View-Based 3-D CAD Model Retrieval With Deep Residual Networks

Chao Zhang, Guanghui Zhou, *Member, IEEE*, Haidong Yang, Zhongdong Xiao, and Xiongjun Yang

***Abstract*—In industrial enterprises, effective retrieval and reuse of three-dimensional (3-D) computer-aided design (CAD) models could greatly save time and cost in new product development and manufacturing. Consequently, this article proposes a novel view-based approach for 3-D CAD model retrieval enabled by deep learning. This article constructs a multiview model dataset in industrial domain that collects solid and line views of database models. Since views contain rich information for differentiating these models, the problem of model retrieval is defined as a view recognition problem. Then, the extended deep residual networks (ResNets) are successfully trained to facilitate the model retrieval. With the learned networks, engineers could take a group of views, an engineering drawing, or even a hand-drawn sketch that represents their query intents as input and acquire the relevant 3-D CAD models and embedded knowledge for product lifecycle reuse. The experimental results demonstrate the effectiveness and efficiency of the approach.**

***Index Terms*—Deep learning, model retrieval, residual networks (ResNets), three-dimensional (3-D) computer-aided design (CAD) model, view-based approach.**

I. Introduction

RAPID advances in new generation information technologies facilitate the development and application of knowledge-based intelligent industrial applications in modern industrial enterprises [1]. Specifically, with the wide application of computer-aided design (CAD) systems in industrial enterprises, a huge number of three-dimensional (3-D) CAD models have been generated and stored in enterprise repositories. These models contain plenty of embedded knowledge, such as topological knowledge, geometrical knowledge, and theoretical knowledge [2], which is worthy of product lifecycle reuse (PLR) [3] for enhancing the efficiency and intelligence of industrial product development and manufacturing. For example, in the context that more than 75% of product designs are case-based designs or adaptable designs [4], designers could directly reuse the similar 3-D CAD models or their embedded knowledge for the intelligent functional decomposition, physical design, and geometrical implementation of a slightly changed new product [5]. Thus it can be seen that the effective reuse of the preexisting 3-D CAD models could help industrial enterprises stay competitive within the changing market by supporting intelligent industrial applications such as intelligent physical design and manufacturing decision-making [6]. Nevertheless, 3-D CAD model reuse in industrial domain is still made difficult by the growing model complexity and insufficient model retrieval tools. As a result, model reuse in industrial enterprises has been found to be considerably low since engineers must take much time on seeking out the reference models.

To overcome the above obstacles in 3-D CAD model reuse, many approaches have been proposed in recent years. Generally, there are two steps for these approaches to be applied in model reuse. First, they represented each 3-D CAD model via a descriptor, such as information descriptor [7], geometric descriptor [8], or shape distribution descriptor [9]. Then, a model retrieval tool is developed to measure the similarity between query descriptor and each of descriptors of database models for model reuse. These approaches provide some way to model reuse. However, they suffer from two main drawbacks: 1) the retrieval efficiency and accuracy deteriorate with the increase of models in database as each model needs a complex descriptor, which may result in less effective in practical application; 2) they do not support PLR as the descriptor of each 3-D CAD model is specially designed for a concrete reuse purpose, such as design reuse or manufacturing reuse. Therefore, it is necessary to develop a novel approach for 3-D CAD model reuse in industrial domain.

In industrial enterprises, engineers prefer to visualize their ideas so as to make them more clearly understandable when communicating with each other. For example, designers usually express their preliminary design thinking via a sketch, through which they can communicate, and cooperate with others conveniently. Naturally, the understandable views of a 3-D CAD model could be a better choice than a complex descriptor for query input when model reuse. With these observations in mind and also inspired by the great success achieved by deep learning

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in computer vision [10], [11], this article introduces a deep learning approach for the effective view-based 3-D CAD model retrieval. To use a deep learning approach for model retrieval, we represent a 3-D CAD model as a collection of views, including solid views and line views, from 26 fixed viewpoints that are commonly used in engineering drawing. Then, we construct a multiview dataset named MV560 that collects multiple views of 560 3-D CAD models in industrial domain. These views contain rich semantics to represent engineers' query intents as well as differentiate 3-D CAD models. Hence, the problem of 3-D CAD model retrieval could be defined as a view recognition problem, namely image retrieval [12]. For view recognition, we design a new kind of residual block (ResBlock) whose feasibility and effectiveness are demonstrated through residual learning on a large-scale 3-D model dataset—ModelNet40. On that basis, we train two deep residual networks (ResNets), namely FilterNet and RankNet, stacked by the proposed ResBlocks on MV560 to find the relevant 3-D CAD models from the model library for model reuse in industrial domain. Given a query input represented by a group of views (at least one view), FilterNet is carried out to filter database models in the relevant categories, and RankNet is used to calculate the similarity between the input and relevant models and push top results to engineers. The experimental results presented in this article demonstrate the effectiveness and efficiency of the approach.

The reminder of the article is organized as follows. Section II summarizes the representative works related to this article. In Section III, we introduce an overview of the approach for view-based 3-D CAD model retrieval. Section IV constructs a multiview dataset named MV560 in industrial domain. In Section V, FilterNet and RankNet stacked by the proposed ResBlocks are trained on MV560. Section VI shows the experimental results that demonstrate the effectiveness of the approach. Section VII concludes this article.

II. Related Works

This section presents the state-of-the-art approaches that relate to the research topic of the article, including 3-D CAD model reuse and convolutional neural networks (CNN).

A. 3-D CAD Model Reuse

Nowadays, 3-D CAD model reuse has become an active research topic and many approaches have been developed on this subject. These approaches could be divided into two types including semantics-based approach [13]–[15] and model-based approach [3], [16], [17].

Semantics-based approach utilizes a semantic descriptor, such as ontology [18] or information descriptor [19], to capture design, process, or manufacturing semantics of 3-D CAD models from the knowledge-level perspective. For example, Qin *et al.* [13] employed a domain ontology to represent heterogeneous 3-D CAD models and then developed a semantics-based approach for model retrieval; Liu *et al.* [20] proposed an enhanced explicit semantic analysis method for product model retrieval in construction industry; Xu *et al.* [15] developed a descriptor similarity estimation approach for process reuse-oriented effective 3-D CAD model retrieval. Semantics-based approach could facilitate 3-D CAD model retrieval by taking a semantic descriptor of the target 3-D CAD model as input. However, semantics-based approach could not support PLR as each kind of descriptor is elaborated for concrete reuse purpose, such as design reuse or manufacturing reuse. In addition, it may be less effective in practical application since the construction of semantic descriptor is relatively complicated. Semantic descriptor is also hard to be understood by engineers when taking it as input for model retrieval.

Model-based approach is another means of model reuse, which could overcome partial obstacles caused by semantics-based approach. Model-based approach first employs a feature descriptor, such as shape distribution descriptor [16], [17] or geometric descriptor [8], to capture features of 3-D CAD models from the model-level perspective. Then, a model matching algorithm is developed to calculate the similarity between the input descriptor of a target model and each of descriptors of historical 3-D CAD models. For example, Renu and Mocko [21] designed a geometric descriptor that described the surface area differences and tessellation area distribution differences to facilitate model reuse; Zhuang *et al.* [22] represented a 3-D CAD model via a shape descriptor and proposed a model retrieval algorithm based on the information provided by the descriptor. Model-based approach obtains some benefits in practical application by using a feature descriptor instead of a semantic descriptor for model retrieval. For example, it could be more convenient and understandable for engineers to input a query 3-D CAD model for model retrieval when using such approach. However, Wang *et al.* [3] showed that the feature descriptor could not differentiate complex models, which may influence the retrieval accuracy of model-based approach. In addition, since model-based approach takes a complete model as input, it may not support design reuse, especially conceptual design reuse, as the model is not even designed or established at that stage.

