



Process-aware Part Retrieval for Cyber Manufacturing using Unsupervised Deep Learning

Xiaoliang Yan^a, Zhichao Wang^a, Jacob Bjorni^b, Changxuan Zhao^a, Mahmoud Dinar^b, David Rosen^a, Shreyes Melkote (1)^a

^aGeorge W. Woodruff School of Mechanical Engineering, Georgia Institute of Technology, Atlanta, GA, USA, 30332

^bDepartment of Mechanical Engineering, California State University Sacramento, Sacramento, CA, USA, 95819

Cyber manufacturing service, which connects end users with manufacturers over the internet, is significantly hampered by the lack of an automated part retrieval method. The state-of-the-art is focused on automatic shape retrieval, which does not consider manufacturing process requirements, such as material properties. This paper proposes a manufacturing process-aware part retrieval method using deep unsupervised learning that considers both part shape and material properties. Part retrieval results show that the proposed method yields 93.0% process and function class label matching precision, which outperforms the shape-only part retrieval model and supervised learning models trained with process, function, or both labels.

Digital manufacturing system, Machine learning, Automated part retrieval

1. Introduction

Cyber manufacturing services, as envisioned, seek to connect designers with manufacturers via an internet marketplace [1]. This vision has not been realized partly due to the lack of an efficient manufacturing service search engine that identifies and ranks manufacturers capable of producing a query part design. A possible solution is to compare the similarity between the query part and previously manufactured parts in an existing database. By retrieving the most similar parts, candidate manufacturers for the query part can be identified. Group Technology (GT) was an early attempt to group various parts and products with similar design and/or production process requirements in an existing database based on standard part encoding and classification rules [2, 3]. Although GT is still used in practice, it is not fully automated and requires manual preparation of data utilizing selected encoding rules, which is prone to errors and is laborious to maintain. Furthermore, because different suppliers may choose different encoding rules, GT is also difficult to scale across different encoding systems [4].

Developed as a computationally efficient alternative to manual grouping of 3D objects, shape descriptors have been studied extensively [4]. Shape descriptors are used to convert a 3D shape into vectorial representations, from which pairwise similarity of 3D shapes can be assessed. Shape descriptors such as D2 shape distribution, spherical harmonics (SH), and heat kernel signature have shown varying levels of efficacy in automated 3D shape retrieval [5]. Recent advances in deep learning and 3D data acquisition have led to growing interest in 3D shape retrieval using deep learning methods. Deep learning methods using different 3D representations such as point cloud, multi-views, and spatial occupancy grids have also been evaluated for shape retrieval [6].

It is evident from the above survey that several methodologies and data representations have been used to represent and automatically retrieve 3D shapes. Such advances have useful applications in 3D data-rich domains such as design and medical scanning [7]. In the context of manufacturing, however, pure shape similarity assessment of 3D CAD models is insufficient for

identifying candidate manufacturers, whose production capabilities depend on other manufacturing capability information such as material properties and achievable part quality. Therefore, this paper seeks to answer the following questions: (1) how important is including non-shape manufacturing capability information (e.g., input material properties) in part retrieval for cyber manufacturing applications? and (2) how can we effectively embed both non-shape manufacturing capability information and shape information using a unified vectorial representation? These questions are answered by developing a deep unsupervised learning-based part retrieval (DUPR) model shown schematically in Figure 1, where both 3D part shape and material properties are embedded in the latent vector representation. Here, we assume that the query part function and the required process can be inferred from shape and material property information, and therefore the process and function labels are assigned to both the query and existing parts only for performance evaluation. We consider process-aware part retrieval to be effective if both manufacturing process and function class labels of retrieved parts match those of the query part. The rationale is that a candidate manufacturer should nominally have produced parts with similar function and manufacturing process requirements. The performance of the proposed methodology is compared with a baseline supervised deep learning-based part retrieval model.

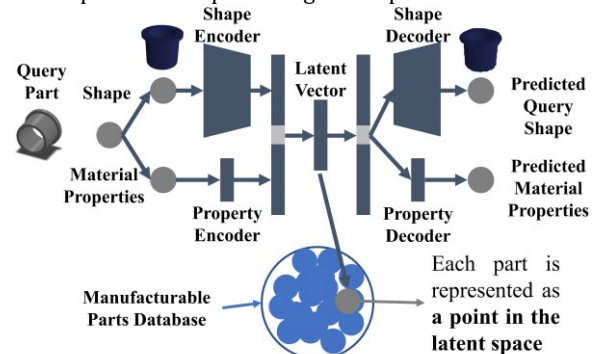


Figure 1. Deep unsupervised learning-based part retrieval (DUPR)

2. Dataset with 3D shapes and material properties

To develop a deep learning-based part retrieval model, a dataset consisting of 3D parts with both function (e.g., bearings, bushings) and manufacturing process class labels (e.g., milling, injection moulding) must be created. In addition, other manufacturing capability information (e.g., material properties) must be associated with shape data.

