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Web 3D Lightweight Learning Framework for Shape Retrieval Based on CNN

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Abstract

With the rapid development of Web3D technologies, it is more and more import and necessary that sketch-based model retrieval. Besides, 3D model displaying over web browser becomes important. In this paper, we propose simplification-based lightweight method for shape to visualize over browser based on mobile Internet environment. Besides, a CNN-based learning method is conducted to obtain the best view of shape. Furthermore, learning framework is presented to conduct the final retrieval. Moreover, a feature fusion method is also used to generate a learning dictionary. In addition, proposed framework can provide new alternatives for shape retrieval in Web3D environment. What is more, the innovation is mainly presented by employing deep learning method to solve the best view of model cross-domains feature learning and fusion problems, based on mobile Internet retrieval results fast and convenient visualization problem. Last but not least, the experiment is realized to verify the feasibility of the framework. Especially, compared with many state-of-the-art mainstream approaches; the results show that the approach was superior.

Keywords: Web 3D, Sketch-Based Model Retrieval, Simplification, CNN, Best View, Learning Dictionary

1. Introduction

With the explosive of web images, Sketch Based Image Retrieval (SBIR) has been a major research field. By contrast, the traditional text based Image retrieval, which need to make manual image annotation and was a very tedious and difficult task with the explosive growth of storage capacities, and hence this situation encouraged research on alternatives for image retrieval using text keyword, which should describe images by other means than text annotations, besides, the defect of text based image retrieval was more and more apparent, that was subjective and biased. Two people will describe a same image, a very likely, by two different descriptions and that will decide by their cultural backgrounds, their world view, their live environment and even their emotional states etc. Moreover, the automatic image description technique that was sought should be objective and should come from the image content itself and not from the person describing it, then it was the SBIR method.

More efforts in this research fields, it was called Content Based Image Retrieval (CBIR)**Error! Reference source not found.** proposed the method, called Query by Visual Example (QVE). NIBLACK et al.**Error! Reference source not found.** also developed the system, called Query by Image and Video Content System (QBIC). In their research, the user submits an "example image" which was collected or hand-drawn, and the system retrieved the database images which looked visually similar to the user query. Finally, the system can show a list of possible similarity images.

However, sometimes it was difficult to find the fit example images to query the images. Therefore, an alternative for querying in an image retrieval system was simply drawing what the user had in mind, which further represents an intuitive way of communication between a user and a CBIR system. This kind of query leads to the Sketch Based Image Retrieval Problem (SBIR). According to Hu et.al.[1], a key challenge in SBIR is to overcoming the ambiguity inherent in sketch". In fact, a sketch included

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fewer features than image for example, only had the contour and some pixels, and there existed very large differences due to the level of the user's hand drawing sketch, such as professional and amateur level.

One salient characteristic of a sketch was the stroke orientation. Orientation was a characteristic that had been exploited widely and richly showing outperforming results in tasks like object recognition and object categorization etc. Furthermore, due to lack of features in a sketch, it was demand that many more robust descriptors should been made use of to exploit the relationship between sketch and images.

Sketch Based 3D Model Retrieval (SBMR) was derivatives of SBIR method. With the 3D technologies increasingly rapidly developed, SBMR has become more and more important in retrieval fields. Then, the methods of SBIR always can totally be applied in SBMR. Therefore, the one of most key of SBMR still was how to efficiently acquire and storage the descriptor of sketch image.

The outline of this paper is as followed: in Sec.2, we present the related work of retrieval method. In Sec.3, we propose our framework. In Sec.4, it explains our framework of lightweight methods and Convolution Neutral Network (CNN)-based learning method for best view in details. Experimental results and comparison evaluation are presented in Sec.5. Sec. 6 concluded the work and looked ahead the future work.

2. Related Research

3D model retrieval was always a hot research topic in computer graphics, information retrieval and pattern recognition in recent years. With the scale and diversity of 3D models data was increasingly rapid growth. How to identify the 3D models data, retrieval, reuse and re-model had become a common concern subject to designers, engineers and researchers.