The above drawbacks of both semantics-based and model-based approaches prevent them from supporting PLR-oriented 3-D CAD model retrieval. Hence, it is still necessary to explore a more effective and efficient model retrieval approach for supporting intelligent industrial applications throughout the product lifecycle.

B. Convolutional Neural Networks

CNN was first proposed by LeCun *et al.* [23] and nowadays has achieved great success in many computer vision tasks, such as image super-resolution [24] and automated melanoma recognition [25]. The basic ideas behind CNN are local connections, shared weights, and pooling. Local connections together with shared weights ensure that CNN could detect local informative features with less adjustable parameters. In addition, pooling equips CNN with some translation invariance. A typical CNN is usually structured as a series of stages, where the first few stages consist of convolutional layers and pooling layers and the last few stages are constituted by fully connected (FC) layers (usually one FC layer) and a k-way (k deeps on the number of categories) softmax followed. In the first few stages, each convolutional layer aims to detect the local informative features with m kernels of $n \times n$ convolution filters that contains a set of adjustable shared weights; and each pooling layer aims to merge semantically similar features into one [23]. In addition, the last few stages produce a vector of scores, where each score represents the probability of the input being in a category.

The key issue that influences the performance of CNN is its architecture. With the rapid increase of computer power, many successful architectures have been designed nowadays to improve the performance of CNN. The representative CNN architectures include AlexNet [26], VGGNet [27], GoogLeNet [28], DenseNet [29], and ResNet [30]. According to their performance reported on ImageNet dataset, ResNet achieves the highest accuracy for image recognition with relatively less operations required for a single forward pass and also less parameters. Therefore, we take ResNet as base architecture for view-based 3-D CAD model retrieval. The rest of the article will introduce how to use ResNet for 3-D CAD model retrieval in industrial domain.

III. Overview of the Approach

In industrial enterprises, engineers usually visualize their creative ideas via understandable engineering drawings or vivid 3-D CAD models, with which they can communicate and corporate with each other conveniently. In this context, they may also prefer to use the understandable views of a 3-D CAD model, such as solid views, line views, engineering drawings, and hand-drawn sketches, to express their query intents when model reuse. Inspired by the above fact, we propose a view-based approach for 3-D CAD model retrieval enabled by FilterNet and RankNet that take ResNet as base architecture. Given a query input represented by m views ($m \geq 1$), the similarity between the input and database models is calculated as

$$\mathrm{Sim} = \frac{\sum_1^m (W_p \times F_p) \circ R_s}{m} \tag{1}$$

where F_p is the output vector of FilterNet representing the classification probability that could help preliminarily filter database models in the relevant categories for the input; Rs is the output score of RankNet that measures the similarity between the input and each of models in the relevant categories; W_p is a matrix used for matching dimensions between F_p and Rs; and $\circ$ means elementwise product.

The overview of the approach is as shown in Fig. 1, which involves learning process and retrieval process. Here learning process includes multiview dataset creation, data augmentation, and residual learning; and retrieval process includes intent expression, retrieval, and results ranking.

Learning process aims to learn functions for model retrieval based on the training dataset. To this end, a multiview dataset is first created by collecting both solid views and line views of each of 3-D CAD models in industrial domain from 26 fixed viewpoints. Since data augmentation has been shown helpful for deep learning [26], we then augment the dataset by random view rotation, translation, and horizontal reflection. Finally, FilterNet and RankNet stacked by the proposed ResBlocks are employed

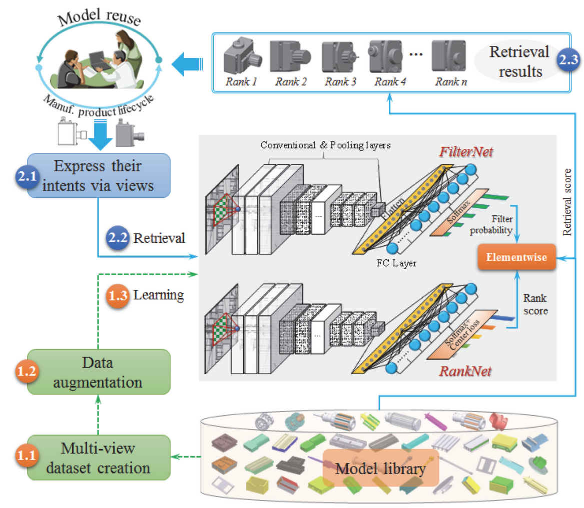


Fig. 1. View-based 3-D CAD model retrieval.

to learn functions for model retrieval, which are determined by the adjustable weights of the networks [23]. During this process, taking RankNet as an example, RankNet takes a view in the dataset as input and produces a vector of scores. Each score represents the similarity of the input view to a concrete 3-D CAD model in model library. The essence of the learning is to make the expected 3-D CAD model of the input view have the highest score of all models in model library. To this end, a center-softmax loss function is designed to compute the error between the output scores of RankNet for a given input view and the expected scores of the view. Then, backpropagation [23] is conducted to minimize the error by updating the adjustable weights of RankNet in each successful iteration of learning. If the error is below a given threshold or a prespecified number of iterations have been executed, the learning process comes to an end and the functions for model retrieval will be learned.

There are also three steps for 3-D CAD model retrieval with the learned FilterNet and RankNet. First, engineers at different stages of product lifecycle could use flexible views including solid views, line views, engineering drawings, and hand-drawn sketches to express their query intents. Then, FilterNet calculates the category relevance and RankNet further measures the similarity of each model in the relevant categories for a given input through a forward pass. Finally, the relevant 3-D CAD models ranked by their similarity scores are pushed to engineers. Engineers could reuse these models directly or learn their embedded knowledge such as topological structure, geometrical knowledge, and theory knowledge [2] for new product development and manufacturing.

IV. Database Creation

To our best knowledge, there is not yet a challenging real-word dataset in industrial domain for learning a network for view-based 3-D CAD model retrieval. Therefore, this section provides a way for dataset creation and also creates a multiview dataset named MV560 that collects multiple views from each of 560 3-D

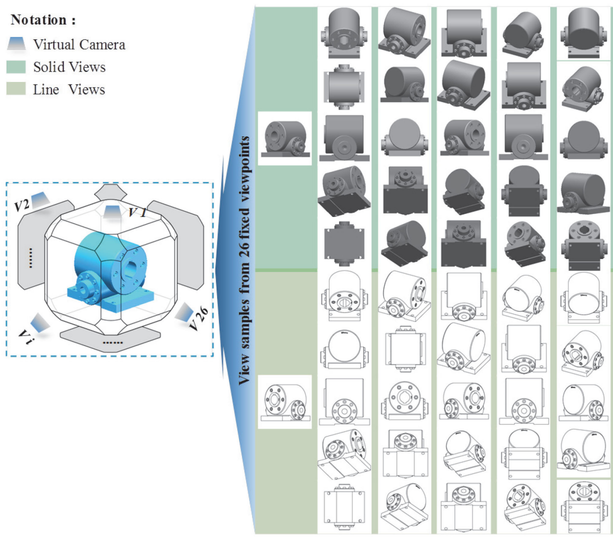


Fig. 2. View samples from 26 fixed viewpoints.

