Deep Learning Representation using Autoencoder for 3D Shape Retrieval

Zhuotun Zhu, Xinggang Wang*, Song Bai, Cong Yao, Xiang Bai

Abstract

We study the problem of how to build a deep learning representation for 3D shape. Deep learning has shown to be very effective in variety of visual applications, such as image classification and object detection. However, it has not been successfully applied to 3D shape recognition. This is because 3D shape has complex structure in 3D space and there are limited number of 3D shapes for feature learning. To address these problems, we project 3D shapes into 2D space and use autoencoder for feature learning on the 2D images. High accuracy 3D shape retrieval performance is obtained by aggregating the features learned on 2D images. In addition, we show the proposed deep learning feature is complementary to conventional local image descriptors. By combing the global deep learning representation and the local descriptor representation, our method can obtain the state-of-the-art performance on 3D shape retrieval benchmarks.

Article info

Article history:
Received 28 February 2015
Received in revised form 10 July 2015
Accepted 23 August 2015
Available online 8 April 2016

Keywords:
3D Shape Matching
3D Shape Retrieval
Autoencoder
Shape Representation

1. Introduction

With the fast development of 3D printer, Microsoft Kinect sensor and laser scanner, etc., there are more and more digitized 3D models that need to be recognized. Thus it is critical to study how to build an efficient 3D shape search engine. However, due to the intrinsic complex structure of 3D shape, it is hard to handle 3D shape using a simple representation for efficient search.

Along with the development of computer vision and machine learning, deep learning methods have been proven to be very effective for visual recognition. For example, deep convolutional neural network (CNN) [1] has achieved the state-of-the-art performance for object recognition on the ImageNet dataset [2] and for object detection on the PASCAL dataset [3]. One reason of the success of deep learning for visual recognition is that the deep learning methods can automatically learn the features with the superior discriminatory power for image representation, rather than using hand-crafted image descriptors. Currently, in the context of 3D shape recognition, shape descriptors are mainly hand-crafted and deep learning representation has not been widely applied. It seems that it is hard to directly apply deep learning methods to 3D shape representation, since deep learning methods need a large amount of data to bridge the visual gap among training examples from the same object category; and it is unlikely to learn a good representation using a few data with large visual variation.

The above developments of deep learning are in a supervised way and are not suitable for retrieval task. From the aspect of unsupervised deep learning, Hinton and Krizhevsky [4] proposed the autoencoder algorithm with the application of image retrieval, which is then used for some other specific tasks like face alignment [5]. Training autoencoder does not require any label information. The autoencoder can be regarded as a multi-layer sparse coding network. Each node in the autoencoder network can be regarded as a prototype of object/image/shape. From the bottom layer to the top layer, the prototype contains richer semantic information and becomes a better representation. After the autoencoder network is learnt, the coefficients obtained by reconstructing image/shape based on prototypes are used as feature for 3D shape matching and retrieval. Since the autoencoder can learn feature adaptively to training data, it can get excellent performance for image retrieval.

Until now, few approaches based on deep learning frameworks have been proposed to deal with 3D shape retrieval. Following [6], Fang et al. [7] trained a deep neural network using Eigen-shape descriptor and Fisher-shape descriptor as target values to guide the network. Heat shape descriptor developed from Heat Kernel Signature is fed into the network. Wu et al. [8] constructed a large-scale 3D CAD model dataset to train a convolutional deep belief network. This network learns the distribution of 3D shapes with different categories and arbitrary poses. Therefore, adopting deep...
Different from recent works in [7] and [8], we adopt view-based approaches. Motivated by other view-based 3D shape methods [9,10], in which a 3D shape can be projected into many 2D depth images, we aim to use autoencoder to learn a 3D shape representation based on the depth images obtained by projection. As shown in Fig. 1, a 3D shape is projected into many different depth images; the learnt autoencoder can reconstruct the depth images nicely. Matching 3D shape based on the autoencoder features can be converted to a set-to-set matching problem, conventional set-to-set distance, like the Hausdorff distance, can be adopted. Our autoencoder based 3D shape representation is a deep learning representation; compared to the representations based on local descriptor, e.g. SIFT, it is a global representation. This global deep learning representation and the representation based on local descriptors are complementary to each other.

