A Flexible Approach for Retrieving Geometrically Similar Finite Element Models Using Point Cloud Autoencoders

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Abstract: For the development of complex products like vehicle components, knowledge about previous solutions is a key factor. Complete solutions or parts thereof can often be reused if a similar previous model can be identified. To gain independence from the individual experience of single engineers about previous models and a tedious search process, identifying and retrieving the most similar models from large databases offers great potential. Accordingly, this paper introduces a method to achieve this kind of shape retrieval based on engineering data. 3D geometries are represented as point clouds and reduced to one single vector with an autoencoder to identify similarities in the latent space. The method can be used in a flexible way to identify global or local similarities as well as to emphasize different parts of the structure in the similarity search. The method is evaluated on an industrial dataset containing real-world engineering data.

1 INTRODUCTION

New car models are most often not developed from scratch, but build upon previously established basic concepts and knowledge. Multiple car models are commonly based on one shared platform in order to save cost, increase flexibility and manage complexity (Muffatto, 1999). The car models originating from the same platform often share principal parts of the design, like the body in white, while individualising other segments. Additionally, different product families can exist, where similar car body styles like SUVs are clustered and share similarities. Because of this, car models from the same company are usually not inherently different as there are relations to at least some other models.

In addition to these general similarities between different car models, knowledge is also transferred between unrelated models. During the structural design process, finite element (FE) models are simulated to predict performance values without conducting many expensive hardware tests. When a model does not satisfy required target values, changes have to be made to the geometry to improve the results. Classical optimization approaches are often not feasible in such complex models with multiple objectives, so that engineers have to take the decisions on how to change the model. The solutions highly depend on the individual skills and experience of the responsible engineer. Therefore, knowledge is an important factor in the automotive industry, for general car concepts as well as for the detailed design.

To facilitate and objectify the structural design process, it would be beneficial to have the possibility to search a large database with all models of a company for similar models compared to a model currently under development. Since similarities to previous models often exist, it is likely that solutions could be transferred from past processes. Having information about similar models from the complete database would enable the engineer to consider solutions from many models, in contrast to only using limited personal knowledge about similar models. Since models frequently share some common features, while the complete models are more different, the consideration of local similarities could also be of interest to obtain the most relevant results. To maximize the benefit for an engineer, the possibility to flexibly choose the desired local area for the similarity search would be advantageous.

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In this paper, we propose a method to retrieve the most similar finite element models from a database to an arbitrary input model. The models are represented as point clouds, whose dimensionality is reduced with an autoencoder. The obtained latent vectors are then used for the assessment of similarity and the subsequent retrieval of the models. Depending on the sampling strategy of the point clouds, global and local similarities can be retrieved as well as putting emphasis on different aspects of the geometry. We show that meaningful models can be retrieved with our method, that can then be used by engineers for the transfer of previous solutions in similar situations.

2 STATE OF THE ART

Geometric engineering data can be available in different data formats. Computer Aided Design (CAD) models e.g. consist of Boundary Representation (B-Rep) objects, Constructive Solid Geometry (CSG) or combinations thereof (Xu et al., 2021), while finite element (FE) models used for simulations are meshed models defined by a number of nodes and elements. Other possible formats of geometric engineering data include e.g. surface meshes for additive manufacturing or mathematically defined curves like Non-Uniform Rational B-Splines (NURBS) for exchange formats (Starly et al., 2005).

Data formats like these are naturally unstructured and cannot directly be used for comparison. Therefore, a representation of the data is a necessary first step for the retrieval of models with similar geometric characteristics. In this section, we first introduce different possibilities for 3D data representations in Section 2.1, before we present previous approaches of shape retrieval in the engineering domain in Section 2.2.

2.1 3D Data Representation

A multitude of approaches exist to transform unstructured 3D data into usable representations. A common approach is to convert the data into a format for which established algorithms can be applied. Similar to 2D images consisting of pixels, 3D data can be approximated by a volumetric grid consisting of voxels (Maturana and Scherer, 2015). Another common option to allow the use of algorithms proven in 2D is the projection of the 3D data to a 2D space by taking images from defined viewpoints (Su et al., 2015). The use of hand-crafted features or basic shape descriptors usually leads to a high explainability, but previous knowledge about the data is required to chose adequate descriptors (Bustos et al., 2005).