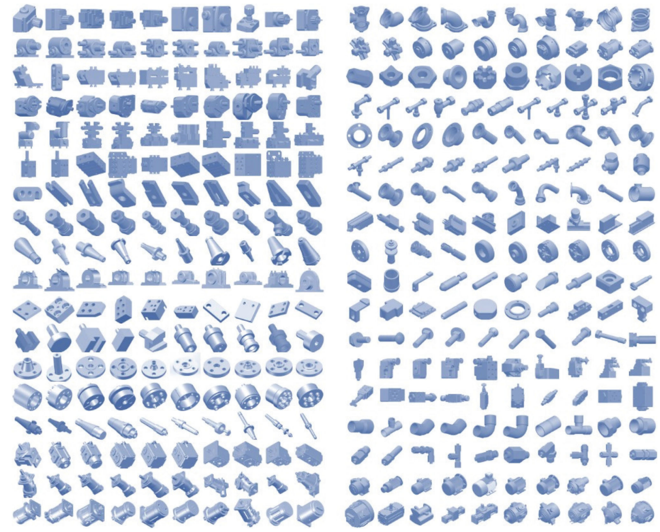


Fig. 3. Illustration of partial views of MV560 dataset.

CAD models in 56 categories, ten parts models for each category. Multiple views could capture as much information as possible from a 3-D CAD model, which makes it easy for a network to understand the model. As shown in Fig. 2, we collect multiple views of a 3-D CAD model using a virtual camera that captures both solid views and line views from 26 fixed viewpoints. Each viewpoint corresponds to a surface (26 in total) of the polyhedron, as shown in the left of Fig. 2. These viewpoints are commonly used in engineering drawings and could capture almost all shape information of a 3-D CAD model. In addition, the reason for collecting both solid views and line views is that a thus learned network could support more retrieval modes. For example, engineers could use a solid view, a line view, an engineering drawing, or even a hand-drawn sketch to express their query intents. It should be noted that both solid views and line views are grayscale images as colors do not provide much information for differentiating 3-D CAD models. This contribution makes it possible for a network to take both solid views and line views as input.

Specifically, we construct a MV560 dataset that collects 52 views (26 solid views and 26 line views) of each of 560 3-D CAD models with size 256 $\times$ 256 (as shown in Fig. 3). In addition, a robust deep learning approach usually requires a large training dataset. Then, we augment the dataset following the data augmentation method used in [26], where random image rotation in range [0°, ..., 45°], random 224 $\times$ 224 patches extraction from the original views, random image translations, and horizontal reflections are used. MV560 finally contains the augmented views with size 224 $\times$ 224. In addition, 85% of views in MV560 are used for training purpose and the rest 15% for validation purpose.

V. Using ResNet for 3-D CAD Model Retrieval

In this section, we describe how FilterNet and RankNet are learned on MV560 dataset for 3-D CAD model retrieval in industrial domain.

A. Brief Introduction of ResNet

ResNet is first proposed by He *et al.* [30] for image recognition. Nowadays, it also exhibits excellent performance in many other computer vision tasks such as image super-resolution [24]. The key idea of ResNet is a set of stacked ResBlocks. Let x and H(x) be the input and output of each ResBlock, respectively. Then the ResBlock is expressed in a general form

$$H(x) = F(x, \{W_i\}) + W_s x \tag{2}$$

where W_i is a set of adjustable shared weights in each convolutional layer, and W_s is a square matrix used for matching dimensions. The first term in (2) asymptotically approximates a residual mapping F(x) = H(x)-x. The second term acts as a shortcut that directly output the input x or x with the extra entries padded for matching dimensions.

This article takes ResNet as base architecture for FilterNet and RankNet considering the following reasons. On the one hand, ResNet achieves the state-of-the-art performance on many computer vision tasks such as ImageNet classification, detection and localization, which shows that the residual learning principle of ResNet is generic and might be transformed into view-based 3-D CAD model retrieval. On the other hand, 3-D CAD model retrieval in industrial domain takes several different kinds of views such as solid views and line views as input, where ResNet could handle this situation by generalizing these views via residual mapping, while preserving their invariance features via identify mapping (see Fig. 10). Experimental results presented in this article demonstrate the effectiveness of ResNet in 3-D CAD model retrieval domain.

B. Learning Architecture

To use ResNet for 3-D CAD model retrieval, we propose a new means of implementing the ResBlock [Fig. 4(d)]. We remove the batch normalization layers in residual mapping compared with the original ResBlock [30] [Fig. 4(b)] and variant ResBlock [31] [Fig. 4(c)]. This is motivated by the following

TABLE I
ARCHITECTURES FOR 3-D CAD MODEL RETRIEVAL

Layer name	Output size	18-layer			34-layer	101-layer
		Original	Variant	Proposed	Proposed	Proposed
Conv 1	112×112	7×7, 64, stride 2				
ResBlock 1_x	56×56	$\begin{bmatrix} 3\times 3, 64 \\ 3\times 3, 64 \end{bmatrix} \times 2$			$\begin{bmatrix} 3\times 3, 64 \\ 3\times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times 1, 64 \\ 3\times 3, 64 \\ 1\times 1, 256 \end{bmatrix} \times 3$
ResBlock 2_x	28×28	$\begin{bmatrix} 3\times 3, 128 \\ 3\times 3, 128 \end{bmatrix} \times 2$			$\begin{bmatrix} 3\times 3, 128 \\ 3\times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128 \\ 1\times 1, 512 \end{bmatrix} \times 4$
ResBlock 3_x	14×14	$\begin{bmatrix} 3\times 3, 256 \\ 3\times 3, 256 \end{bmatrix} \times 2$			$\begin{bmatrix} 3\times 3, 256 \\ 3\times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times 1, 256 \\ 3\times 3, 256 \\ 1\times 1, 1024 \end{bmatrix} \times 23$
ResBlock 4_x	7×7	$\begin{bmatrix} 3\times 3, 512 \\ 3\times 3, 512 \end{bmatrix} \times 2$			$\begin{bmatrix} 3\times 3, 512 \\ 3\times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times 1, 512 \\ 3\times 3, 512 \\ 1\times 1, 2048 \end{bmatrix} \times 3$
FC 1	1×1	Average pooling, *n*-d FC, *n*-way softmax (*n* depends on the total categories of dataset)				
Parameters		82M			163M	328M
Training time on ModelNet40 (*h*)		5.4	5.5	5.1	8.0	22.6

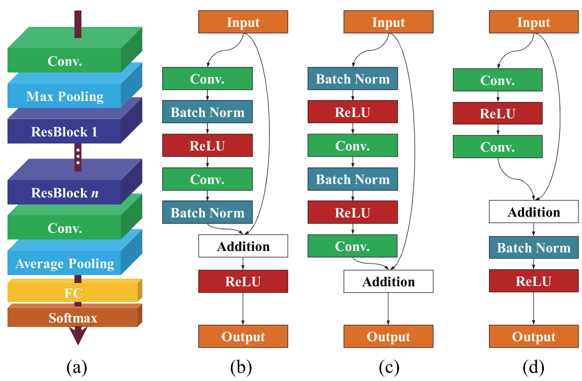


Fig. 4. ResNet architecture. (a) Overall architecture of ResNet for 3-D CAD model retrieval. (b) Original ResBlock. (c) Variant ResBlock. (d) Proposed ResBlock.

fact: compared to the real-word 3-D objects like flowers and animals, 3-D CAD models in industrial domain have more regular shapes restricted to engineering drawing specifications and manufacturing capabilities, and consist of many standard features like hole and groove. However, the batch normalization layer in residual mapping normalizes the features, which may result in less effective in 3-D CAD model retrieval. In addition, the effectiveness of the proposed ResBlock is demonstrated on both ModelNet40 dataset (Fig. 5) and MV560 dataset (Fig. 7). The proposed ResBlock is implemented as follows. The top left of Fig. 4(d) performs residual mapping, which consists of two convolutional layers and an activation ReLU [26] right after the first convolutional layer. The top right of Fig. 4(d) is a shortcut, which involves two situations: 1) it performs identify mapping when the input and output are of the same dimensions; 2) it uses a convolutional layer to match dimensions when they are different. The entire ResBlock outputs the addition of the residual mapping and shortcut after a batch normalization layer [32] and an activation function ReLU.