In summary, the main contributions of this paper are: (1) A new method to learn deep learning representation for 3D shape using autoencoder; (2) combining the global deep learning representation with local descriptor representation and obtaining the state-of-the-art 3D shape retrieval performance.

It is worth noting that we extended the conference version [6] in this manuscript as follows: (1) in Section 1, we added the discussions on recent deep learning methods for 3D shape analysis; (2) in the Section 2, we enriched it with the detailed description of LFD descriptor; and (3) in Section 5, we added new evaluation protocols (the precision-recall curve) and experiment results on the NTU dataset.

The remainder of this paper is organised in the following part: In Section 2, we offer an overview of the previous work on the content-based 3D shape retrieval. In Section 3, we present an explicit description of our method to extract the global features of 3D shape. In Section 4, we briefly depict the local descriptor formerly implemented in [11] on 3D shape. Experimental results and extensive evaluation are then carried out in Section 5. At last, we conclude this paper in Section 6.

2. Related work

Based on the main idea that “two 3D models are similar if they look similar with each other from all viewing angles”, there are plenty of view-based approaches that have been regarded as the most discriminative methods on literature [12]. Since our shape descriptor is also view-based, we mainly discuss some effective, competing view-based approaches during the following part.

![Fig. 1. A specific illustration of our method to reconstruct 2D images. Note that the first row displays the original depth images in gray-scale of the 3D shape, while the second row shows the reconstructed ones corresponding to the images of the first row. And the black dots indicates those extracted from other different views.](image-url)
Zernike moments coefficients [23]. Finally, the dissimilarity between two objects is measured by the minimum distance of all group matching pairs. The LFD is insensitive to similarity transform, geometry degeneracy and noise, etc, thus shows better performance than other competing approaches.

3. Deep learning representation using autoencoder

In this Section, given a 3D shape model S, we show how to perform autoencoder initialized with deep belief network for S and then conduct 3D shape retrieval based on the calculated shape code. As shown in Fig. 2, we illustrate a specific flow chart about the whole procedure.

3.1. Depth projection image

Different from shapes of 2D images, 3D models represent the 3D objects using a collection of points in 3D space, connected by various geometric entities such as lines, curved surfaces, etc. In our method, the autoencoder initialized by a DBN described in Section 3.2 is used to reconstruct the gray-scale depth 2D images as input and acts as a low-dimensional coding method. Thus, projecting a 3D model to a collection of 2D images is required to make it possible. For a 3D shape model S preprocessed by scale and translation normalization, from a host of angles of view, we collect 2D projections set of S defined as

\[ P(S) = \{ V_1, V_2, ..., V_{Np} \} \]  

where \( N_p \) denotes the number of projections for each model.

More specifically, Fig. 3 illustrates how we obtain a series of projections for the shape S viewed from different angles both in azimuth and elevation.

3.2. Deep belief network

The deep belief network (DBN) [24–26] is a generative graphical model, or alternatively a type of deep neural network, composed of multiple layers of latent variables ("hidden units"), with connections between the layers but not between units within each layer. When trained on plenty of examples in an unsupervised way, a DBN can probabilistically reconstruct the inputs by learning a stack of Restricted Boltzmann Machines (RBMs), where each of the previous RBM’s hidden layer serves as the visible layer for the next. That is to say, each time a new RBM is added to the stacked structure of DBN, then the new DBN has a better variational lower bound in the log probability of the data than the previous DBN [4].

We introduce the “pretraining” procedure as shown in Fig. 4 for binary units, then generalize to real-valued units and show that it works well. The pixels correspond to the “visible units” since their states can be observed; as for the feature detectors, they correspond to the “hidden units”. The energy of a joint configuration \((v, h)\) for the visible and hidden units is defined in [27] as

\[ E(v, h) = - \sum_{i \in \text{visible}} a_i v_i - \sum_{j \in \text{hidden}} b_j h_j - \sum_{ij} w_{ij} v_i h_j, \]  

where \( v_i, h_j \) denote the binary states of visible unit \( i \) and hidden unit \( j \) respectively; \( a_i, b_j \) are their biases and \( w_{ij} \) is the connection weight between them.