Currently, a relatively complete sketch based 3D model retrieval system mainly was in following systems**Error! Reference source not found.Error! Reference source not found.Error! Reference source not found.**. In the system of SBMR, there was two key points: the 2D transformation and the extraction of the sketch feature of 3D model. The quality of these two steps directly determined the accuracy of the search results.

Funkhouser et al.**Error! Reference source not found.** proposed a 3D model retrieval engine, which support the switch between 3D and 2D. The method of 3D spherical harmonic was used. EITZ et.al**Error! Reference source not found.**,**Error! Reference source not found.Error! Reference source not found.** realized 2D/3D based retrieval algorithm by using Bag-of-words and HOG. But these methods didn't the pre-process before retrieval. it maybe affected the result due to the ambiguity stroke of sketch or amateur drawing level caused the sketch error express the user purpose. Therefore, LI et al.**Error! Reference source not found.** proposed the step of doing pre-process operate before retrieval starting; it would check the user hand-drawing sketch and display the possible sketch which tally with the user demand.

So far, sketch retrieval had formed 8 benchmark, they were as following: Snograss and Vanderwart**Error! Reference source not found.** proposed the standard line drawings (1980), Cole et al.'s**Error! Reference source not found.** line drawing benchmark (2008), Saavedra and Bustos's**Error! Reference source not found.** sketch dataset (2010), Yoon et. al.'s**Error! Reference source not found.** sketch-based 3D model retrieval benchmark (2010), Eitz et al.**Error! Reference source not found.** proposed sketch-based shape retrieval benchmark, Eitz et al.**Error! Reference source not found.** proposed sketch recognition benchmark (2012) Small-scale benchmark-**Error! Reference source not found.**: SHREC'12 Sketch Track Benchmark (2012) large-scale: SHREC'13[24]Sketch Track Benchmark (2013)**Error! Reference source not found.**. These benchmarks played an important role in the research and application of sketch retrieval.

On the other hand, cross-domain convolution neutral network approach have been successfully used in sketch-based 3D retrieval, such as learning two Siamese Convolutional Neural Networks (CNNs)**Error! Reference source not found.** and learning Pyramid Cross-Domain Neural Networks (PCDNN)**Error! Reference source not found.**. These methods can obtain excellent accuracy, however, they don't focus on how to obtain the best view image, only impose the minimal assumptions on choosing views for the whole dataset and i.e. 3D models in the dataset are up-right.

2.1 State-Of–The-Art

Dalal et al.**Error! Reference source not found.** presented the descriptor of Histograms Of Gradient (HOG), it can capture edge of gradient structure that was very characteristic of local shape. Besides, translations or rotations made very little difference if they were smaller that the local spatial or orientation bin size. However, due to HOG followed a pixel-wise strategy they represent of sketch image always produced many zeroes in the final histogram, because the sketch was sparse by nature. Saavedra et al.[28] proposed the improved descriptor of Histograms of Edge Local Orientations (HELO), HELO was a cell-wise strategy; therefore, it seems to be very appropriate for representing sketch-like images. Saavedra proposed the soft computer of HELO (S-HELO), it computer cell orientations in a soft manner using bilinear and tri-linear interpolation, and took into account spatial information, then, it computed an orientation histogram using weighted votes from the estimated cell orientations. FU et al.**Error! Reference source not found.** also improved the HOG descriptor, namely, Binary HOG descriptor (BHOG). It can be faster than Hog descriptor to compute the feature vectors and take up less memory.

In order to enhance the robust against noise in sketch images Chatbri et al.**Error! Reference source not found.** introduced an adaptation framework based on scale space filtering. Firstly, the sketch images were filtered by the Gaussian filter to smooth the sketch image, then, it extracted skeleton of sketch image. Weiss et al.**Error! Reference source not found.** proposed the Spectral Hashing Algorithms (SHA). SHA sought compact binary codes of feature data so that the Hamming distance between code words correlated with semantic similarity. WANG et al.**Error! Reference source not found.** conducted a review paper which introduced the hashing methods in detail. They divided the hashing algorithms into 2 categories: locality sensitive hashing and learn to hash. Due to locality sensitive hashing method did not consider the data distribution.