As shown in Fig. 4(a), we stack numbers of ResBlocks to construct a ResNet that serves as the base architecture for both FilterNet and RankNet toward 3-D CAD model retrieval. Based on the above three ResBlocks, we implement three different 18-layer ResNets to see the benefits of the proposed ResBlock. We also train three different ResNets including an 18-layer ResNet, a 34-layer ResNet, and a 101-layer ResNet stacked by the proposed ResBlocks to obtain the benefits of network depth for 3-D CAD model retrieval. As shown in Table I, the first convolutional layer in each ResNet uses 64 kernels of convolution filters with size 7×7 to preprocess the input views. The rest convolutional layers use 3×3 convolution filters. In addition, the first convention filter in ResBlock 1_1, 2_1, 3_1, and 4_1 performs down-sampling with a stride of 2. The other convention filters learn a deep hierarchical representation of the input views at stride 1. The last FC layer together with a n-way softmax ($n = 56$ for FilterNet and $n = 560$ for RankNet on MV560 dataset) produces a vector of scores representing the relevance of database models for a given input.

C. Details of Learning

FilterNet aims to learn separable features of each of 56 categories in MV560 dataset such that it could preliminarily filter models in the relevant categories for a given input by calculating classification probability. To this end, softmax loss function is used for FilterNet learning, which is defined as

$$L_s = -\frac{1}{n}\sum_{i=1}^{n}\left(y^{(i)}\log\hat{y}^{(i)} + \left(1 - y^{(i)}\right)\log\left(1 - \hat{y}^{(i)}\right)\right) \quad (3)$$

where $\hat{y} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_{\mathrm{k}}\}$ is the output scores of all k categories in FilterNet; $y = \{y_1, y_2, \ldots, y_{\mathrm{n}}\}$ is the labels of the input views; and n is the minibatch size.

RankNet aims to learn discriminative features of each model in the same category such that it could measure the similarity between input and each model in the relevant categories. Here, center loss [33] combined with softmax loss is used as the loss function for RankNet learning, which is defined as

$$\begin{aligned} L_{c+s} &= \lambda L_c + L_s \\ &= \frac{\lambda}{2}\sum_{i=1}^{n}\|x_i - c_{y_i}\|_2^2 + L_s \end{aligned} \quad (4)$$

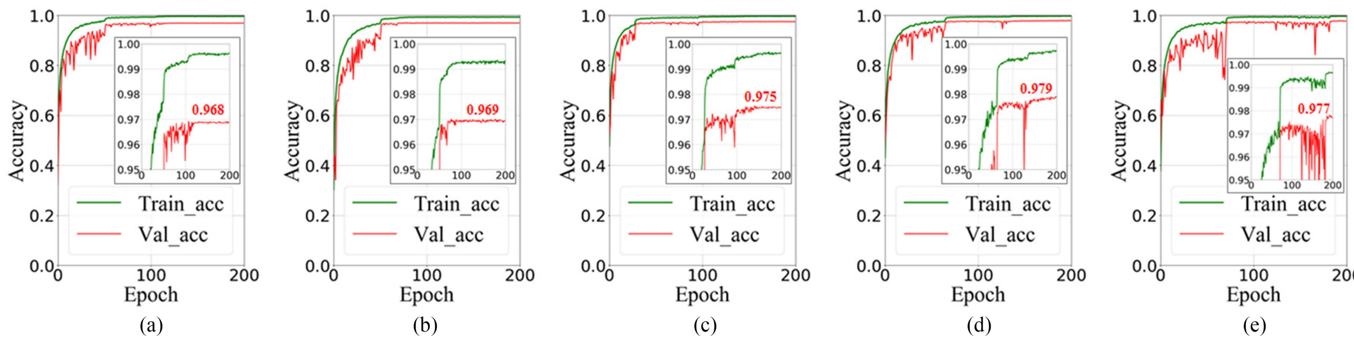


Fig. 5. Pretraining on ModelNet40 dataset with ResNet18 stacked by the (a) original ResBlocks, (b) variant ResBlocks, and (c) proposed ResBlocks, respectively; and (d) ResNet34 and (e) ResNet101 stacked by the proposed ResBlocks. Notice that each rectangle inside the picture is the partial enlarged view of the picture.

where x_i denotes the ith output deep feature of the FC layer of RankNet, belonging to the y_ith 3-D CAD model in MV560 dataset; Cy_i denotes the y_ith model's center of deep features; λ is used to balance the two loss functions, which is set to 0.1 according to [33].

To minimize the loss function, stochastic gradient descent (SGD) with backpropagation is employed here for adjustable weights update [26]. The update rule for each weight w in convolution filters is defined as

$$v_{i+1} := \tau \cdot v_i - \mu \cdot \epsilon \cdot w_i - \epsilon \cdot \left\langle \frac{\partial L}{\partial w} |w_i \right\rangle D_i \tag{5}$$

$$w_{i+1} := w_i + v_{i+1} \tag{6}$$

where i is the iteration index; τ is the momentum; v represents the momentum variable; μ is the weight decay; ε is the learning rate; and D_i represents the ith minibatch.

1) Pretraining on ModelNet40 Dataset [34]: Since MV560 is a small dataset that may be hard to evaluate the proposed ResBlock, we pretrain ResNet on a large-scale dataset—ModelNet40 and then fine tune it for MV560. ModelNet40 contains 40 popular object categories such as people, flower and airplane, 100 objects for each category. We conduct the training/validation/testing split as 70%/15%/15%. The details of learning ResNet on ModelNet40 are as shown in Fig. 5, where softmax loss and SGD optimizer with the same hyper-parameters as FilterNet and RankNet on MV560 are used. The results show that the proposed ResBlock takes less time for training but produces the best validation performance compared with the original ResBlock and variant ResBlock (see Table I and Fig. 5). In addition, the proposed ResBlock could be stacked into a very deep ResNet, namely ResNet34 [Fig. 5(d)] and ResNet101 [Fig. 5(e)], which also obtain nice validation accuracy.

2) Sensitive Analysis on MV560 Dataset: To obtain better results on MV560, we conduct several sensitive analysis experiments by learning ResNet with the proposed ResBlock on MV560 from scratch. First, we compare two ResNet18 learned by SGD optimizer and ADAM optimizer [35], respectively. Here, ADAM uses the default parameters in [35]; and SGD uses a minibatch size of 32, weight decay of 0.0001, and momentum of 0.9. A learning rate of 0.01 is used at start and divided by 10 at 50 epochs and 150 epochs. The results show that SGD provides a faster convergence [Fig. 6(a)] and also a higher validation accuracy [Fig. 6(b)] compared with ADAM. We further learn ResNet18 with different batch sizes [Fig. 6(c)] and find that ResNet18 with batch size of 32 achieves the highest validation accuracy [Fig. 6(d)]. Therefore, we use the SGD optimizer with a minibatch size of 32, weight decay of 0.0001, and momentum of 0.9 for FilterNet and RankNet learning. We also train ResNet18, ResNet34, and ResNet101 with the above training method to see the influence of network depth on MV560. As shown in Fig. 6(e) and (f), since ResNet18 achieves best validation performance, we employ ResNet18 as base architecture for both FilterNet and RankNet.

