Title:
Development of a 3D Shape Retrieval Model with Neural Network-based Feature Extraction

Authors:
Gwanghee Park, parkgh@hyundai.com, Hyundai Motor Company
Soo In Lee, sooin.lee@hyundai.com, Hyundai Motor Company
Sinyoung Kang, NewYoung@hyundai.com, Hyundai Motor Company

Keywords:
Deep Learning, 3D Classification, 3D Shape Retrieval, Point Cloud

DOI: 10.14733/cadconfP.2024.87-92

Introduction:
Artificial intelligence is exerting a significant influence on various industrial fields such as the automotive industry and other manufacturing industries, impacting product development processes. To keep up with these waves, they are facing the challenge of processing, understanding, and utilizing vast amounts of data generated during product development. Particularly, the unique character of engineering data and the complexity of preprocessing make data acquisition and analysis difficult [1]. Due to the structural complexity of 3D Computer-Aided Design (CAD) data and the lack of analysis techniques related to it, applications utilizing artificial intelligence with industrial 3D CAD data are reported to be quite limited. Furthermore, the datasets employed in most previous research have relatively simplistic geometries and a limited number of classes/subclasses. However, in industrial domains, notably within mobility manufacturing, the 3D CAD datasets have complex geometries, extensive class/subclass diversity, and inherent data imbalances among classes.

Services that find similar 2D images and provide information related to the input images, similar to those used by portal sites such as Google, have become actively utilized. This approach of searching images without relying on textual information is known as "Content-Based Image Retrieval (CBIR)," and it is a strategic response by the industrial sector to effectively adapt to the shift from text-centric communication to image-centric communication.

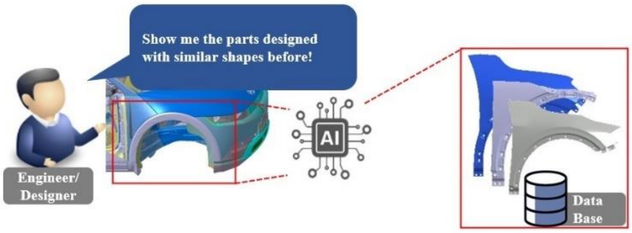

Fig. 1: Shape retrieval user scenario for engineers.

3D CAD data holds significant importance in automobile design. In comparison to the past, when design was carried out with only 2D drawings, it has become much easier to identify errors or issues during the design process visually. Additionally, it is now possible to assess clearances/interferences between adjacent components, assembly feasibility, package reviews, and more, all before the actual vehicle assembly. Therefore, providing a service that facilitates the easy retrieval of 3D CAD data with similar shapes, as shown in Fig. 1., improves the design efficiency and mobility design process through 3D data-centric communication. This study aims to assess the applicability of a 3D shape feature extraction methodology and shape-based retrieval models, previously demonstrated to yield performance, to complex industrial datasets.

Research Methodology:

The aim of this study is to extract the shape features of 3D data through a deep neural network and build a similar shape retrieval model using these features. To achieve this, we proposed appropriate methods for data acquisition and 3D CAD data preprocessing and outlined the structure and applications of the deep neural network for shape feature extraction.

Data

Among the various deep learning research that utilizes 3D data, point-based deep learning research has gained considerable attention [2]. Point clouds have the unique characteristic of being unordered, unlike images or voxels, making it challenging to learn deep neural network models. However, methodologies have been researched to address these issues. Point-Net, a prominent model that utilizes point clouds, resolves these problems while maintaining a lightweight model structure compared to models adopting other preprocessing methods [3]. A model with relatively few parameters provides significant advantages in terms of computational speed. Additionally, it provides benefits in terms of model maintenance.