In recent years, great progress has been made on learning directly on non-euclidean data. PointNet (Qi et al., 2017) is a well known architecture taking point clouds as input without further preprocessing. This is advantageous compared to other approaches because of its efficiency and compact representation, while having the ability to describe geometric details. Similarly, systems learning directly on meshes were introduced, transforming convolutional algorithms to the mesh domain (Hanocka et al., 2019). Other recent approaches are based on graph representations (Shi and Rajkumar, 2020).

A more specific option to reduce data to one descriptive vector are autoencoders. As neural networks, these use an encoder to reduce the dimensionality of the input data to one latent vector and a decoder to retrieve an output resembling the input. They are trained by minimizing the difference between input and output. In recent years, approaches using autoencoders directly on point clouds led to promising results (Achlioptas et al., 2018; Yang et al., 2018).

2.2 Engineering Shape Retrieval Approaches

Shape retrieval has been a longstanding problem in the engineering domain and has inspired a multitude of approaches. Many of these are based on shape descriptors that represent the geometry in a simplified way. Examples are the use of shape distribution histograms (Li et al., 2011; Hong et al., 2006), Opitz Coding (Zehtaban and Roller, 2013), attribute adjacency graphs and surface line distribution (Ma et al., 2019) or distance distribution histograms (Zhuang et al., 2017). Other similar approaches not only aim at the retrieval of parts with global similarity, but offer the possibility for partial retrieval by partitioning models into segments (Tao et al., 2013; Ji et al., 2023; Bai et al., 2010). However, the segmentation in these approaches is fixed for each model, leading to an inflexible process without taking into account the engineer's specific needs. Approaches based on shape descriptors as described above are often geared towards a specific dataset or use case and their generalization to other datasets is not proven (Bustos et al., 2005). Additionally, most previous approaches are based on the retrieval of CAD models. They are limited to CAD formats and not applicable to similarity searches for data formats like finite elements.

An approach that does not suffer from these restrictions was introduced by (Krahe et al., 2022). In this approach, an autoencoder is used together with point cloud representations to describe CAD models for similarity search. Bickel et al. also use an autoencoder in their approach, but combine it with a projection of vertices of meshed models onto a sphere to obtain a matrix representation (Bickel et al., 2023). Another approach using autoencoders is based on multi-view projections of 3D shapes to 2D images (Zhu et al., 2016). All of these approaches focus only on global similarity. Furthermore, the methods were evaluated based on datasets consisting of different classes, considering if retrieved parts belong to the same class as the input model. There, the goal is to identify models for potential reuse (Krahe et al., 2022). While this is sufficient based on the specific use case, the focus of our proposed approach is the discovery of similarities between different variants of the same class to enable knowledge transfer on a more detailed level.

Our goal of a shape retrieval method that is not dependent on specific data formats like CAD models, that generalizes well to diverse shapes and that can be used for global or local shape retrieval in a flexible way has yet to be fully addressed.

3 METHODOLOGY

For our proposed shape retrieval method, the geometry is first represented as point clouds. These are then used as an input for an autoencoder, that reduces the dimensionality of the representation to one latent vector. Based on these vectors, the similarity search and retrieval is performed. We introduce our database in Section 3.1, the processing of the geometry to obtain relevant point clouds in Section 3.2 and the architecture of the point cloud autoencoder in Section 3.3. Finally, we explain our method of retrieving similar geometries in Section 3.4.

3.1 Database

The data used in this work originates from the car development process at BMW, consisting of meshed models of car bonnets from previously performed FE simulations. Figure 1 shows the parts considered for an exemplary model.

3145 complete models based on 37 different car projects were retrieved from our database. The focus of our work is on the retrieval of similar parts from the same class, where the inner sheet is used as exemplary part. The inner sheet is a part present in every car that is crucial for its stability and stiffness as well as for crash functionality. Some exemplary inner sheets from different car models are shown in Figure 2. For evaluation purposes, the method is additionally applied to a dataset consisting of the five different classes of parts shown in Figure 1.

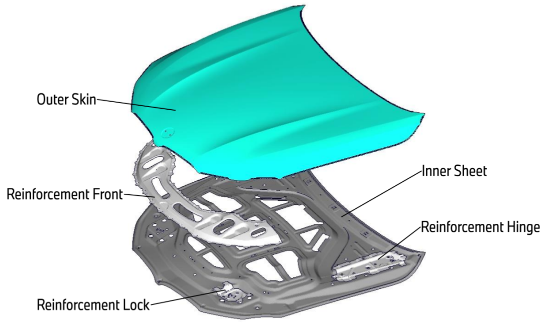


Figure 1: Explosion view of parts from an exemplary bonnet.