We curated and processed a subset of publicly available 3D parts data from the FabWave CAD repository [6], which was categorized by researchers at North Carolina State University into part function classes, as shown in Figure 2. In total, 1,354 parts consisting of 9 part function classes (see Table 1) were selected from the repository. Of these, 800 parts were randomly selected for training, while the remaining 554 parts were used for validation.



Figure 2. Example 3D CAD models and part function classes

A total of 45 distinct materials associated with the 9 function classes were collected. Of these, 16 selected material examples are shown in Table 1 with their respective function class associations. These materials were manually extracted from part catalogues of McMaster-Carr. The corresponding material properties (density, ultimate tensile strength, and melting point) were obtained from MatWeb and used for training the deep learning part retrieval models. Each part in the function class was randomly assigned a material and its properties based on the associations indicated in Table 1.

Based on the function class and material properties, each part was assigned a manufacturing process label (e.g., turning, milling, injection moulding). Note that some parts may require additional process(es) to produce them. Here, the process class label only indicates the process that creates the primary functional feature(s) of the part. While these parts can potentially be made using other processes, we consider each part is made by either milling, turning, or injection moulding. Additional assumptions are made to simplify the manufacturing process label assignment: (1) metal

parts are not injection moulded, and (2) the primary production process for axis-symmetric parts is turning.

In this work, a voxel representation was used to train the deep learning-based part retrieval models. 3D CAD models were voxelized with resolution of $128 \times 128 \times 128$.

3. Deep unsupervised part retrieval (DUPR) model

3.1. Model architecture and training

The architecture of the DUPR model is based on the 3D Autoencoder model [8], and is shown in Figure 3. In addition to the shape encoder-decoder pair, the DUPR model also has a property encoder-decoder pair that is used to encode material property information shown in Table 1. The objective function of the DUPR model consists of the shape reconstruction loss and the property prediction loss, as follows:

$$L = \|\hat{x} - x\|_2 + \lambda \|\hat{p} - p\|_2 \quad (1)$$

where x is the input to the shape encoder, $\hat{x}$ is the output of the shape decoder, p is the input to the property encoder, $\hat{p}$ is the output of the property decoder, and λ is a weight tuning parameter, which is set to 1. Both encoders and decoders are trained with the objective to minimize loss L . The models were constructed and trained using PyTorch, a python-based deep learning library, on a high-performance computing node (PACE Phoenix Cluster with 1 NVIDIA Tesla V100 16GB GPU). All components of the DUPR model were trained simultaneously on the training dataset for 20 epochs. The batch size was set to 1 for training with Adaptive moment estimation (Adam) as the optimizer. The learning rates were set to 6×10^{-5} .

3.2. Models for comparison

To evaluate the importance of the material property information in part retrieval, a shape-only autoencoder model was constructed and trained to compare with the DUPR model. The architecture of the shape-only autoencoder follows exactly the shape encoder-decoder pair of the DUPR model. The only difference between the two models is the exclusion of material properties in the shape-only autoencoder model. The model was trained on the same dataset for 20 epochs. The loss function in Eq. (1) was modified to exclude material property loss (second term). In addition, we also evaluate the performance of directly concatenating material properties to the latent shape vector as an alternative strategy to combine both types of information.

To determine the most effective method to embed material property information with shape information, a manufacturing process classifier and a function classifier were trained using the supervised deep-learning models shown in Figure 4. In addition, a multilabel model is trained with respect to both function and process labels.