The network assigns a probability to every possible couple of a visible vector and a hidden one by the following function

\[ p(v, h) = \frac{1}{Z} e^{-E(v, h)}, \]  

where the “partition function” \( Z \) is given by the sum of all possible pairs between visible and hidden vectors

\[ Z = \sum_{v, h} e^{-E(v, h)}. \]
The probability that the network assigns to a visible vector, is defined as the sum of all possible hidden vectors
\[
p(v) = \frac{1}{Z} \sum_h e^{-E(v,h)}.
\]

The probability of a training image can be increased by adjusting the biases and weights to lower the energy of that image but to increase the energy of the rest, especially for those that own low energy and thus are assigned high probability by the network but to increase the energy of the rest, especially for these that own low energy and thus are assigned high probability by the network and make great contribution to the partition function. The mathematically derived derivative of the log probability of a visible vector to a weight is simple:
\[
\frac{\partial \log p(v)}{\partial w_{ij}} = \langle \nabla h_j \rangle_{\text{data}} - \langle \nabla h_j \rangle_{\text{model}}.
\]
where the angle brackets denote expectations under the exact distribution specified by the subscript that follows. Thus, utilizing stochastic gradient descent (SGD) as the learning approach is a very simple way in the log probability of training data
\[
\Delta w_{ij} = \epsilon (\langle \nabla h_j \rangle_{\text{data}} - \langle \nabla h_j \rangle_{\text{model}}),
\]
where the \( \epsilon \) is the learning rate.

Because of the RBM's restricted structure that there are no direct connections within hidden units, it is pretty easy to obtain an unbiased sample of \( \langle \nabla h_j \rangle_{\text{data}} \). Given a training image as the visible vector \( v \), the binary state \( h_j \) of every hidden unit \( j \) is set to 1 with the probability
\[
p(h_j = 1 | v) = \sigma \left( b_j + \sum_{i \in \text{visible}} w_{ij} v_i \right),
\]
where \( \sigma(x) \) denotes the sigmoid function defined by the formula
\[
\sigma(x) = \frac{1}{1 + \exp(-x)}.
\]

Given a hidden vector \( h \), it is also quite easy to obtain an unbiased sample of a visible unit's state as a consequence of no connections within visible units. The first equation corresponds with the construction of binary visible units and the second one with linear visible units, where \( N(\mu, \sigma) \) is a Gaussian with mean value \( \mu \) and standard deviation \( \sigma \).
\[
p(v_i = 1 | h) = \sigma \left( a_i + \sum_{j \in \text{hidden}} w_{ij} h_j \right), \quad \text{or}
\]
\[
v_i = N \left( a_i + \sum_{j \in \text{hidden}} w_{ij} h_j, 1 \right).
\]

Obtaining an unbiased sample of \( \langle \nabla h_j \rangle_{\text{model}} \), however, is much more tough. It can be done by beginning with any random state of a visible vector and performing alternating Gibbs sampling for quite a long time. One iteration of Gibbs sampling is used to update all the hidden units in parallel applying (8) followed by updating all the visible units in parallel applying (9).

Fortunately, a much faster learning algorithm was proposed in [28]. This algorithm begins by setting the visible units' states to a training vector. Then the whole hidden units' binary states are calculated in parallel applying (8). After those binary states have been probabilistically chosen for the hidden units, a “confabulation” is produced via setting each visible unit \( v_i \) to 1 with probability as in (9). Update the states of the hidden units once more in order that they can represent features of the confabulation. Then the adjustment of the weight is formulated by
\[
\Delta w_{ij} = \epsilon (\langle v_i h_j \rangle_{\text{data}} - \langle v_i h_j \rangle_{\text{recon}}),
\]
where the \( \langle v_i h_j \rangle_{\text{data}} \) is the fraction of times that the visible unit \( i \) and the hidden unit \( j \) are on together when the hidden units are driven by data, and \( \langle v_i h_j \rangle_{\text{recon}} \) is the corresponding part given by the confabulation. A same learning rule is used to adjust the biases.