3. Proposed Framework

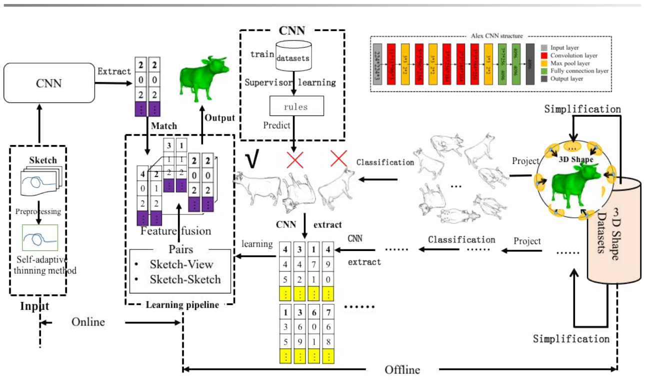

Figure 1. The overview of proposed framework.

The framework mainly consists of two parts, one is lightweight pipeline, and the other is CNN-based learning method. The overview of proposed framework can be seen in Figure 1. In the on line stage, we use self-adaptive thinning methodError! Reference source not found. to eliminate the noise of sketch.

4. Framework Description

In this section, the lightweight pipeline of shape and CNN-based learning method are proposed. This is the core content of our proposed framework.

4.1 Lightweight Pipeline of Shape

Quadratic Error Metric (QEM) algorithm is proposed by Kettner et al.**Error! Reference source not found.**. In this paper, we still adopted this method. However, we use different datasets to realize this lightweight process.

Firstly, the orthogonal List and max heap data structure is adopted. The time complexity of the construct of orthogonal list is $O(t*m)$, where t denotes the count of edges, m represents the count of vertices.Obviously, the time complexity of the Orthogonal List will descend, step by step, along with the mesh simplification. As is known to all, orthogonal list usually is used to represent sparse matrix. The simplified mesh was just a sparse matrix. Therefore, orthogonal list would be better than others' data structure, such as half-edge structure. Because of this, it will obviously excel in time consuming facet. Besides, it's believed that Heap sort was better than the others' sort algorithms, such as bubble sort. The time complexity of heap sort is $O(n*\log_2^n)$. Therefore, our method in time consuming has some advantage. The detail process will be seen in Figure 2.

However, there are still many problems in above method mesh saliency is considered to better check the contour of mesh, in order to preserve the total structure of shape. Mesh saliency is proposed by Lee et.al.**Error! Reference source not found.**. The principal curvature can better measure the steep degree of the surface. When the principal curvature is larger, the surface will be greatly changed. Figure 3, it illustrates how to calculate the principal curvature of surface.

Figure 3, the value of the normal vector along the direction of tangent vector, would be changed, then, the maximum and the minimum value are the principal curvature of the vertex P. In the vertex P, we define Jacobian matrix as follows:

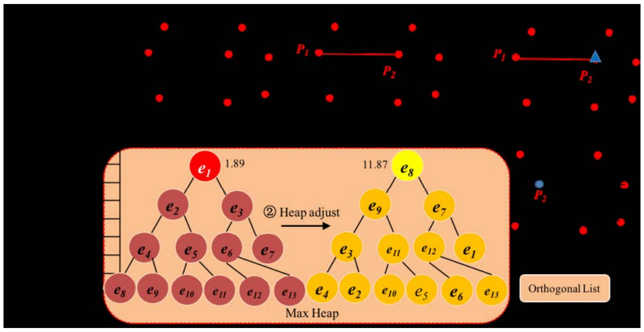

Figure 2. The overview of proposed method based on QEM.