3.2 Sampling of Points

The input format required by our autoencoder are point clouds. Since our database consists of meshed models, their nodes can directly be considered as points. For other engineering data formats, methods like ray tracing can be employed to obtain point cloud representations. To make use of the autoencoder, a consistent input size is needed. We chose an input size of 1024 points for a balance of detailed representation and efficiency and sample this number of points from each of the original point clouds in different ways.

Depending on the desired kind of similarity, it is possible to sample points from only the edges of a part, from all of its points or a combination thereof. When sampling only from the edges, more emphasis is put on the outer contour of the parts, while considering all points leads to a higher importance of the 3D structures. When representing complete inner sheets, we randomly sample half of the points from the edges of each part and half from the rest of the existing points as a middle ground between the options. Figure 3 shows the obtained point cloud representation of the parts from Figure 2.

In order to retrieve models with a locally high similarity, points can be sampled from a smaller area of each part. We propose to define a circle around the area of interest with an arbitrarily chosen center and radius, and sample points only inside this circle. To account for the different sizes of the parts from different car projects, the center of the circles is defined relatively considering the bounding box dimensions of each part. If not stated otherwise, points are sampled from all relevant nodes for this approach, since depending on the chosen area no edges might be present. Figure 4 shows the sampled sections for exemplary parts, location and radius.

Important similarity information might not only

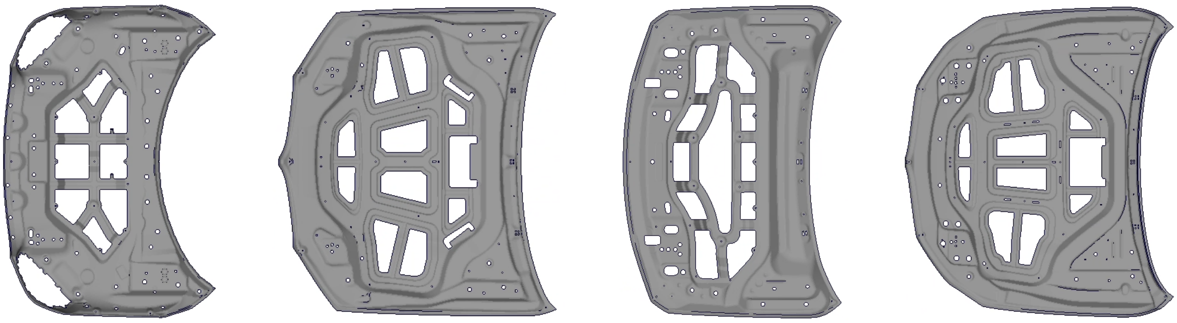


Figure 2: Exemplary inner sheets, rendered from meshes, viewed from top.

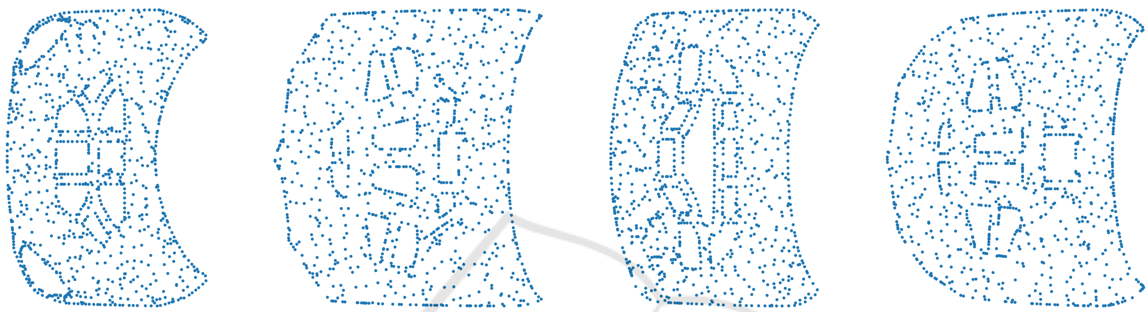


Figure 3: Exemplary sampled point clouds, viewed from top.

be present in individual parts, but also in the relative location of a bonnet's assembled parts towards each other or the distances between them. To consider this information in the similarity search, the complete assembly can be used as a basis. A center and radius are defined as explained above, while instead of a circle, a sphere is defined as a boundary. The points are then sampled inside this sphere for all assemblies, considering all sections of parts lying within the defined sphere. This is shown in Figure 5 for exemplary models.