Table 1. Representative part materials, their properties, and function classes

Materials	Density (g/cm ³)	Tensile Strength (MPa)	Melting Point (°C)	Bearing	Bushing	Miter Gear	Shaft Collar	Socket Head Screw	Rect. Gear Rack	Headless Screw	Rotary Shaft	Machine Key
1018 Carbon Steel	7.87	440.0	1205				X	X	X			X
2024 Aluminium	2.78	186.0	502				X	X			X	
303 Stainless Steel	8.00	690.0	1400			X	X			X	X	
360 Brass	8.49	338.0	885				X	X	X	X		
400 Nickel	8.86	517.0	1300					X		X		
6061 Aluminium	2.70	310.0	582				X			X		
660 Lead Bronze	8.93	240.0	977	X	X							
Acetal	1.41	66.0	176	X		X	X		X	X		
Buna-N Rubber	1.00	6.9	120	X								
EPDM	0.86	17.0	150		X							
Grade 2 Titanium	4.51	344.0	1665					X		X		
Nylon	1.15	75.3	220	X	X	X	X	X	X	X		
PEEK	1.45	160.0	343	X	X			X				
PTFE	2.17	25.6	331	X	X					X		
PVC	1.39	23.9	114	X	X					X		
PVDF	1.77	115.0	164	X								

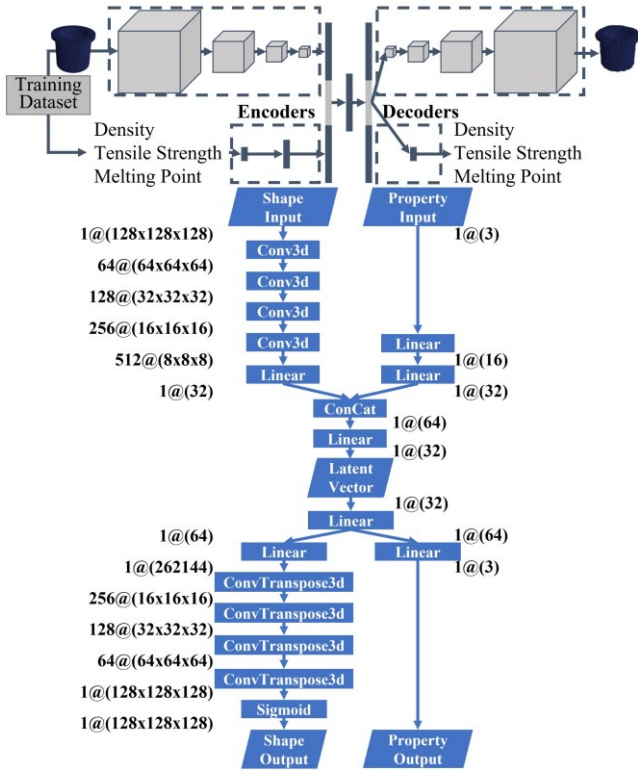


Figure 3. DUPR Architecture

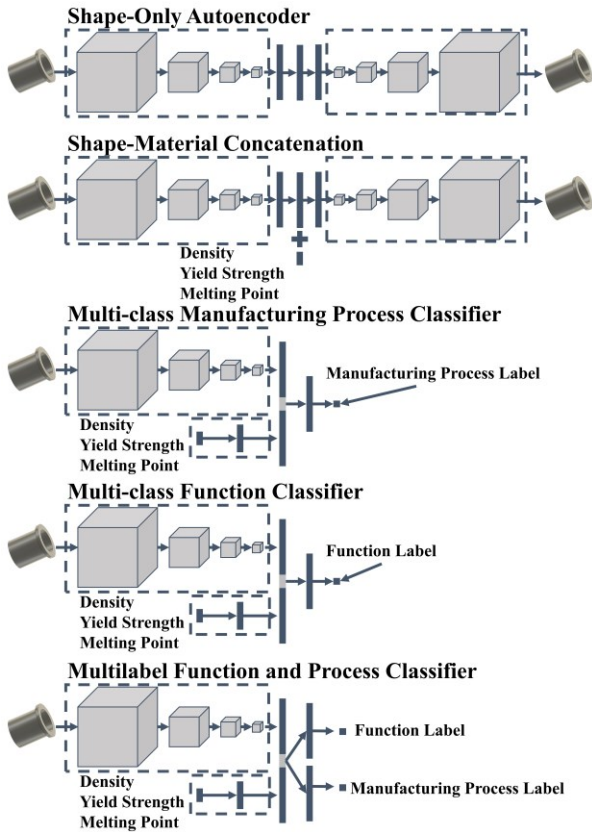


Figure 4. Models built for comparison

Supervised learning-based classifiers have been shown to effectively retrieve parts with manufacturing metadata (e.g., dimensions) [6]. The architecture of the supervised learning-based classifiers follows that of the shape and material property encoders in the DUPR model. However, instead of a full decoding network, a single fully connected linear layer is applied to the

encoding networks, which reduces the vectorial representation to the number of classes (3×1 for the process classifier and 9×1 for the function classifier). A SoftMax layer follows the linear layer to assign a probability to each class. All three classifier models were trained on the same training dataset for 20 epochs using a batch size of 1 with the cross-entropy loss as the objective function. For the multilabel classifier, the combined loss function is the sum of function label cross-entropy loss and process label cross-entropy loss.