3) Fine Tuning on MV560: The adjustable weights of FilterNet are initialized with the weights of the ModelNet40 pretrained ResNet18. RankNet weights are initialized with the weights of FilterNet. The learning process and validation accuracy are as shown in Fig. 7, from which we have the following observations. First, both FilterNet and RankNet stacked by the proposed ResBlock produces the best validation performance compared with the original and variant [see Fig. 7(b) and (d)]. Second, Fig. 7(e) and (f) demonstrate that network with pretraining could provide a faster convergence and also slightly better validation accuracy.

VI. Experiments and Discussions

This section presents the experimental results of the proposed approach for 3-D CAD model retrieval. Here, all the experiments are conducted on a PC with a 3.70 GHz Intel Core i7 processor, 16GB Memory, and a NVIDIA GeForce GTX 1080Ti GPU.

A. Retrieval Experiments

To estimate the influence, mean reciprocal rank (MRR) measure [18] is employed in this article as it is a common assessment scheme used in retrieval systems. MRR is able to measure the performance of a retrieval system by considering the impact of the order of results. Let n be the number of retrieved results.

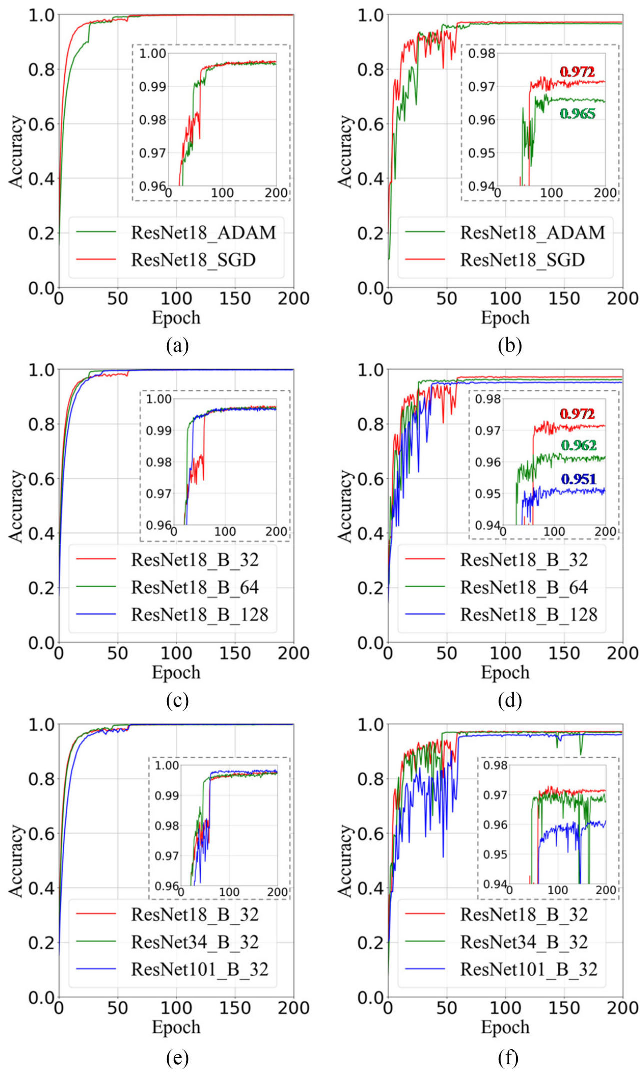


Fig. 6. Sensitive analysis of the proposed ResBlocks on MV560. (a) Training and (b) validation performance comparison between ADAM and SGD; (c) training and (d) validation performance comparison between different batch sizes (32, 64, 128); (e) training and (f) validation performance comparison between ResNet18, ResNet34, and ResNet101 with batch size of 32.

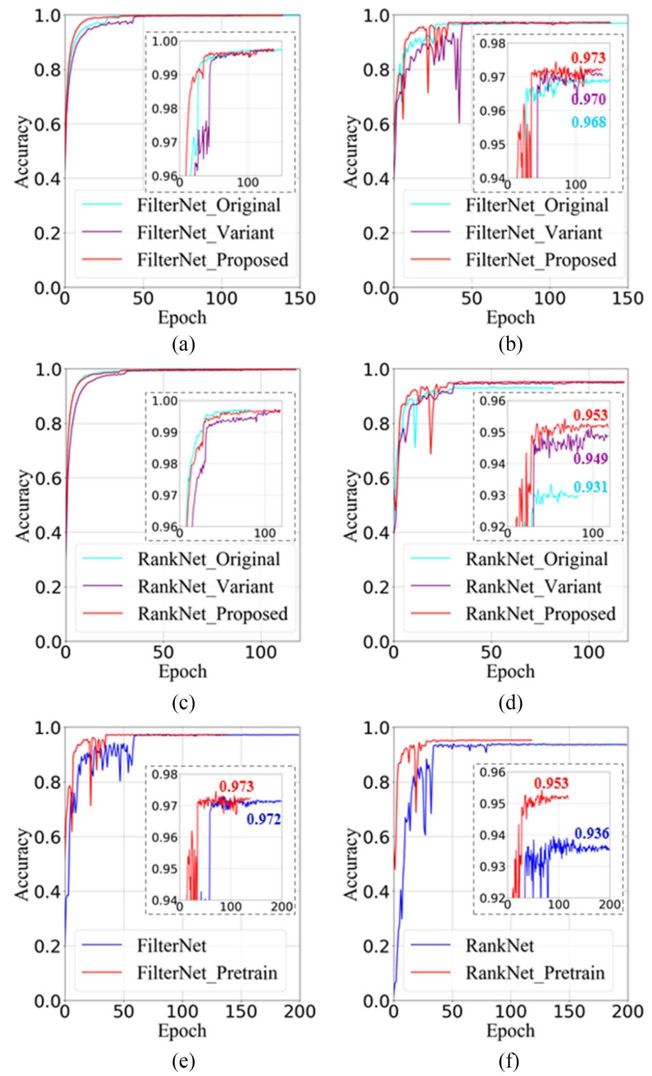


Fig. 7. Fine-tuning on MV560: (a) test and (b) validation accuracy of FilterNet and (c) test and (d) validation accuracy of RankNet, with ResNet18 stacked by the original, variant, and proposed ResBlocks, respectively. Validation performance of (e) FilterNet and (f) RankNet with or without pretrain, using the proposed ResBlocks.

MRR is then defined as

$$\mathrm{MRR} = \frac{\sum_{i=1}^{n}\left(\frac{1}{i} \times \mathrm{Rank}_i\right)}{\sum_{i=1}^{n}\left(\frac{1}{i}\right)} \tag{7}$$

where $\mathrm{Rank}_i = 1$ if the ith result is a relevant result, and zero if the ith result is a less relevant or wrong result.