In our experiments, this fast learning procedure works out well even though it is just approximating the derivative of the log probability with respect to the training data.

3.3. Fine-tuning the autoencoder

After pretraining a DBN which acts as initialization of an autoencoder, a global fine-tuning procedure replaces the former stochastic, binary activities with crucial, real-valued probabilities and uses backpropagation through the whole structure of autoencoder to adjust the weights as well as biases for a reconstruction model. By minimizing the root mean squared reconstruction error
\[
\sqrt{\sum_i (\langle v_i \rangle_{\text{data}} - \langle v_i \rangle_{\text{recon}})^2},
\]
we finally obtain a deep-structured, optimal reconstruction model of the 2D depth images as input.

To sum up, the whole autoencoder system is depicted in Fig. 5. Pretraining consists of a stacked RBMs where the hidden units in the previous layer acts as the visible units of the next layer. Then the “unfolded” autoencoder initialized by DBN is fine-tuned to obtain a better reconstruction performance. Finally, the code layer that is an efficient representation of the input image is utilized to conduct 3D retrieval.

3.4. Set-to-set distance

After projecting 3D model and then reconstructing 2D depth images, we get a low-dimensional representation of \( S \) with a code set \( C \)
\[
C(S) = \{ c_1, c_2, \ldots, c_{Np} \},
\]
where \( Np \) denotes the number of projection images of each model; and \( c_i^j \) (\( i = 1, 2, \ldots, Np \)) denotes the coding vector corresponds to the projection \( V_i \) with respect to that shape model \( S \), defined by
\[
c_i^j = (c_{i1}, c_{i2}, \ldots, c_{in}),
\]
where \( n \) denotes the dimensionality of every code vector; \( c_{ij} \) is the value of \( j \)-th dimensionality corresponding to code vector \( c_i^j \).

Based on the effective and efficient autoencoder, we can obtain the quantified distance within each 3D model by defining specific distance method given any two shape model \( S_A \) and \( S_B \), whose code sets are as follows
\[
\begin{align*}
C(S_A) &= \{ c_A^1, c_A^2, \ldots, c_{A_{Np}} \}, \\
C(S_B) &= \{ c_B^1, c_B^2, \ldots, c_{B_{Np}} \},
\end{align*}
\]
where \( A_i \) and \( B_i \) denote the \( i \)-th projection index of model \( S_A, S_B \) respectively.

We use one variant of “Hausdorff Distance” to define the distance of \( S_A \) to \( S_B \), given by
\[
D(S_A, S_B) = \frac{1}{Np} \sum_{i=1}^{Np} \min \{ d(c_A^i, c_B^i) \},
\]
where \( d(c_A^i, c_B^i) \) denotes one specific distance function between two vector, such as p-norm distance in “Euclidean Space”, algebraic distance, etc. Depending on the distance of any two models, shape retrieval could be directly done according to the ranked list.

4. Bag of features representation

In this Section, we describe the local descriptor formerly implemented by Ohbuchi et al. [11] on 3D shape. Considering that our method autoencoder mentioned above is a global descriptor, it
is much reasonable to boost a better performance if combining with a local descriptor. Bag-of-Features using Scale-invariant feature transform (BoF-SIFT) model is selected as the local description for a 3D model. Different from previous work in [11] that considers the SIFTs of each depth image separately, we put all SIFTs in a single bag, i.e., rotation normalization is not conducted.

We first learn the visual word vocabulary with size of 1500 in a randomly selected subset of all features via K-means off-line. In order to encode the set of SIFTs in each 3D model, we conduct Vector Quantization proposed in [29] to get a histogram representation that counts the number of SIFTs belonging to each visual word. Before computing the pairwise distance among the models, all the histogram is $L_1$ normalized. We will display the good property of extraordinary complementarity between autoencoder and BoF-SIFT in Section 5.

5. Experiments

In this Section, we test our method on two widely used, standard datasets of 3D shapes and compare our results with the state-of-the-art approaches for 3D shape retrieval. The algorithm is implemented in MATLAB and experiments are carried out on a laptop machine with Intel(R) Core(TM) i5-3210 M CPU(2.5 GHz) and 4 GB memory.