Therefore, a preprocessing method for utilizing point clouds is applied in the research. The 3D CAD data was converted into point cloud format through a systematic process during the data preprocessing. CAD data stored in CATIA's CATIA Graphical Representation (CGR) format were first converted into Stereolithography (STL) format using CATIA V5 and then transformed into point cloud format based on the mesh information of the STL files. To observe the performance difference of deep learning models based on the number of points, point cloud datasets with 512/1024/2048/4096 points were created. After preprocessing, noise was added to the point cloud (Jittering) and the order of points was shuffled (Shuffling) to enhance the robustness of the deep learning model. The dataset consists of 3D CAD data for 26 car models, classified based on car type and parts. The number of 3D CAD data for each car model for this research is around 1,100, totally around 29,000. The dataset encompasses approximately 1,200 class labels (low-level units) and around 300 subclass labels (mid-level units).

Model

The core of the shape retrieval model developed in this study is how to accurately represent the shape feature of 3D CAD data within a deep neural network latent space.

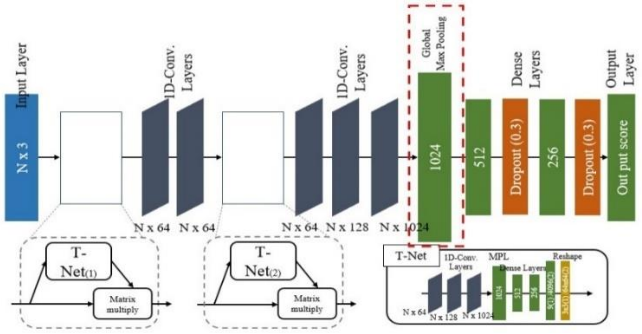

Fig. 2: Classification model architecture.

Most deep learning models pass through multiple complex neural networks to represent compressed data information in the latent space, enabling processes like classification, segmentation, and retrieval. This study develops a 3D-based shape retrieval model with two stages:

1. Classification model: A deep neural network model is trained to classify part numbers based on the input point cloud data. During this process, the model's global features are trained to represent the geometric information of the input data.

2. Shape retrieval algorithm: By measuring the distances between vectors transformed into global feature representations, similar shapes are recommended based on the input data.

The architecture of the classification model with deep neural network referenced Point-Net, as shown in Fig. 2. Point-Net structure showed meaningful performance to create a shape retrieval models in previous studies, maintains result consistency even if the sequence of input points changes, achieved through a mini-network called T-net [3]. For the previous Point-Net model, it was trained based on the open dataset ModelNet40. Because the dataset used in the study had special characteristics (complexity, diversity, and imbalance), the Point-Net structure model was newly trained. The performance of the newly trained model was analyzed compared to the pre-trained model.

The shape retrieval algorithm developed in this study determines the retrieval results based on the distances between data represented in the latent space. As described in Fig. 3, the query 3D CAD data is preprocessed and passed through the trained deep learning model to represent it in the latent space, which serves as the global feature. Then, data with closer distances in the latent space are sorted sequentially. In accordance with this sorted order, the shape retrieval results are presented as the representative shapes of the dataset.

Cosine similarity and Euclidean distance were used to measure the similarity between data represented in the latent space. As a higher cosine similarity or lower Euclidean distance indicates higher similarity, both methods can be adopted as a basis for similarity comparison. The performance of retrieval based on each similarity comparison method was analyzed.

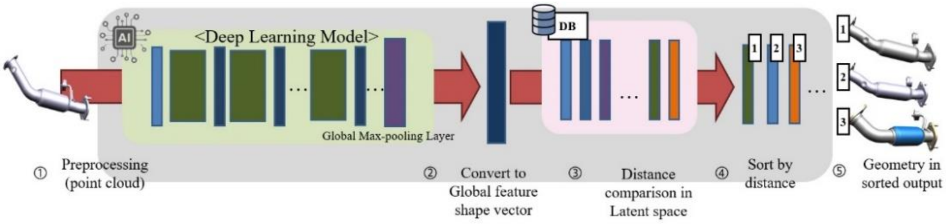

Fig. 3: Shape retrieval algorithm architecture.