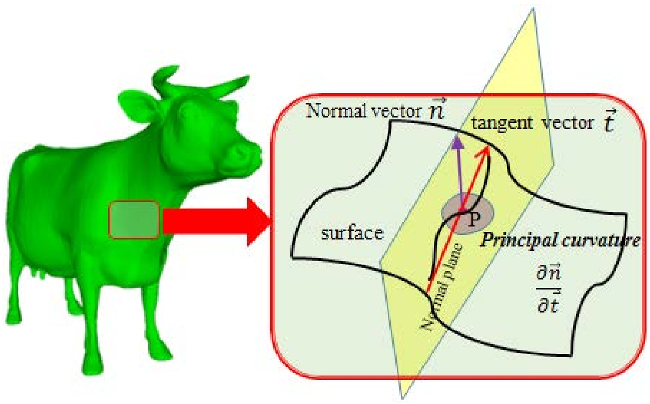

Figure 3. The geometry structure of surface in cow shape.

$$\mathrm{J}=\begin{bmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \\ \frac{\partial z}{\partial u} & \frac{\partial z}{\partial v} \end{bmatrix} = \begin{bmatrix} \Psi_u & \Psi_v \end{bmatrix}.$$

Like-wise, the cosine angle of two vectors can be defined as follows:

$$\text{Cosine } (\vec{\omega}_1, \vec{\omega}_2) = \vec{\omega}_1^T \vec{\omega}_2 = \left(\mathrm{J}\overline{\omega_1}\right)^T \left(\mathrm{J}\overline{\omega_2}\right) = \overline{\omega_1}\left(J^T J\right)\overline{\omega_2}.$$

Definition 1: Inner product operation,

$$\mathrm{I} = J^T J = \begin{bmatrix} \Psi_u^T \Psi_u & \Psi_v^T \Psi_u \\ \Psi_u^T \Psi_v & \Psi_v^T \Psi_v \end{bmatrix}$$

Here , the term I is named as inner product operation.

Then $\omega = \overline{\omega}^T \boldsymbol{I} \vec{\omega}$ denotes the square of the length of the tangent vector.

Definition 2: Outer produce operation:

$$\Theta = \begin{bmatrix} \frac{\partial^2 \Psi}{\partial u^2}\vec{n} & \frac{\partial^2 \Psi}{\partial u \partial v}\vec{n} \\ \frac{\partial^2 \Psi}{\partial u \partial v}\vec{n} & \frac{\partial^2 \Psi}{\partial v^2}\vec{n} \end{bmatrix},$$

Θ is called outer product operation.

According to the above defines, the curvature of a normal vector $\vec{n}$ can be obtained, along the direction of tangent vector $\vec{t}$.

$$\kappa_n\left(\vec{t}\right) = \frac{\vec{t}^T \Theta \vec{t}}{\vec{t}^T I \vec{t}} \tag{1}$$

According formulas 1, in order to obtain the extreme value, the relative differential operation is conducted, then the formulas 2 can be obtain.

$$\frac{\partial\ \kappa_n\left(\vec{t}\right)}{\partial \vec{t}} = 0 \tag{2}$$

The result of formulas 2 is obtained, then the related value is took into formulas 1, finally, we can calculate the two values (k_1, k_2). Surely, in some condition, $\mathrm{k}_1 = \mathrm{k}_2$.

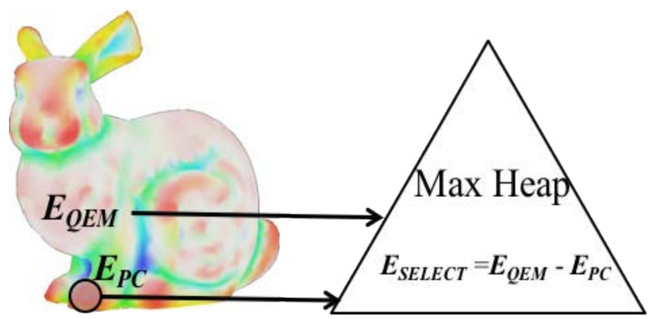

Figure 4. Edge select based on Principal Curvature.

Figure 4 our simplification process of edge selection is shown. According to QEM method, $\boldsymbol{E}_{QEM}$ can be obtained, which generally is a set, only the mesh geometry topology structure is by consideration. What's more, the selected edges to simplify or edge collapse can be represented as following. $\mathbf{E}_{\text{Select}} = \mathbf{E}_{\text{QEM}} - \mathbf{E}_{PC}$.