We conduct several retrieval experiments to obtain the benefits of the proposed approach. Fig. 8(a) illustrates four group retrieval experiments with FilterNet and RankNet, which include the retrieval performance comparison of the proposed approach with the original approach and variant approach when taking a solid view (1st group), a line view (2nd group), an engineering drawing (3rd group), and a hand-drawn sketch (4th group) as input, respectively. The results demonstrate that the combination of FilterNet and RankNet could produce very nice results in top 10 with flexible views as input, especially considering that there are only 10 models in each category of MV560. This contribution facilitates PLR by supporting flexible views, namely solid views, line views, engineering drawing, and hand-drawn sketch, as input. In addition, the proposed approach slightly outperformances the original and variant approaches in terms of less retrieval time and also the nicer output orders of the most relevant results (marked with green) and less relevant results (marked with purple) or wrong results (marked with red). As shown in Fig. 8(b), when using only RankNet for retrieval, the proposed approach obtains even more obvious advantages compared with the original and variant approaches, which achieves the best MRR performance. In addition, the combination of FilterNet and RankNet [Fig. 8(a)] achieves a significant MRR performance improvement compared with RankNet only [Fig. 8(b)]. The above contributions make the proposed approach be a good choice for supporting PLR-oriented 3-D CAD model retrieval.

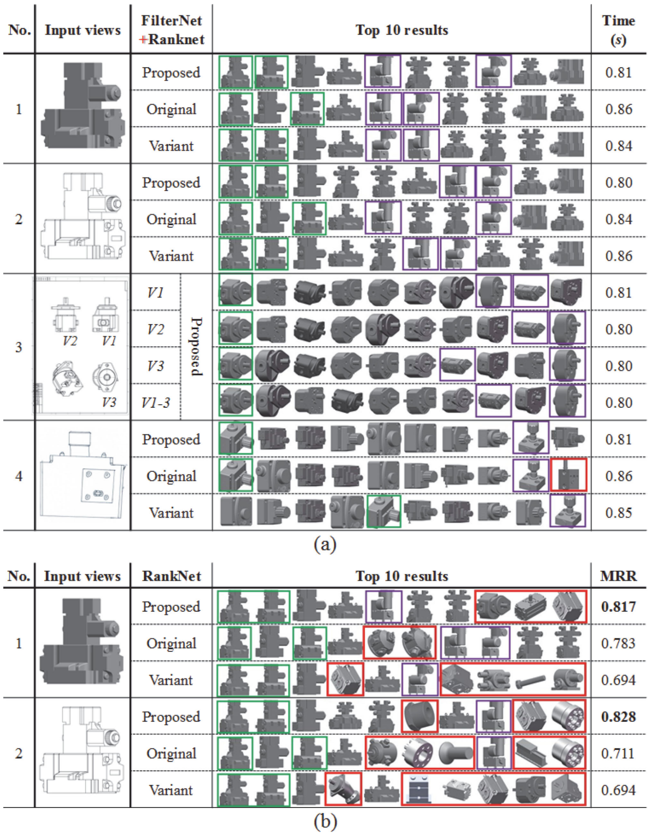


Fig. 8. Retrieval experiments with (a) the combination of FilterNet and RankNet and (b) RankNet only. Notice that the results marked with green, purple, and red represent the most relevant results, results in the right category but less relevant and wrong results, respectively.

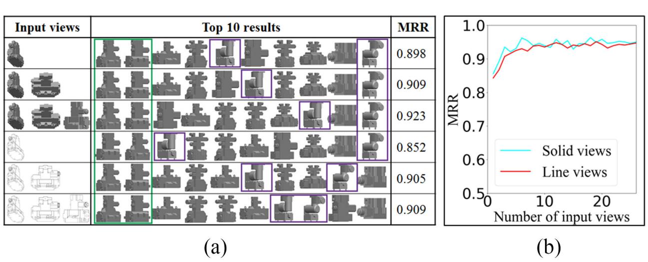


Fig. 9. Exploring experiments on the influence of the number of input views. (a) Illustration of the influence of view numbers on retrieval results, where 1–3 solid and line views are taken as the input, respectively. (b) MRR versus number of input views, obtained by the average of five experimental results.

B. Exploring the Influence of the Number of Input Views

Since the number of input views may influence the retrieval performance of the proposed approach [see the 3rd group results in Fig. 8(a)], we conduct five independent experiments to explore the influence.

Partial results of one of the experiments are shown in Fig. 9(a). The average MRR of five experimental results is shown in Fig. 9(b), from which the following observations can be obtained. First, the average MRR increases with the number of input views at start and gets saturated when the number of input views is greater than three. Second, the learned network usually produces slightly better results when taking solid views as input. It is reasonable as the intricate lines in each line view make noises for view recognition. Lastly, it should also be noted that, with a single input view, the learned network may also produce nice results if the view contains rich information for the target 3-D CAD model [see Fig. 8(a)].

TABLE II
COMPARISON WITH THE METHODS IN INDUSTRIAL DOMAIN

Method	Input mode	Retrieval time (s)	MRR
EMD	Complete models	1.00–7.80	0.818
MHD	Complete models	0.85–3.00	0.866
Proposed	Flexible views	0.80	**0.931** (3 views)

The best performance achieved by our approach for each item.

C. Comparison With the State-of-the-Art Approaches

This section compares the performance of the proposed approach with the state-of-the-art approaches in industrial domain and 3-D object retrieval domain, respectively.

In industrial domain, the proposed approach is compared with earth mover's distance (EMD) [3] and modified Hausdorff distance (MHD) [17]. As shown in Table II, the flexibility of input, retrieval time, and retrieval performance between these methods are involved in this experiment. First, the current approaches usually support one input mode such as a complete model, which may result in less effective in practical application. As mentioned above, the proposed approach could support flexible input views including solid views, line views, engineering drawings, and even hand-drawn sketches, thus being a better choice for PLR-oriented 3-D CAD model retrieval. Second, the retrieval time of the proposed approach is significant less than EMD and MHD. In addition, the retrieval time of the current approaches will increase with the number of models in model library as they must calculate the similarity between the query input and each of models in model library. However, the retrieval time of the proposed approach is independent with the number of models in model library, and only depends on the parameters inside the network. Lastly, we also find that the proposed approach achieves the best MRR performance compared to EMD and MHD, which attributes to the excellent performance of residual learning on view recognition.

In 3-D object retrieval domain, the classification and retrieval performance of the proposed appraoch are compared with MVCNN [36], GVCNN [37], and TCL [38] on ModelNet40 Dataset. For comparison, the learned ResNet34 [Fig. 5(d)] stacked by the proposed ResBlocks is used as FilterNet since it achieves the best validation accuracy on ModelNet40 Dataset. The learned ResNet34 is further fine-tuned to learn RankNet using the same learning method as that on MV560 dataset. According to Table III, the proposed FilterNet achieves the best classification accuracy compared with those approaches. Especifially when taking only one view as input, FilterNet constitutes an absolute gain of 8.5% in classification accuracy

TABLE III
CLASSIFICATION AND RETRIEVAL RESULTS ON MODELNET40 DATASET

Method	Test config. # views	Classification (Accuracy)	Retrieval (mAP)
GVCNN, 12×	1	75.0%	-
FilterNet, 12×	1	**83.5%**	-
MVCNN, 12×	12	89.9%	70.1%
MVCNN, metric, 12×	12	89.5%	80.2%
GVCNN, 12×	12	92.6%	81.3%
GVCNN, metric, 12×	12	92.6%	85.7%
TCL, 12×	12	-	86.7%
TCL+softmax loss, 12×	12	-	88.0%
FilterNet, 12×	12	**94.4%**	-
FilterNet+RankNet, 12×	12	-	**87.1%**

*metric = low-rank Mahalanobis metric learning.
The best performance achieved by our approach for each item.