3.4. Model evaluation

The unsupervised and supervised learning models were evaluated by observing the training losses (Figure 5). In addition, the supervised learning models were evaluated using the classification accuracy on the validation dataset, which consisted of 554 unseen test parts. It is evident from Figure 5 that all models converged to a low loss at 20 epochs. The DUPR model has a higher loss compared to the shape-only autoencoder, which can be attributed to the inclusion of material properties in the loss function. The process classifier converged slower than the function classifier, which is due to differences in classification objectives. It is evident that both the function classifier and the process classifier reached a high level of validation accuracy as seen in Figures 5(c) and 5(d). The average class validation accuracy of the process classifier was 94.6%, and the average class validation accuracy for the function classifier was 97.2%. These results indicate that the models are well-trained for the part retrieval experiment.

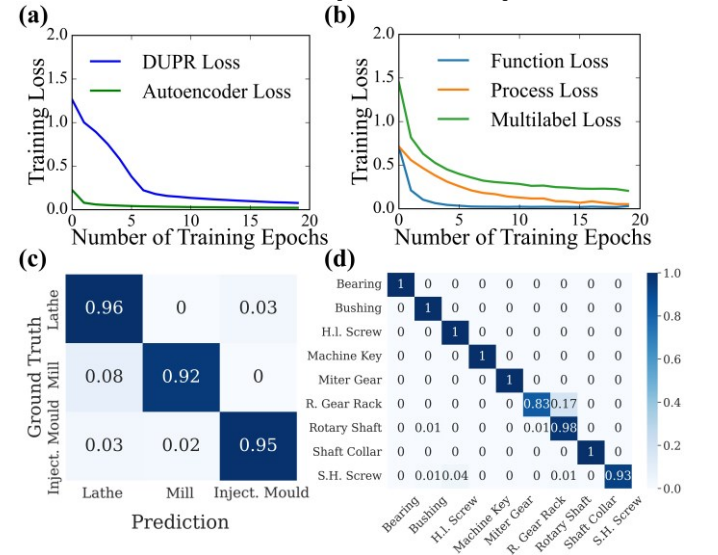


Figure 5. (a) Training losses of DUPR model vs. Shape-only Autoencoder, (b) training losses of function classifier vs. manufacturing process classifier vs. multilabel classifier, (c) validation confusion matrix of manufacturing process classifier, and (d) validation confusion matrix of function classifier

4. Part retrieval experiment

4.1 Part retrieval workflow and metric

The previous section presented six models that differed in their training objectives (i.e., shape and material vs. shape-only, supervised vs. unsupervised learning). In this work, each part has 32×1 latent vectors derived from each trained model, with the exception of shape-material concatenation, which outputs 35×1 latent vector by directly concatenating the material properties. All parts in the manufacturable parts database are embedded as latent vectors using each of the six models. As shown in Figure 6, the query part input to the models is converted to a latent vector from which pairwise similarities between the latent vector of the query part and all latent vectors in the manufacturable parts database are computed. The vectorial cosine distance is used as the similarity

metric to retrieve the closest matching parts.

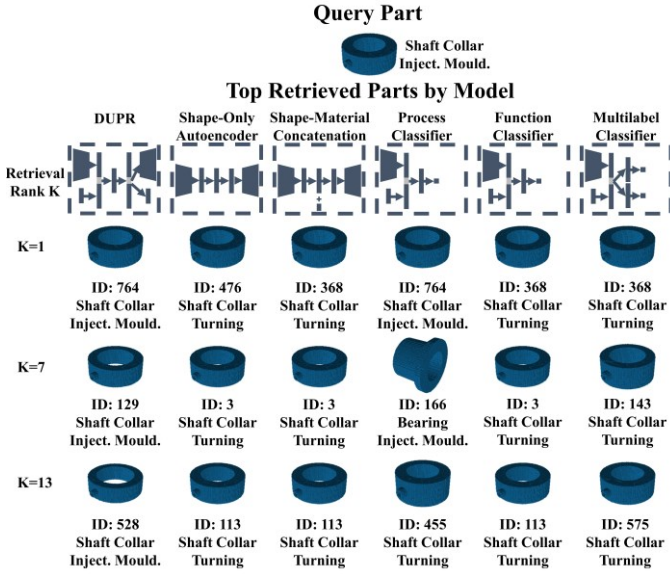


Figure 6. Example part retrieval workflow and results

4.2. Model performance evaluation in part retrieval

To evaluate the performance of the part retrieval models, we compared the function and process class labels of the retrieved parts with those of the query part. In this work, Precision at K is used as the performance metric, which computes the ratio between the number of relevant items to the total number of retrieved items, K [6]. For each of the 554 test query parts, the top 20 best matching parts from the training dataset were retrieved. Table 2 summarizes the part retrieval performance based on the precision at K of process class label, function class label, and combined process and function class labels.