3.3 Point Cloud Autoencoder

As basis for the retrieval, the point cloud autoencoder proposed by (Achlioptas et al., 2018) is chosen because of its competitive results for different tasks. The input is a 3D geometry represented as point cloud with a size of N points times three dimensions. The autoencoder consists of five 1D convolutional layers with a kernel size of one as an encoder, and three fully-connected layers as a decoder. As loss function, the chamfer distance is chosen to account for the permutation-invariance of point clouds. The input point clouds are normalized. More information about the point cloud autoencoder can be found in (Achlioptas et al., 2018). Figure 6 shows the principal architecture of the point cloud autoencoder.

3.4 Retrieval Process

After the training of the autoencoder with the sampled point clouds is completed, the most similar models to an arbitrary input point cloud can be retrieved. A point cloud with the appropriate number of points is sampled from the test model and encoded with the trained autoencoder to obtain a latent representation. The cosine distance is calculated between this representation and all other latent representations from the dataset, as shown in Equation 1 for exemplary vectors **a** and **b**. The n most similar models, having the lowest cosine distance, are retrieved and returned to the engineer for further use.

$$d_{cos}(\mathbf{a},\mathbf{b}) = 1 - \frac{\mathbf{a}\cdot\mathbf{b}}{||\mathbf{a}||_2\,||\mathbf{b}||_2} \tag{1}$$

4 RETRIEVAL RESULTS

The main focus of our work lies on the retrieval of similar models from the same class, which we present in Section 4.2. For evaluation purposes and comparison with previous methods, we additionally consider a multi-class setting in Section 4.1. In both cases, we sample 1024 points from each part in different ways and train the autoencoder for 50 epochs. For the size of the latent vector, we use 128 dimensions.

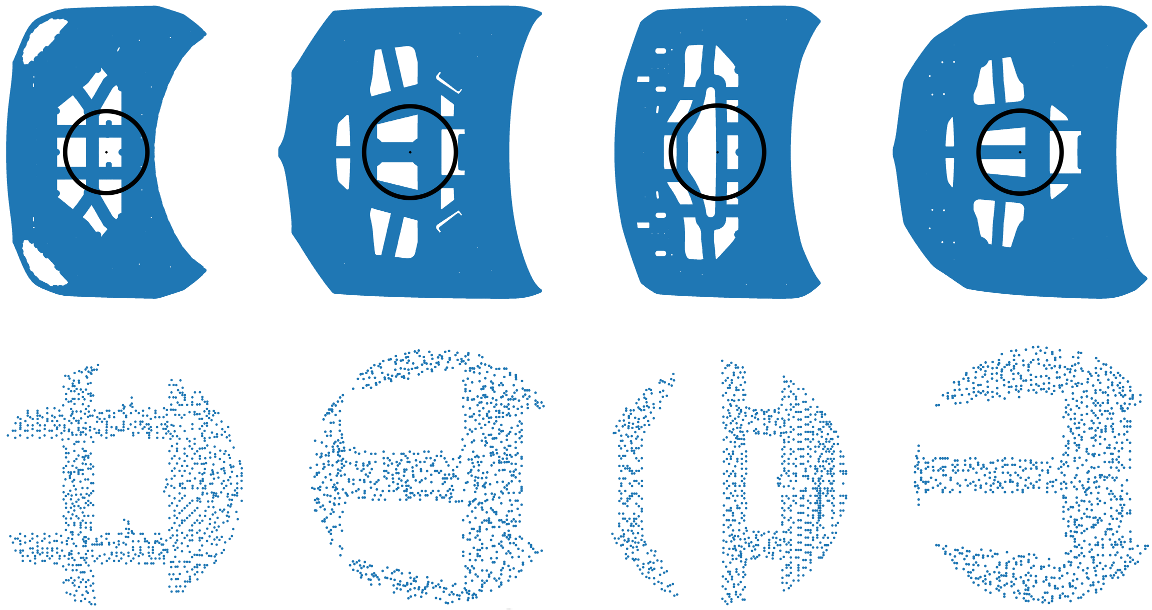


Figure 4: Exemplary sampled circle sections from the center with radius = 250 mm, viewed from top.

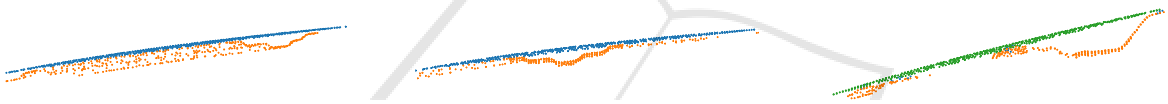


Figure 5: Exemplary sampled sphere sections from the center with radius = 250 mm, viewed from the side. Different colors indicate different parts.