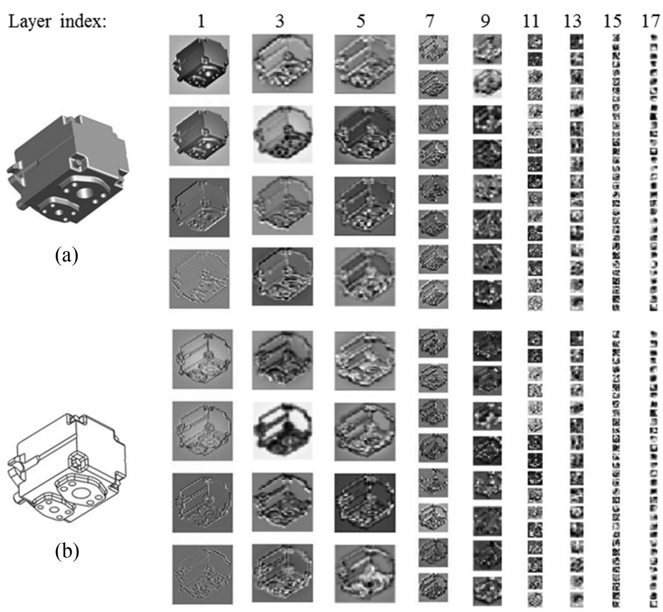


Fig. 10. Inside a RankNet. The output of each odd convolutional layer of the learned RankNet applied to (a) a solid view and (b) a line view, respectively.

compared with GVCNN. This contribution facilitates the practical application of the proposed approach in PLR-oriented 3-D CAD model retrieval, since views of target model are infrequent at design stage. In addition, the combintion of FilterNet and RankNet achieves comparable mean average precision (mAP) for retrieval, which outperforms MVCNN, GVCNN, and TCL, but underperforms TCL plus softmax. However, since TCL is a variant of triplet loss, the construction of triplets is still a complex problem. Considering the above fact, the proposed approach could be a good choice for PLR-oriented 3-D CAD model retrieval.

D. Understanding the Learned Network

To understand the learned network, we visualize the output of each odd convolutional layer of RankNet with the proposed ResBlocks applied to a solid view [Fig. 10(a)] and a line view [Fig. 10(b)], respectively. We have the following three observations. First, RankNet does not try to represent the entire input view at high layers but represents its invariance features. Second, the higher layer detects the greater invariance of the input view from the lower layer. Lastly, the representations for solid views and line views are different at the first few layers and tend to be similar at the last few layers. The reason might be that both the solid view and line view are collected from a same 3-D CAD model and have same high-level invariance features. RankNet calculates the scores that measure the similarity of each of models in model library for a given input based on the detected high-level invariance features.

E. Discussion of the Potential Applications

Inspired by the great success achieved by deep learning in computer vision tasks, this article proposes a deep learning-enabled approach for view-based 3-D CAD model retrieval in industrial domain. The experimental results indicate that the proposed approach achieves the state-of-the-art performance in industrial domain, which could be a good choice for PLR-oriented 3-D CAD model retrieval. The proposed approach could facilitate intelligent industrial applications such as intelligent physical design and manufacturing decision-making by retrieving relevant 3-D CAD models and reusing their embedded knowledge. In addition, the potential applications of the proposed approach should not be confined to 3-D CAD model retrieval. It also could provide visual sense for machine tools by simply equipping these machine tools with real or virtual cameras. In this situation, for example, machine tools could understand a part by taking a picture of the part or its corresponding engineering drawing as input. Then, machine tools produce the optional machining strategies such as cutting tools and parameters based on the retrieved model and its embedded knowledge. Since the proposed approach could be regarded as the visual sense of industrial devices, it might be integrated with other senses like tactile sense and auditory sense via cross-modal learning [39], [40] to explore more industrial applications.

VII. CONCLUSION

This article proposed a novel view-based 3-D CAD model retrieval approach enabled by FilterNet and RankNet, which could support intelligent industrial applications throughout the product lifecycle by effectively reusing the 3-D CAD models and their embedded knowledge. Here, FilterNet learned separable features of each category in MV560 dataset with softmax loss, which could preliminarily filter models in the relevant categories for a given input; RankNet learned discriminative features of each model in the same category with center-softmax loss, which could further measure the similarity between the input and each model in the relevant categories and output top results ranked by similarity scores. With the learned FilterNet and RankNet, engineers at different stages of product lifecycle could take flexible views such as solid views, line views, engineering drawings, or even hand-drawn sketches as input for 3-D CAD model retrieval. The main contributions of this article are as follows. First, this article provided a new insight into 3-D CAD model retrieval in industrial domain by defining the problem of model retrieval as a view recognition problem. Second, the article proposed a new framework for 3-D CAD model retrieval by combing FilterNet and RankNet that take ResNet stacked by the proposed ResBlocks as base architecture. Third, this article constructed a multiview model dataset named MV560, which is, to our best knowledge, the first dataset in industrial domain that collects both solid views and line views for 3-D CAD model retrieval. Lastly, this article proposed a more efficient ResBlock for view-based 3-D CAD model retrieval according to the results obtained by the retrieval experiments. The retrieval performance comparison experiments further demonstrated that the proposed approach outperformed the state-of-the-art approaches for 3-D CAD model retrieval in industrial domain, and also achieved comparable classification and retrieval performance on ModelNet40 compared to MVCNN, GVCNN, and TCL.

Potential medium-term future studies related to this article are as follows. First, we plan to extend MV560 dataset and make it as a benchmark for view-based 3-D CAD model retrieval in industrial domain. Second, we plan to integrate the proposed approach with cross-modal learning to explore more intelligent industrial applications. Lastly, since there are many other famous CNN architectures like GoogLeNet and DenseNet, we plan to take these architectures as bases for FilterNet and RankNet and explore their influence on MV560.

References

[1] G. Zhou, C. Zhang, Z. Li, K. Ding, and C. Wang, “Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing,” *Int. J. Prod. Res.*, vol. 0, pp. 1–18, 2019, doi: 10.1080/00207543.2019.1607978.

[2] C. Zhang, G. Zhou, Q. Lu, and F. Chang, “Generating significant subassemblies from 3D assembly models for design reuse,” *Int. J. Prod. Res.*, vol. 56, no. 14, pp. 4744–4761, Jul. 2018.

[3] P. Wang, Y. Li, J. Zhang, and J. Yu, “An assembly retrieval approach based on shape distributions and Earth Mover’s Distance,” *Int. J. Adv. Manuf. Technol.*, vol. 86, no. 9, pp. 2635–2651, Oct. 2016.

[4] C. Zhang and G. Zhou, “A view-based 3D CAD model reuse framework enabling product lifecycle reuse,” *Adv. Eng. Softw.*, vol. 127, pp. 82–89, Jan. 2019.

[5] F.-w. Qin, L.-y. Li, S.-m. Gao, X.-l. Yang, and X. Chen, “A deep learning approach to the classification of 3D CAD models,” *J. Zhejiang Univ. Sci. C*, vol. 15, no. 2, pp. 91–106, Feb. 2014.

[6] X. Lin, K. Zhu, and Q.-G. Wang, “Three-dimensional CAD model matching with anisotropic diffusion maps,” *IEEE Trans. Ind. Informat.*, vol. 14, no. 1, pp. 265–274, Jan. 2018.

[7] S. M. Jeon, J. H. Lee, G. J. Hahm, and H. W. Suh, “Automatic CAD model retrieval based on design documents using semantic processing and rule processing,” *Comput. Ind.*, vol. 77, pp. 29–47, Apr. 2016.

[8] K.-M. Hu, B. Wang, J.-H. Yong, and J.-C. Paul, “Relaxed lightweight assembly retrieval using vector space model,” *Comput. Aided Des.*, vol. 45, no. 3, pp. 739–750, Mar. 2013.