Table 2. Part retrieval performance by model

K	1	5	10	15	20
Process Class Precision at K					
DUPR	95.7%	91.8%	88.2%	85.8%	83.8%
Shape-only Autoencoder	72.2%	70.0%	67.8%	66.6%	65.5%
Function Classifier	78.2%	72.2%	71.7%	72.3%	71.6%
Process Classifier	95.8%	94.4%	93.6%	93.2%	92.4%
Shape-material Concatenation	75.5%	71.2%	69.2%	67.3%	66.1%
Multilabel Function and Process Classifier	76.5%	75.0%	74.3%	74.7%	74.5%
Function Class Precision at K					
DUPR	95.7%	91.6%	87.6%	83.7%	80.3%
Shape-only Autoencoder	96.8%	93.1%	88.2%	84.0%	80.2%
Function Classifier	98.9%	98.3%	98.1%	97.5%	97.0%
Process Classifier	91.0%	84.9%	79.8%	76.1%	73.2%
Shape-material Concatenation	95.5%	93.0%	88.7%	84.3%	80.4%
Multilabel Function and Process Classifier	98.6%	97.8%	97.2%	96.5%	96.0%
Process and Function Class Precision at K					
DUPR	93.0%	86.4%	80.2%	75.1%	71.2%
Shape-only Autoencoder	70.6%	67.5%	63.3%	59.9%	57.0%
Function Classifier	77.3%	71.6%	71.1%	71.6%	70.9%
Process Classifier	88.1%	81.8%	76.1%	72.3%	69.0%
Shape-material Concatenation	73.6%	68.6%	64.5%	60.5%	57.5%
Multilabel Function and Process Classifier	76.0%	74.1%	73.2%	73.2%	72.7%

It is evident that the DUPR model outperforms the shape-only autoencoder model in terms of both process and function class label precision at 1 (93.0%). The shape-only autoencoder performs slightly better than the DUPR model in only function label precision at 1 (96.8%). However, the much worse performance of the shape-only autoencoder in process class label precision at 1 (72.2%) and the combined process and function class labels precision at 1 (70.6%) indicates that shape alone is insufficient for part retrieval in the context of cyber manufacturing

search, where process class matching is essential to identify a suitable manufacturer with the necessary capabilities.

The supervised learning models can result in high precision of process or function class label at the cost of induced bias. For example, the part function classifier reaches 98.9% precision at 1, but only 78.2% of the retrieved parts satisfy the process class label matching requirement. Such bias toward the training objective is also observed in parts retrieved by the process classifier. Importantly, the DUPR model still performed well at 95.7% for process class precision at 1, which suggests that shape and material similarities are significant factors in determining process similarity. When considering the combined class labels precision, the DUPR model clearly performs the best, surpassing all supervised models. Note that the process and function labels are only available for the experiment presented here. The availability of class labels is a prerequisite for supervised learning. In practice, however, it can be laborious and challenging to label parts based on process or function. It is observed that a change in the training objective from process to function can alter the part retrieval results significantly, which highlights the need for unsupervised learning methods that reduce the impact of training bias.

5. Conclusions

In this paper we proposed a deep unsupervised learning-based part retrieval (DUPR) model, which considers both shape and material properties of query parts as inputs to retrieve the closest matching parts from a previously manufactured parts database. Through a comparative parts retrieval experiment, it was shown that (1) including manufacturing capability information (e.g., material properties) in the part retrieval model significantly improves the retrieval precision when both part function and process class labels are considered, and (2) the proposed DUPR model reduces bias in training and outperforms the supervised learning models yielding a combined process and function class precision at 1 of 93.0%. Future research will consider other manufacturing capability information such as part quality and production quantity. In addition, most data presented in the experiment are axisymmetric. While the presented method is also applicable to prismatic parts, additional pre-processing such as part orientation alignment and fixture placement should be further studied. An immediate application of the proposed method is to combine it with an instant quoting system for cyber manufacturing services, which requires incorporating pricing data in the part retrieval method presented here.

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