} does not mine the contribution of different angle views to the final descriptor, the representativeness of the final descriptor is not strong.

3. Method

In this section, we give a comprehensive and detailed introduction to our proposed method. Our framework consists of two parts: feature extraction and similarity weighting, metric learning and shape retrieval.

3.1. Feature Extraction and Similarity Weighting

In order to solve the dimensional difference between 3D shape and 2D sketch, we rendered the 3D shape from multiple different viewpoints into multiple 2D views. We adopted the multi-view rendering method in MVCNN\cite{3}. Specifically, we use the centroid of each shape as the origin of the spherical coordinate system. Most of the models placed in such setting conform to the human default upright form, and in line with the habit of human observation of objects, in the X-axis, Y-axis formation of the horizontal facing up 30 degrees, pointing to the coordinate origin, respectively, set around the Z-axis and 45 degrees apart from each other 8 virtual cameras to generate rendering views, a total of 8 different angles of rendering views. Figure 1 presents the rendering results in that setting of virtual cameras.

![Figure 1. The rendering effect of a spider model from eight views.](image)

We use ResNet\cite{5} which with a size of 50 and without the final fully connected layer as the basic architecture to design two networks (Sketch-ResNet and View-ResNet) with the same structure but independently trained for feature extraction of sketches and views. The specific architecture details of the networks are shown in figure 2. One sketch and eight views with size 224×224 are respectively processed into 1 sketch feature vector and 8 view feature vectors with size of 2048 through the Sketch-ResNet and View-ResNet.
Since the views from different angles are not the same as the sketches, the degree of contribution to the description of the model is also different. In order to distinguish the degree of contribution of views from different angles to the final descriptor, we design a similarity weighting module before the metric learning to quantify the scores of different angles. We define the feature vector as $f$ which is obtained by feature extraction. Then compare the similarity of 1 sketch feature vector and 8 view feature vectors one by one, the equation is as follows:

$$d_i = \| f_s - f_{m_i} \|_2,$$  \hspace{1cm} (1)

and $s$ is the sketch feature vector, $m_i (1 \leq i \leq 8)$ is the view feature vectors, and $\| \cdot \|_2$ is the Euclidean distance. Then we get a distance vector with size of 8 and the smaller the distance $d_i$, the higher the degree of similarity. So as to quantify the value of distance to the degree of similarity, we use equation (2) to normalize the distance vector.

$$N_i = 1 - \frac{d_i - d_{min}}{d_{max} - d_{min}}.$$  \hspace{1cm} (2)

After the normalization, we leverage the group module method of GVCNN[8] to process $N_i$ and 8 view feature vectors to get the final descriptor of the shape. We set the numbers of group to 10 and use the scores vector $N_i$ to calculate the group scheme and group weight of the views. Finally, eight view feature vectors are processed by intra-group view pooling and group fusion to obtain 2048D final view descriptor. Since there is only 1 input sketch, the 2048D sketch feature vector is directly used as the final descriptor of the sketch.

### 3.2. Metric Learning and Shape Retrieval

After obtaining the final descriptors of the sketch and the shape, we introduced the Siamese Network[6] for metric learning. We modify the contrastive loss into the following form:

$$L(D_S, D_V, y) = y\Delta^2 + (1 - y)\text{Max}(\phi - \Delta, 0)^2.$$  \hspace{1cm} (3)

$D_S$ and $D_V$ are the descriptors of sketch and view respectively. When $D_S$ and $D_V$ are from the same class, $y = 1$. When $D_S$ and $D_V$ are from different classes, $y = 0$. And $\Delta$ is the Euclidean distance between $D_S$ and $D_V$. The $\phi$ is a margin that defines the degree of similarity. Through the metric learning, the distance between descriptors of the same class could be close to 0 and the distance between descriptors from different classes could be greater than $\phi$. Figure 3 shows the overall framework of our method.
Figure 3. The overall framework of our method.

After training, we get the Sketch-ResNet and View-ResNet with parameters. And these two networks are used to perform 3D shape retrieval in the following steps:

- Firstly, a sketch $S$ is used as a query input and all views $V_{M_i}$ ($1 \leq i \leq 8$ and $M$ is the total amount of the shape) are used as the gallery data $G_M$.
- Then, the feature vectors of $Q$ and $G_M$ are obtained through Sketch-ResNet and View-ResNet with parameters. After the processing of similarity weighting module, the final descriptors $D_{G_M}$ of the gallery data $G_M$ are obtained. The feature vector of $Q$ is used as the final descriptor $D_Q$.
- Finally, calculate the Euclidean distance $E_M$ between $D_Q$ and $D_{G_M}$, and select the $N(1 \leq N \leq M)$ results with the smallest distance as Top-$N$.

4. Experiment
In this section, we executed experiments and evaluated the framework on SHREC’13 dataset[9]. The SHREC’13 dataset is a large scale dataset based on the largest collection of human sketches built by[10] and Princeton shape benchmark[11]. The SHREC’13 dataset contains 90 classes of shapes and sketches, and each class has 80 instances. We divided the 80 instances into 50 training samples and 30 test samples. We set the initial learning rate to 0.0005, margin $\phi$ to 0.5, batch size to 1, training epoch to 400 and minimized the loss in equation (3).

In order to verify the superiority of our method, we set the same experimental parameters and removed the similarity weighting module, and directly used the view pooling module in MVCNN[3] to obtain the final descriptors for metric learning. Figure 4 is a comparison based on precision-recall curves between the result of our complete framework and the result of removing the similarity weighting module. Figure 5 shows the retrieval results on the SHREC’13 dataset. It can be seen that our method is excellent for retrieval results with similar contours of objects, but the learning of detailed features is not good enough.
Figure 4. Comparison on the SHREC’13 dataset based on the precision-recall curves.

When the recall is small, the precision of both are relatively high. With the continuous increase of recall, the curve of the method without similarity weighting module drops rapidly to a lower value, while the method with the complete framework has a slower downward trend.

Figure 5. Some examples of retrieval results on the SHREC’13 dataset. The bounding box denotes the correct results.

5. Conclusion
In this paper, we used a multi-angle viewpoint rendering method to convert the 3D shape into 2D views to reduce the dimensional difference between shape and sketch, and designed two networks with the same structure but independently trained for feature extraction of sketches and views. In order to further explore the similarity between views from different angles and sketch, we designed the similarity weighting module to strengthen the distinction of views from different angles, thus forming a more accurate and informative final descriptor for metric learning. The experimental results on the SHREC’13 dataset proved the feasibility and superiority of the proposed method.

6. References
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