[9] Q. Chen, B. Fang, Y.-M. Yu, and Y. Tang, “3D CAD model retrieval based on the combination of features,” *Multimed. Tools Appl.*, vol. 74, no. 13, pp. 4907–4925, Jul. 2015.

[10] A. A. Liu, W. Z. Nie, Y. Gao, and Y. T. Su, “View-based 3-D model retrieval: A benchmark,” *IEEE Trans. Cybern.*, vol. 48, no. 3, pp. 916–928, Mar. 2018.

[11] B. Leng, Y. Liu, K. Yu, X. Zhang, and Z. Xiong, “3D object understanding with 3D convolutional neural networks,” *Inform. Sci.*, vol. 366, pp. 188–201, Oct. 2016.

[12] J. Yang, B. Jiang, B. Li, K. Tian, and Z. Lv, “A fast image retrieval method designed for network big data,” *IEEE Trans. Ind. Informat.*, vol. 13, no. 5, pp. 2350–2359, Oct. 2017.

[13] F. Qin, S. Gao, X. Yang, M. Li, and J. Bai, “An ontology-based semantic retrieval approach for heterogeneous 3D CAD models,” *Adv. Eng. Informat.*, vol. 30, no. 4, pp. 751–768, Oct. 2016.

[14] R. Huang, S. Zhang, X. Bai, C. Xu, and B. Huang, “An effective subpart retrieval approach of 3D CAD models for manufacturing process reuse,” *Comput. Ind.*, vol. 67, pp. 38–53, Feb. 2015.

[15] C. Xu, S. Zhang, B. Huang, X. Li, and R. Huang, “NC process reuse oriented effective subpart retrieval approach of 3D CAD models,” *Comput. Ind.*, vol. 90, pp. 1–16, Sep. 2017.

[16] Z. Li, X. Zhou, and W. Liu, “A geometric reasoning approach to hierarchical representation for B-rep model retrieval,” *Comput. Aided Des.*, vol. 62, pp. 190–202, May 2015.

[17] J. Zhang, J. Pang, J. Yu, and P. Wang, “An efficient assembly retrieval method based on Hausdorff distance,” *Robot. Comput. Integr. Manuf.*, vol. 51, pp. 103–111, Jun. 2018.

[18] C. Zhang, G. Zhou, Q. Lu, and F. Chang, “Graph-based knowledge reuse for supporting knowledge-driven decision-making in new product development,” *Int. J. Prod. Res.*, vol. 55, no. 23, pp. 7187–7203, Dec. 2017.

[19] R. Wen, W. Tang, and Z. Su, “Topology based 2D engineering drawing and 3D model matching for process plant,” *Graph. Models*, vol. 92, pp. 1–15, Jul. 2017.

[20] H. Liu, Y. Liu, P. Pauwels, H. Guo, and M. Gu, “Enhanced explicit semantic analysis for product model retrieval in construction industry,” *IEEE Trans. Ind. Informat.*, vol. 13, no. 6, pp. 3361–3369, Dec. 2017.

[21] R. Renu and G. Mocko, “Retrieval of solid models based on assembly similarity,” *Comput. Aided Des. Appl.*, vol. 13, no. 5, pp. 628–636, Sep. 2016.

[22] T. Zhuang, X. Zhang, Z. Hou, W. Zuo, and Y. Liu, “A Novel 3D CAD model retrieval method based on vertices classification and weights combination optimization,” *Math. Probl. Eng.*, vol. 2017, p. 12, Jan. 2017, Art. no. 6049750.

[23] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, pp. 436–444, May 2015.

[24] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee, “Enhanced deep residual networks for single image Super-Resolution,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Honolulu, HI, USA, 2017, pp. 1132–1140.

[25] L. Yu, H. Chen, Q. Dou, J. Qin, and P. A. Heng, “Automated melanoma recognition in dermoscopy images via very deep residual networks,” *IEEE Trans. Med. Imag.*, vol. 36, no. 4, pp. 994–1004, Apr. 2017.

[26] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” *Commun. ACM*, vol. 60, no. 6, pp. 84–90, Jun. 2017.

[27] K. Simonyan and A. Zisserman, “Very deep convolutional networks for Large-Scale image recognition,” in *Proc. Int. Conf. Learn. Representations*, San Diego, CA, USA, 2015. Available: https://arxiv.org/abs/1409.1556

[28] C. Szegedy *et al.*, “Going deeper with convolutions,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Boston, MA, USA, 2015, pp. 1–9.

[29] G. Huang, Z. Liu, L. v. d. Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Honolulu, HI, USA, 2017, pp. 2261–2269.

[30] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Las Vegas, NV, USA, 2016, pp. 770–778.

[31] K. He, X. Zhang, S. Ren, and J. Sun, “Identity mappings in deep residual networks,” in *Proc. Eur. Conf. Comput. Vis.*, Amsterdam, Netherlands, 2016, pp. 630–645.

[32] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in *Proc. J. Mach. Learn. Res.*, Lille, France, 2015, pp. 448–456.

[33] Y. Wen, K. Zhang, Z. Li, and Y. Qiao, “A discriminative feature learning approach for deep face recognition,” in *Proc. Eur. Conf. Comput. Vis.*, Amsterdam, Netherlands, 2016, pp. 499–515.

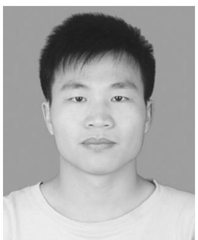
[34] W. Zhirong *et al.*, “3D ShapeNets: A deep representation for volumetric shapes,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Boston, MA, USA, 2015, pp. 1912–1920.

[35] D. P. Kingma and J. L. Ba, “Adam: A method for stochastic optimization,” in *Proc. Int. Conf. Learn. Representations*, San Diego, CA, USA, 2015, pp. 1–11. Available: https://arXiv:1412.6980

[36] H. Su, S. Maji, E. Kalogerakis, and E. Learned-Miller, “Multi-view convolutional neural networks for 3D shape recognition,” in *Proc. IEEE Int. Conf. Comput. Vis.*, Santiago, Chile, 2015, pp. 945–953.

[37] Y. Feng, Z. Zhang, X. Zhao, R. Ji, and Y. Gao, “GVCNN: Group-View convolutional neural networks for 3D shape recognition,” in *Proc. IEEE/Comput. Vis. Found. Conf. Comput. Vis. Pattern Recognit.*, Salt Lake City, UT, USA, 2018, pp. 264–272.

[38] X. He, Y. Zhou, Z. Zhou, S. Bai, and X. Bai, "Triplet-center loss for multi-view 3D object retrieval," in *Proc. IEEE/ Comput. Vis. Found. Conf. Comput. Vis. Pattern Recognit.*, Salt Lake City, UT, USA, 2018, pp. 1945–1954.
[39] H. Liu, F. Wang, F. Sun, and B. Fang, "Surface material retrieval using weakly paired cross-modal learning," *IEEE Trans. Automat. Sci. Eng.*, vol. 16, no. 2, pp. 781–791, Apr. 2019.
[40] H. Liu, F. Wang, F. Sun, and X. Zhang, "Active visual-tactile cross-modal matching," *IEEE Trans. Cogn. Developmental Syst.*, vol. 11, no. 2, pp. 176–187, Jun. 2019.



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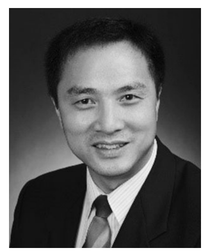

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