5.1. Princeton shape benchmark (PSB)

The Princeton Shape Benchmark [12] dataset provides a repository of 3D models and software tools for comparing different shape-based models. It’s created to promote the use of standardized datasets and evaluate methods for research in matching, classification, clustering, and recognition of 3D models. Each model of the 3D shape consists of the polygonal geometry surface of the corresponding shape. There are totally 1814 models and the base classification is partitioned equally into training and testing sets. The training set with 90 classes, 907 models is used to attain parameters of shape models through training procedure, while the other with 92 classes, equal number of models for comparison with other algorithm. In addition, the number of models belonging to the same class in the base classification varies from each class and ranges from 4 to 50. Some 3D models from the PSB are randomly selected to be exhibited in Fig. 6.

5.2. Engineering shape benchmark (ESB)

The Engineering Shape Benchmark [30] is particularly proposed to evaluate shape-based searching methods relevant to the mechanical engineering domain. More specifically, the ESB dataset has totally 867 3D CAD models classified into 45 classes with the number of models ranging from 4 to 58 in a class. The 3D models contained in the ESB cover a wide variety of real-world engineering models so that different methods can compete with each other more fairly. As shown in Fig. 7, we randomly select some models in the ESB to show engineering properties of the models.

5.3. National taiwan university benchmark (NTU)

The National Taiwan University Benchmark [9] provides 3D models for the purpose of 3D shape retrieval, matching, recognition and classification. Based on functional similarities, 549 3D models mainly for vehicles and household items are classified into 47 categories. As shown in Fig. 8, we give illustrations of the randomly selected models from NTU.
5.4. Implementation details

As described in Section 3.1, we set the number of each model’s projection to 64 (8 × 8) on the dataset. Then the total raw grayscale images with real value in the range of [0, 1], preprocessed by transform invariant low-rank textures (TILT) [31] to eliminate the large orientation variance, served as the visible units of the DBN’s first layer.

More specifically, the visible units of the first RBM layer were the normalized value of the depth images’ pixels. When training higher level layer, the visible units of a RBM were set to the activation probabilities of the previous RBM’s hidden units. As for the hidden units, they had stochastic binary value except the top layer’s hidden units, which had stochastic real-valued states calculated from the unit standard deviation Gaussian whose mean value was defined by the input from that RBM’s logistic visible units. The real-valued states are in the range [0, 1], compared to the binary states either 0 or 1, allowed the low-dimensional codes to take good advantage of continuous data and could avoid unnecessary sampling noise. Note that we trained each RBM for 40 epochs using mini-batches of size 100 and adopted a learning rate of 0.1 for the linear-binary RBMs, 0.001 for the top layer RBM.

With the DBN structure constructed, we initialized an autoencoder with the weights trained from the DBN and fine-tuned them using backpropagation as described in Section 3.3. The autoencoder consisted of an encoder with the designed layers and a symmetric structure for the decoder. The hidden units in the last layer were linear while all the other units were logistic. The deep, well-trained autoencoder was able to find how to convert each depth image into low-dimensional code that leads to a discriminative description and well reconstruction.
Then all the parameters including weights and biases are well-trained in an unsupervised way, we used them to obtain the low-dimensional code for projections of 3D models on the dataset. For the PSB and NTU datasets, we constructed an encoder with the layer structure of 5184 \((72 \times 72)\)-1000-500-250-30 while a structure of 5184 \((72 \times 72)\)-2000-500-100-20 for the ESB. In addition, we only used the testing set to both train the parameters and evaluate our results for the PSB while experiments were done on the whole dataset of the ESB and NTU since they are not divided into training and testing sets.

Finally, we define the distance function as mentioned in Section 3.3 as

\[
d(C_A, C_B) = \| C_A - C_B \|_p, \quad p = 2, \quad (15)
\]

where \( \| x \|_p = (|x_1|^p + |x_2|^p + \ldots + |x_n|^p)^{\frac{1}{p}} \), please note that \( x \) is a vector in the \( n \)-dimensional real vector space \( \mathbb{R}^n \).