Results:

The results of the shape retrieval model are divided into two main steps. The first step involves the evaluation of the classification model's training results. The evaluation of the training model results was conducted to verify the impact of the number of points per data and assess how effectively the deep neural network extracts the 3D CAD data's geometric information. The second step encompasses the evaluation of the 3D shape retrieval results. Quantitative metrics for evaluating the retrieval algorithm were employed, in addition to a qualitative assessment of how well the shape retrieval model identified similarity using actual 3D CAD data as a reference.

Classification Model Results

The performance of the classification model was examined by varying the number of points per data. Accuracy, Top 5 accuracy (where the true class is among the top 5 predicted by the model), Precision, Recall, and F1-score for both Macro and Weighted Averages per class were used as evaluation metrics. The results for each case were recorded in Tab. 1.

Analyzing the impact of the number of points per data during the classification model training process revealed that the highest accuracy was observed when using 2048 points among the set point numbers (512, 1024, 2048, 4096). While the accuracy increased as the number of points increased from 512 to 1024 and 2048, it was predicted to converge after a certain point based on the results from 4096 cases. This observation aligns with the fact that as the number of points increases, finer details become more distinguishable; however, beyond a certain step, the differences in the representation of finer details reach saturation. This convergence phenomenon can also be observed in previous studies. Moreover, when assigning class labels based on mid-level units rather than low-level units (part numbers), the accuracy exhibited no significant difference despite a substantial reduction in the number of classes.

	Condition	*Model Performance*							
No	*Point Cloud #*	*Accuracy*	*Accuracy (Top 5)*	*Macro Avg.*			*Weighted Avg.*		
				Precision	*Recall*	*F1-score*	*Precision*	*Recall*	*F1-score*
1	512	0.763	0.879	0.710	0.730	0.697	0.766	0.763	0.743
2	1024	0.766	0.877	0.721	0.739	0.705	0.772	0.766	0.746
3	2048	0.796	0.892	0.730	0.763	0.726	0.795	0.796	0.777
4	4096	0.772	0.884	0.715	0.730	0.701	0.777	0.772	0.753
*Mlu**	2048	0.769	0.873	0.766	0.749	0.743	0.788	0.769	0.770
*Ref**	2048	0.868	0.982	0.820	0.811	0.807	0.875	0.868	0.867

(**Mlu* :Model trained with mid-level units class labels, **Ref* : Reference model trained with ModelNet40)

Tab. 1: Performance of the classification model.

Shape Retrieval Algorithm Results

The results of the shape retrieval algorithm are described in Tab. 2. From the results of the similarity calculations between embedding vectors derived from the trained model; it was observed that using cosine similarity outperformed using Euclidean distance in all cases. Therefore, the conclusion was reached that cosine similarity is a more suitable method for measuring similarity in the shape retrieval model using the trained classification model.

	Condition	*Performance – Cosine Similarity*			*Performance –Euclidean Distance*		
No	*Point Cloud #*	*mAP@10*	*mAP@100*	*MRR*	*mAP@10*	*mAP@100*	*MRR*
1	512	0.628	0.555	0.657	0.621	0.552	0.654
2	1024	0.637	0.566	0.663	0.632	0.564	0.660
3	2048	0.644	0.577	0.666	0.643	0.576	0.664
4	4096	0.651	0.578	0.678	0.640	0.571	0.669
*Mlu**	2048	0.610	0.494	0.649	0.597	0.483	0.636
*Ref**	2048	0.556	0.442	0.596	0.546	0.435	0.589

(**Mlu* : Model trained with mid-level units class labels, **Ref* : Reference model trained with ModelNet40)

Tab. 2: Performance of the shape retrieval algorithm.

Furthermore, as the number of points increased from 512 to 1024 and 2048, the retrieval performance improved, like the trend observed in the classification results. However, unlike the classification results, the retrieval performance continued to increase even with 4096 points, particularly when employing cosine similarity for similarity calculation. Thus, while the accuracy of the classification model approached convergence beyond a certain step, the performance of the retrieval algorithm showed potential for improvement. It's important to note that as the number of points increases, the computational load within the model increases, potentially affecting the speed of the shape retrieval system. Furthermore, when trained on the mid-level units, it was observed that there was a noticeable decrease in retrieval performance, indicating that class labels by low-level units (part numbers) better represents the features of 3D shapes. Therefore, a final model was selected, considering overall factors such as classification accuracy, retrieval algorithm precision, and computational load, and it was used for a web application program.