4.2 CNN-Based Learning Method for Best View

SVM classifier has been used to classify the multi-view images, which is projected from the model in many different view-points. This method was adopted in Eitz et al.**Error! Reference source not found.** We uniformly put 102 cameras on the bounding sphere of the model; so that a model can be projected into multiple view images. However, of course, many of these images are what we don't need, that is bad view images. Therefore, we need to train an intelligent classifier to classify these view images. This can eliminate the negative interference of the bad viewpoint image for our retrieval results. This method is adopted by ZHAO et al**Error! Reference source not found.** to acquire the best-view images of a model. Specially, in this paper, CNN-based supervisor learning method is used to generate best view of Shape. In particular, the famous Alex convolution neutral network structure is used to obtain the best view. As a matter as fact, Alex convolution neutral network have successfully obtained good result in image classification. Our proposed method can be seen in Figure 5.

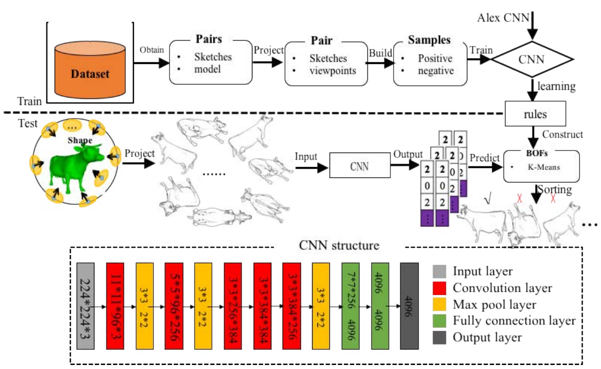

Figure 5. The overview of best view of shape based on CNN

Figure 5, the process of learning method for best view of shape can be seen. Especially the steps of how to obtain the best view of shape is as following.

Step 1: Obtain pairs set. We obtain several pairs of sketches $\mathbb{S} = \{j \in M \mid s_j\}$ and model $\mathcal{H}$ from data sets, such as SHREC 2013[24] dataset. Next, we project the shape into *N* different viewpoints images, which is represent as the term $\mathbb{V} = \{i \in N \mid v_i\}$. In this way, a pair set can be generated, it can have represented as following $\mathbb{P} = \{i \in N, j \in M \mid (v_i, s_j)\}$.

Step 2: construct related positive and negative pairs. In order to finish the classification tasks, we must construct many different positive and negative pairs. In generally, the pair of bad view and sketch is often believed as a negative pair, whereas, the one of good view and sketch is a positive pair. However, who is good view or bad view is unknown. Above all, in fact, at least, there not exists the related views dataset. Therefore, we assume that the hand-drawn sketch is good view. Furthermore, the positive pair set can be denoted as following. $\mathbb{P}_p = \{j \in M, k \in M, j \neq k \mid (s_j, s_k)\}$. Moreover, the negative pairs are relative more. In fact, bad views can easily obtain. The negative pairs can be denoted as following, $\mathbb{P}_N = \{k \in N, j \in M \mid (v_k, s_j)\}$.

Step 3: Similarity measure: In order to measure the similarity relationship of each pair, we define a function to represent their relation. The equation is as equation (3).

$$S_{cnn}(x, y) = \sum_{i,j}^{N} \exp\left(-\frac{d_{euc}^2\left(f_i(x), f_j(y)\right)}{2\sigma^2}\right) \quad (3).$$

Where, the term x, y represent sketch and view image, respectively, the function f is denoted as the feature extracted by the CNN. Besides, the term σ is a constant value, in this paper, we set it equal 0.2. The function d_{euc} is the Euclidean distance.