5.5. Evaluation methods

In this Section, we introduce statistical description for the retrieval performance of a specific algorithm. The PSB provides open source code for evaluating different algorithms and judging how well one algorithm is compared to others. Thus, the performance can be fairly judged by the same evaluation tools in varieties of perspectives. When any doubt comes to you, please refer to [12] for more details about definition of every evaluation method.

Nearest Neighbor (NN): the percentage of the closest matches that belong to the same class as the query. This statistic offers us an indication of how well a nearest neighbor classifier could perform. As we can see, higher score represents better performance.

First-Tier (FT) and Second-Tier (ST): the percentage of models in the query’s class that appear within the top \( M \) matches. where \( M \) is determined by the size of the query’s class.

The three statistics mentioned above put emphases upon different aspects. The Nearest Neighbor (NN) evaluation merely lays emphasis on the discriminative ability since it only accounts for the most similar one in the retrieved, sorted list. However, the First-Tier (FT) and Second-Tier (ST) indicate how well the average performance of an algorithm taking into consideration the tradeoff between intra-class variation and inter-class discrepancy.

5.6. Retrieval results

We adopt autoencoder described in Section 3 to obtain the distance between any two shape models from datasets. Then we get the retrieval results evaluated by the source code provided in [12]. As shown in Table 1, 2 and 3, we compare the

![Fig. 8](image-url) Exemplar images randomly chosen from the NTU dataset. There are 3D models mainly for vehicles and household items such as trucks, motorcars, bottles, beds, etc.
global-feature-based autoencoder with the other global
descriptors on the three standard datasets to explore the effi-
cacy of using autoencoder to tackle 3D shape retrieval. Com-
pared with other competing approaches including GSMD [20],

**Table 3**
Statistic evaluation of global descriptors on NTU.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>NN(%)</th>
<th>FT(%)</th>
<th>ST(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoencoder</td>
<td>74.8</td>
<td>43.6</td>
<td>55.4</td>
</tr>
<tr>
<td>DESIRE [17]</td>
<td>71.9</td>
<td>42.7</td>
<td>55.4</td>
</tr>
<tr>
<td>LFD [9]</td>
<td>70.0</td>
<td>39.0</td>
<td>50.1</td>
</tr>
<tr>
<td>SH-GEDT [32]</td>
<td>58.8</td>
<td>33.9</td>
<td>46.3</td>
</tr>
</tbody>
</table>

**Table 4**
Statistic evaluation of complementarity on PSB.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>NN(%)</th>
<th>FT(%)</th>
<th>ST(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoencoder + BoF-SIFT</td>
<td>77.5</td>
<td>52.4</td>
<td>65.4</td>
</tr>
<tr>
<td>BoF-SIFT [11]</td>
<td>71.4</td>
<td>45.1</td>
<td>57.6</td>
</tr>
<tr>
<td>CM-BoF + GSMD [10]</td>
<td>75.4</td>
<td>50.9</td>
<td>64.0</td>
</tr>
<tr>
<td>PANORAMA [19]</td>
<td>75.3</td>
<td>47.9</td>
<td>60.3</td>
</tr>
<tr>
<td>CM-BoF [10]</td>
<td>73.1</td>
<td>47.0</td>
<td>59.8</td>
</tr>
<tr>
<td>Hybrid [18]</td>
<td>74.2</td>
<td>47.3</td>
<td>60.0</td>
</tr>
</tbody>
</table>

**Table 5**
Statistic evaluation of complementarity on ESB.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>NN(%)</th>
<th>FT(%)</th>
<th>ST(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoencoder + BoF-SIFT</td>
<td>88.1</td>
<td>55.2</td>
<td>70.2</td>
</tr>
<tr>
<td>BoF-SIFT [11]</td>
<td>88.0</td>
<td>52.4</td>
<td>65.4</td>
</tr>
<tr>
<td>PANORAMA [19]</td>
<td>86.5</td>
<td>49.4</td>
<td>64.1</td>
</tr>
<tr>
<td>Hybrid [18]</td>
<td>82.9</td>
<td>46.5</td>
<td>60.5</td>
</tr>
</tbody>
</table>