The qualitative analysis of the final shape retrieval model is presented in Fig. 4. It confirms that the queried 3D CAD data have similar counterparts within the Top 5 recommendations. Additionally, it was evident that the Top 100 results contained less similar shape. The inclusion of similar shapes with different part numbers (class labels) was also observed by the retrieval results. Thus, we also identified outcomes that cannot be provided by part number-based 3D drawing searches.

Conclusions:

In this study, the following characteristics and results were observed:

1. This study validated the efficacy of 3D shape retrieval model that employed feature extraction methodology based on a classification model. This validation was achieved through training the retrieval model on an industrial dataset with distinctive characteristics, including complexity, diversity, and class imbalance.
2. Through a comparative analysis of the performance of the shape retrieval model trained on an industrial dataset and trained on an open dataset, this study explored the usability and limitations of the shape retrieval model trained with open datasets.
3. Through case studies of preprocessing methods, comparisons of similarity measurements, and other analyses, the performance of the retrieval model was assessed. Factors influencing the model's performance were also examined.

Future research will involve investigating the performance of related deep learning models based on different preprocessing methods for 3D CAD data beyond point clouds. Furthermore, we plan to explore various deep-learning methodologies to extract shape features more accurately from 3D CAD data. Through this, we intend to propose a data analysis based on 3D shape information.

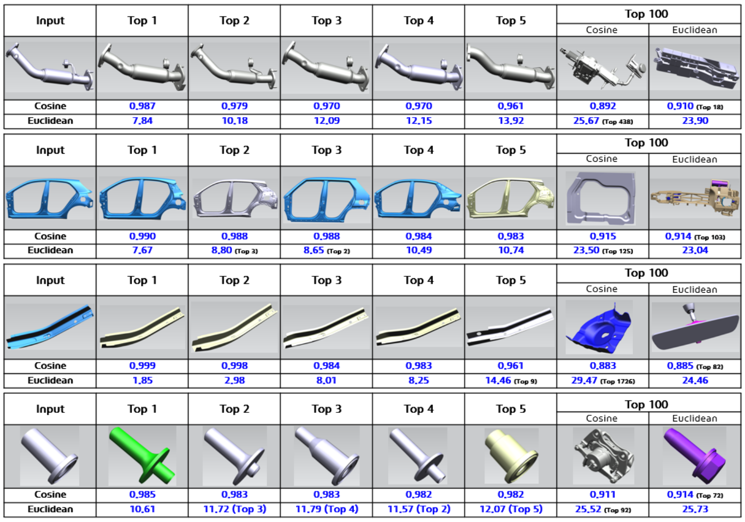

Fig. 4: Shape retrieval algorithm results with vehicle parts.

Gwanghee Park, https://orcid.org/0009-0007-0129-9883
Soo In Lee, https://orcid.org/0009-0000-5306-8891
Sinyoung. Kang, https://orcid.org/0009-0000-4536-8755

References:

[1] Dekhtiar, J.; Durupt, A.; Bricogne, M.; Benoit, E.; Rowson, H.; Kiritsis, D.: Deep learning for big data applications in CAD and PLM – Research review, opportunities and case study, Computers in Industry, 100, 2018, 227-243, https://doi.org/10.1016/j.compind.2018.04.005

[2] Guo, Y.; Wang, H.; Hu, Q.; Liu, H.; Liu, L.; Bennamoun, M.: Deep learning for 3d point clouds: A survey. IEEE transactions on pattern analysis and machine intelligence, 43(12), 2020, 4338-4364, https://doi.org/10.1109/TPAMI.2020.3005434

[3] Qi, C.-R.; Su, H.; Mo, K.; Guibas, L.-J.: PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, 77-85, https://doi.org/10.1109/CVPR.2017.16