Step 4: the positive and negative samples. We define a decision function to obtain the positive and negative sample from above pairs. Besides, according to above similarity measure method, a probability function has to present to perform related decision. The probability is as following equation (4). Moreover, the decision function is as following equation (5).

$$P_{cnn}\left(s_m^j, v_n^i\right) = \frac{S_{cnn}\left(s_m^j, v_n^i\right) - \min\limits_{0 \le k < M} S_{cnn}\left(s_m^k, v_n^i\right)}{\max\limits_{0 \le k < M} S_{cnn}\left(s_m^k, v_n^i\right)} \quad (4)$$

Step 5: BOFs framework. According to above decision function, we can obtain the view image v_n^i as the positive sample or negative sample. The bags-of-features framework can be used to assemble these view images. In order to decrease the size of BOFs, the K-means algorithm is adopted. In this paper, we make the size of BOFs equal 1000.

Step 6: Sorting the views. In order to add the diversity of best view, we have to remove the good view projected from nearby position. In fact, our method can obtain many good views, but they are mostly similar. Therefore, we adopt the Intersect of Unions (IoUs) method to remove these similar view images. A repress function is defined to decrease these views. The repressive function is as following.

$$\Delta(x) = \exp^{\frac{-x^2}{2\sigma^2}} \tag{6}$$

Besides, the sorting method is according to following equation:

$$t_i = s_i + \Delta\left(\max_{\{v_k | v_k \in V_m\}} IoU\left(v_k, v_i\right) \right) \tag{7}$$

Where, the term $s_i \in [0,1]$ is represented the match result between the feature of view v_n^i and BOFs. Besides, the term V_m is a views set projected by the shape $\mathcal{H}$ and $|V_m| = \mathrm{m}$.

4.3 CNN-Based Learning Method for Shape Retrieval

According to Sec 4.2 the best view of shape can be obtained. Next, we can perform shape retrieval between sketch and view images. More specially, we build the pair relationship between sketch and view. Moreover, the learning framework is presented to obtain the feature model. A fusion method is used to build the relation between sketches and views. A pair feature fusion model is proposed by Chopra et al.**Error! Reference source not found.** to perform face verification. Moreover, Wang et al.**Error! Reference source not found.** had been successfully used into shape retrieval based on CNN. Therefore, we also adopt this model to fusion our pair features.

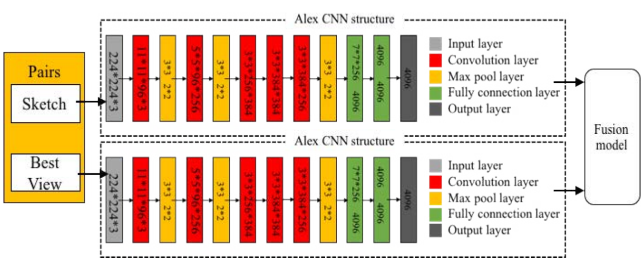

Figure 6. The overview of proposed learning framework.

$$\Psi\left(s_i, v_k; b\right) = (1-b)\alpha D_{Man}^2 + b\beta e^{\gamma D_{Man}} \tag{8}$$

Where, the term b is the binary similarity label, that is – $\mathrm{b} = 0$ or $\mathrm{b} = 1$. Besides, the term D_{Man} is Manhattan distance between the sample s_i and v_k. Moreover, the term α, β, γ is experimental value, we set them equal 5, 0.1, -0.277, respectively.

Hence, we can build a fusion model according to equal 8. In order to enhance the performance of retrieval, we fusion different pairs feature, including sketch and sketch, sketch and view.

Therefore, the fusion model can be represented as followed equation (9).

$$\Psi\left(s_i, s_j, v_k; b\right) = \Psi\left(s_i, s_j; b\right) + \Psi\left(s_i, v_k; b\right) \tag{9}$$

According equation (9), a similarity matrix can be obtained we can directly use this learning matrix to finish the retrieval task.

5. The Experiments

We compared our results using the dataset proposed by National Taiwan University. The dataset was composed of 10119 3D models, besides the dataset of sketches came from the sketch dataset of EITZ et al.**Error! Reference source not found.**, which contained 20000 query sketches. The program ran the following configuration of computer, Core i3 processor, 4M memory. The result of program ran and acquired can be seen in Figure 7.