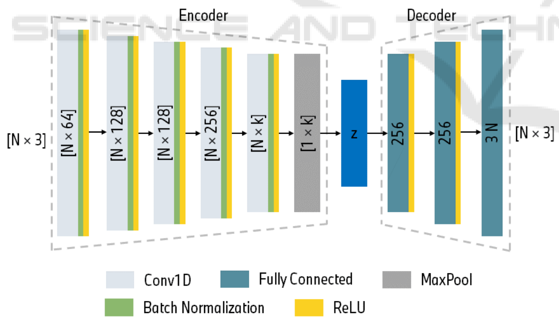


Figure 6: Autoencoder architecture where N is the number of points, z is the latent vector and k is the size of the latent vector. Visualization adapted from (Saha et al., 2021).

4.1 Retrieval of Similar Parts from Different Classes

For the multi-class setting, we train our autoencoder with the dataset consisting of parts from the five different classes shown in Figure 1. Since we only use unique part models and different parts are modified more or less frequently during a vehicle development process, different numbers of parts are obtained per class. Our multi-class dataset consists of 2595 inner sheets, 433 outer skins, 790 front reinforcments, 406 hinge reinforcments and 177 lock reinforcements.

We sample points from both edges and surfaces proportionate to the total numbers of points. Analogously to (Bickel et al., 2023), we use the complete dataset for training and evaluate the performance based on multiple metrics. Retrievals are considered to be correct, if they originate from the same class as the input model. The following metrics are used:

Nearest Neighbour (NN):
Precision of the most similar retrieval result.

First Tier (FT):
Recall results of the best $n-1$ results, where n is the number of models in the relevant class.

Second Tier (ST):
Recall results of the best $2 \cdot (n-1)$ results, where n is the number of models in the relevant class.

The relevant values are retrieved for every model in the dataset and the average resulting values reported in Table 1, divided into individual classes.

(a) Distance 0.0076. (b) Distance 0.021. (c) Distance 0.21.

Figure 7: Global similarity of different models (orange) to the test model (blue) viewed from top. Most similar model in (a), intermediate similarity in (b), least similar model in (c).

Table 1: Shape retrieval results for the multi-class setting. Best: 1.0, worst: 0.0.

	NN	FT	ST
Outer skin	0.991	0.289	0.446
Inner sheet	0.999	0.863	1.0
Reinforcement front	1.0	0.929	0.996
Reinforcement hinge	1.0	0.873	0.957
Reinforcement lock	1.0	0.926	0.994
Complete	**0.999**	**0.822**	**0.941**

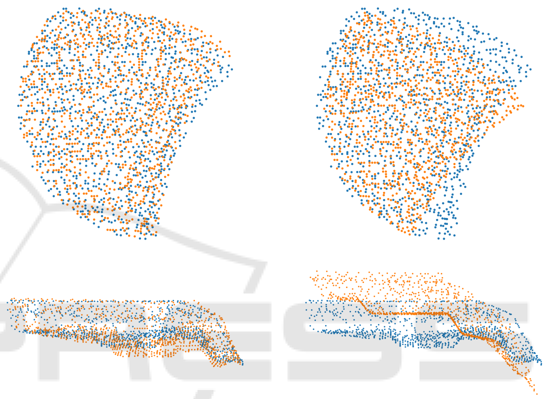
4.2 Retrieval of Similar Parts from a Single Class

Since the use case of interest is the retrieval of similar parts to a newly developed model, one individual inner sheet model is defined as test model and only parts from different car projects are used for training. This process is performed for multiple exemplary test models.

First, we consider the global similarity of individual parts, where points are sampled from complete inner sheet models. Figure 7 shows one exemplary test model together with different models and their indicated similarity values. Figure 7a shows the most similar model from the dataset, Figure 7c the least similar one.

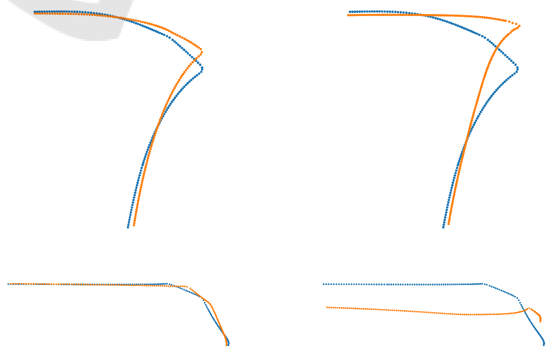
Next, location and radius are defined and points sampled within the circle to investigate local similarities. The autoencoder is trained with only the points from the local sections. Analogously to the global similarity, we use one part as test model and remove the rest of the parts originating from the same car project. The most and least similar models for an exemplary input model are shown in Figure 8 for the corner of the parts.