**Table 6**
Statistic evaluation of complementarity on NTU.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>NN(%)</th>
<th>FT(%)</th>
<th>ST(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autoencoder + BoF-SIFT</td>
<td>78.9</td>
<td>49.0</td>
<td>60.9</td>
</tr>
<tr>
<td>BoF-SIFT [11]</td>
<td>73.1</td>
<td>43.6</td>
<td>56.3</td>
</tr>
<tr>
<td>PANORAMA [19]</td>
<td>78.6</td>
<td>49.0</td>
<td>61.5</td>
</tr>
<tr>
<td>Hybrid [18]</td>
<td>76.2</td>
<td>46.6</td>
<td>59.1</td>
</tr>
</tbody>
</table>

Furthermore, based on the knowledge that autoencoder
reconstructs global information while BoF-SIFT described in Sec-
tion 4 mainly captures the local details, a linear combination of
them is proposed to boost the retrieval performance. More spe-
cifically, we empirically choose the weights as

\[ W_{\text{global}} = W_{\text{local}} \]

We compare our hybrid method (Autoencoder + BoF-SIFT) with
the previous state-of-the-art methods including PANORAMA [19],
CM-BoF and CM-BoF + GSMD [10], and Hybrid [18], which are able
to capture both the global and local information of a 3D shape. For
the retrieval results displayed in Table 4, 5 and 6, we can find that:
our autoencoder shows pretty well complementary property with
the existing local-features-based method BoF-SIFT since all
retrieval results are more or less improved. It’s worth noting that
our hybrid method reaches at least 6% evaluation increment of NN,
FT and ST on the PSB, and at least 4% increment on the NTU
compared with BoF-SIFT [11] alone. Moreover, our hybrid method
gets the-state-of-the-art results on the three datasets except the
evaluation of ST on NTU, which is slightly worse than PANORAMA
[19].

Furthermore, Fig. 9 shows a precision-recall plot of six methods
on the PSB and ESB dataset. The graphic illustrations confirm the
conclusions drawn based on former statistic results. The proposed
autoencoder consistently outperforms other global-descriptors-
based methods. Among all methods, the composite of auto-
encoder and BoF-SIFT achieves relatively the best performance.

6. Conclusions

In this paper, we present a novel view-based 3D shape retrieval
method using autoencoder, which is firstly utilized to 3D shape
retrieval. A set of experiments were carried out to investigate the
effectiveness and efficiency of our method on two standard data-
sets, which shows that the autoencoder outperforms other global
descriptors on retrieval results. Furthermore, the experiments
demonstrate that the autoencoder displays good complementarity
with the local descriptor, since linear combination achieves the
state-of-the-art performance. Our future work might focus on studying the effect of the proposed representation with context-based shape similarity method [33].

Acknowledgement

This work was primarily supported by National Natural Science Foundation of China (NSFC) (No.61222308), and Program for New Century Excellent Talents in University (No.NCET-12-0217), Fundamental Research Funds for the Central Universities (No.HUST 2013TS115). Xinggang Wang was supported by Microsoft Research Fellow Award 2012 and Excellent Ph.D Thesis Founding of HUST 2014.

References

**Cong Yao** received the B.S. and Ph.D. degrees in electronics and information engineering from the Huazhong University of Science and Technology (HUST), Wuhan, China, in 2008 and 2014, respectively. He was a research intern at Microsoft Research Asia (MSRA), Beijing, China, from 2011 to 2012. He was a Visiting Research Scholar with Temple University, Philadelphia, PA, USA, in 2013. His research has focused on computer vision and machine learning, in particular, the area of text detection and recognition in natural images.

**Xiang Bai** received the B.S., M.S., and Ph.D. degrees from Huazhong University of Science and Technology (HUST), Wuhan, China, in 2003, 2005, and 2009, respectively, all in Electronics and Information Engineering. He is currently a Professor with the Department of Electronics and Information Engineering, HUST. He is also the Vice-Director of National Center of Anti-Counterfeiting Technology, HUST. His research interests include object recognition, shape analysis, scene text recognition and intelligent systems.