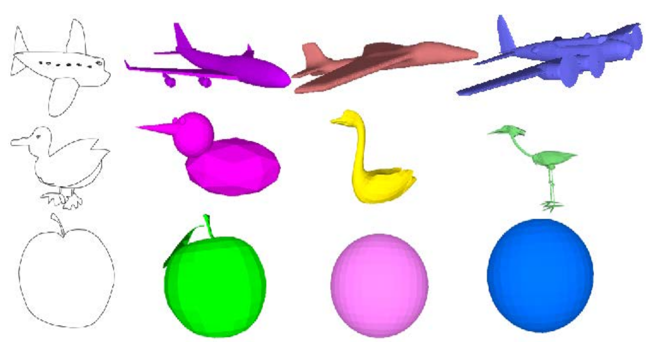

Figure 7. Sketch-based 3D model retrieval.

5.1 Lightweight Pipeline Experiment Result

Through more experiments, our method is further validated. Figures 8 to 11, our method is validated in some different models, including dense model and common model, the method can always select the best fit simplification rate to finish the simplify the mesh.

In the other hand, due to the fact that our methods is solving the question of the model Web 3D visualization. Therefore, we conduct some experiment in clothing model, whose size is over 60M. It's very hard to show in browser. Hence, it is urgent that the clothing model is simplified to better show in browser.

Figure 12, it's not hard to find that the simplified mesh has huge advantage in Web 3D-based visualization facet.

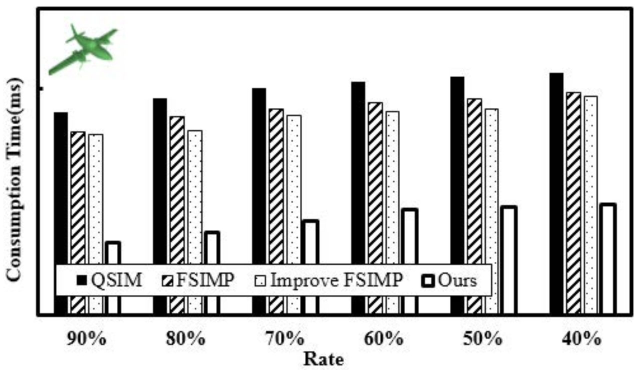

Figure 8. The compared experiment on airplane model.

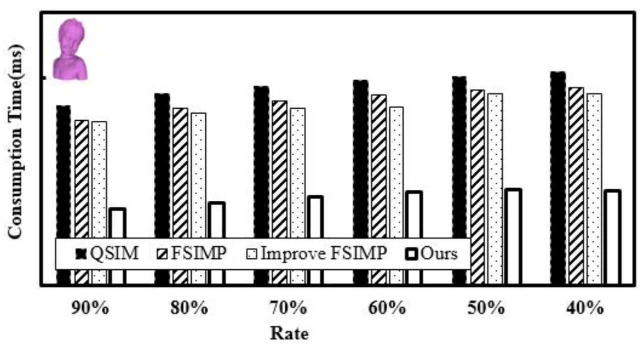

Figure 9. The compared experiment on girl model.

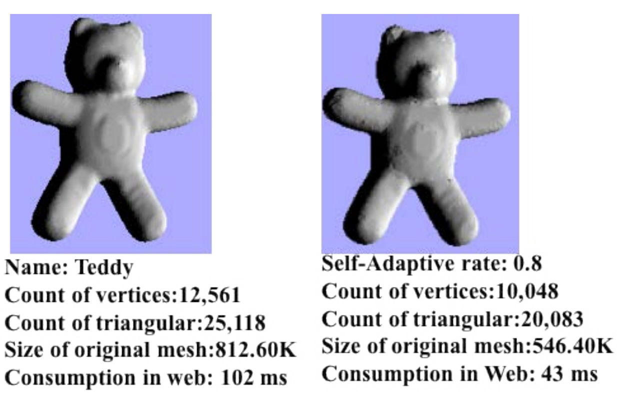

Figure 10. The self-adaptive experiment on Teddy model.