Depending on the kind of similarity that is required, different sampling strategies can lead to dif-



(a) Distance 0.0044. (b) Distance 0.29.

Figure 8: Similarity of most and least similar models (orange) to the test model (blue) for a section in the corner, sampled from all points. Upper row is the view from top, lower row the view from front. Radius = 250 mm.



(a) Distance 0.0011. (b) Distance 0.37.

Figure 9: Similarity of most and least similar models (orange) to the test model (blue) for a section in the corner, sampled only from the edges. Upper row is the view from top, lower row the view from front. Radius = 250 mm.

(a) Distance 0.00043. (b) Distance 0.17.

Figure 10: Similarity of most and least similar models (orange) to the test model (blue) for a sphere section in the center of an assembly. View from side. Radius = 250 mm.

ferent similarity values. In the next example, we sample points from only the contour of the parts from the corner section to obtain the input point clouds. With this, different models are retrieved and shown in Figure 9.

In our final example complete assemblies are considered. Points are sampled within a sphere boundary around a point on the outer skin at the center of the bonnet. Retrieval results are shown in Figure 10.

The number of models used for training varies, since only unique models are considered. Models can have differences in some parts outside the section of interest, leading to a lower number of models for local similarities compared to global similarity.

5 DISCUSSION

The main advantage of our proposed approach lies in its flexibility. Point clouds can be obtained from all common engineering representations of 3D geometry, while the similarity search can be guided by the sampling strategy of the input points. For the local similarity, the section can be chosen completely flexible, in contrast to previous approaches. While we only considered sections in the shape of a circle or sphere, it is generally possible to use any shape for obtaining sections. By adjusting the sampling ratio between the edges and the complete part, engineers can guide the results into the desired direction to obtain the most relevant results.

The presented results show that our proposed method leads to promising results, as models with a high visual similarity to the input model are identified. An objective evaluation is however difficult, since no ground truth about desired levels of similarity is available. To prove the validity of the proposed approach, we additionally used our method with a multi-class dataset, as quantitative evaluation approaches are available for this problem formulation.

The multi-class setting is evaluated according to common metrics from literature. While high values are reached for the complete dataset, big differences are noticeable for the individual classes. The values of the outer skin are significantly behind the rest of the data for the first and second tier metric. A possible reason is the generally high similarity between outer skins and inner sheets. In the same car model, the outer contour of these two parts is predominantly the same, since they are assembled on top of each other. It is likely that similarities are higher between an outer skin and an inner sheet from the same model than two outer skins from more different car models. These results indicate that these geometries were encoded and retrieved according to their geometric similarity, which is suitable for our use case that focuses more on geometric similarity and less on specific classes.

This emphasizes our different focus compared to the related approaches introduced in Section 2.2. While the state of the art primarily focuses on the retrieval of parts from the correct class in a multi-class setting, our goal is the identification of the highest similarity within one class. In this setting, local similarities are of particular interest for applications and can be obtained in a flexible way, opposed to previous approaches that focus on global similarity or fixed local segments.

6 CONCLUSION

In this paper, we presented a method for similarity search and retrieval of 3D engineering data. We used a point cloud autoencoder for representation of geometry and assessed similarity values in its latent space. The results we show originate from real industrial engineering data, showing the method's relevance for real-world application. The key novelty of this paper lies in the flexibility of our method to guide the retrieval process towards desired kinds of similarity. Compared to previous approaches that focus on global retrieval or partial retrieval of fixed segments, local similarity can be retrieved for any section with our method. A further novelty is the retrieval of similar models for arbitrary sections from complete assemblies.

We achieved promising results for a variety of sampling strategies, whose relevance was confirmed by engineers. While the most similar models are unambiguous for many examples, there are other models where engineers can disagree on the most relevant results. Future research activities should therefore include a study about perceived similarity of the models by multiple engineers to enable a more quantitative evaluation. Additionally, a meaningful description of similarity opens up possibilities for more advanced future applications. This could e.g. include automatic quality checks or consideration of simulation results to retrieve relevant models even more precisely.

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