5.2 3D Shape Retrieval Experiment Result

The evaluation of experiment was doing according to the dataset of training and testing. The Precisions-recalls data are compared with other methods. It would be seen as follow:

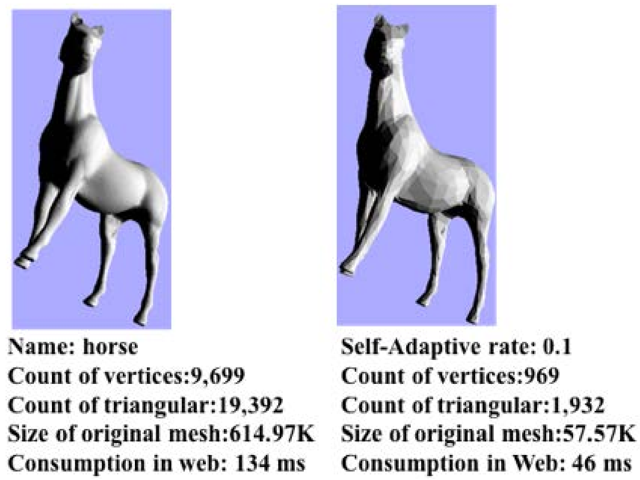

Figure 11. The self-adaptive experiment on horse model.

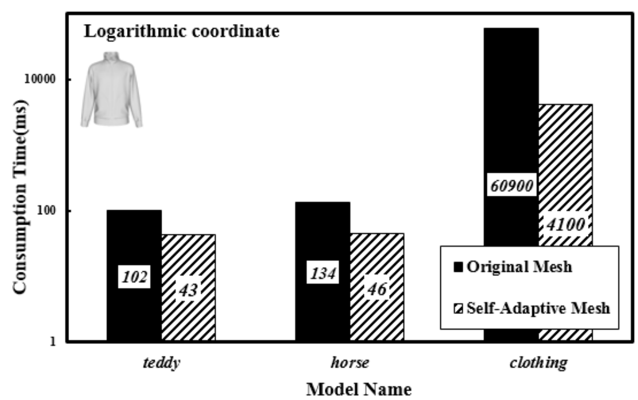

Figure 12. The compared experiment of web visualization.

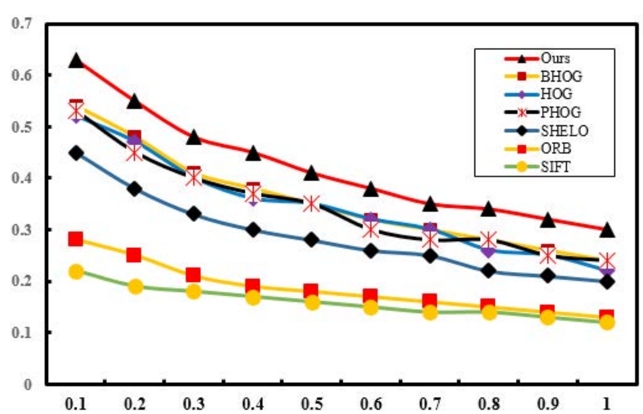

Figure 13. The compared figures in PR curve.

Figures 13, it is not hard found that out methods are feasibility and robustness, what is more, the performance even overtook some excellent methods. Besides, these results obviously show that our methods are excellent and achieved the aim of our design.

6. Conclusion

In this paper, we propose a lightweight learning framework for sketch-based retrieval. The preprocess job is conducted by the algorithms of adaptive thinning. Then, we make use of simplification algorithm to perform lightweight model. Moreover, CNN-based learning algorithm is used to acquire the best view image of shape. Finally, the learning framework has been adopted to obtain the relation between sketch and view. Then a fusion model can be formed to finish the retrieval task. Last but not least, the comparison result shows that our proposed framework is totally feasible and superior. Nonetheless, there are still many jobs need to finished. Above all, in learning network structure, we select the AlexNet Convolution Neutral Network (CNN). In fact, there are many more complex networks such as GoogleNet CNN. Therefore, In the future, we will try to utilize new more complex network structure to improve the performance of our framework

7. Acknowledgements

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