CADOps-Net: Jointly Learning CAD Operation Types and Steps from Boundary-Representations

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Abstract

3D reverse engineering is a long sought-after, yet not completely achieved goal in the Computer-Aided Design (CAD) industry. The objective is to recover the construction history of a CAD model. Starting from a Boundary Representation (B-Rep) of a CAD model, this paper proposes a new deep neural network, \textbf{CADOps-Net}, that jointly learns the CAD operation types and the decomposition into different CAD operation steps. This joint learning allows to divide a B-Rep into parts that were created by various types of CAD operations at the same construction step; therefore providing relevant information for further recovery of the design history. Furthermore, we propose the novel \textbf{CC3D-Ops} dataset that includes over 37k CAD models annotated with CAD operation type labels and step labels. Compared to existing datasets, the complexity and variety of CC3D-Ops models are closer to those used for industrial purposes. Our experiments, conducted on the proposed CC3D-Ops and the publicly available Fusion360 datasets, demonstrate the competitive performance of CADOps-Net with respect to state-of-the-art, and confirm the importance of the joint learning of CAD operation types and steps.

1. Introduction

In today’s digital era, Computer-Aided Design (CAD) is the standard option for designing objects ahead of manufacturing [37, 3, 36]. The parametric nature of CAD models allows engineers and designers to iterate over the parameters of existing CAD models to edit and adapt them to new contexts, such as customizing dental prostheses [33], or modifying mechanical parts [35]. However, this is only possible if the final shape of the CAD model comes with its design history. Unfortunately, this is rarely the case as the design history is often not available for generic 3D shapes [7] or lost when CAD models are exchanged between different CAD applications [14, 18]. Consequently, the research community has put a lot of efforts in relating the geometry of 3D shapes to the CAD design history [18, 13, 32, 7, 45, 43]. This process is known as 3D reverse engineering.

Prior works attempted to recover the CAD design history, considering Constructive Solid Geometry (CSG) based models [7, 32] for simplicity. In CSG, a CAD model is represented by a set of rigidly transformed solid primitives (e.g. cube, sphere, cylinder) and combined using Boolean operations such as union, intersection, and difference [9]. However, modern CAD workflows use feature-based modeling, in which solids are created by iteratively adding features such as holes, slots, or bosses [45, 46]. These high-level features are sequentially created through drawing sketches and applying CAD operations such as ‘extrusion’, ‘revolution’, etc. Figure 1a illustrates an example of feature-based simple CAD model creation. Using this type of CAD mod-
eling, the final model is stored in a data structure called Boundary-Representation (B-Rep). The B-Rep describes the geometry and the topology of the CAD model through faces, edges, loops, co-edges and vertices [18]. However, it does not include information about how these entities are designed. Accordingly, recent efforts in the state-of-the-art have focused on relating B-Reps to the design history [45, 18, 13]. In particular, two main directions have been followed: (1) segmenting the B-Rep faces into CAD operation types (e.g. ‘extrusion’, ‘revolution’) [13, 18] or higher-level machining features (e.g. ‘holes’, ‘slots’) [6] that allowed their creation; (2) inferring a sequence of parametric sketches and extrusions that allowed the design of the B-Rep [45, 41, 38]. While the first group of works have the advantage of relating each face of the B-Rep to various types of CAD operations, they do not describe the relationship between the faces nor the steps of the construction. On the other hand, the works taking the second direction reconstruct the ordered sequence of the design history, including sketches, but they are usually limited to only one CAD operation type (i.e. ‘extrusion’) as a simplification of the search space.

In this work, we combine both directions by segmenting the faces of the B-Reps into various CAD operation types and further decomposing them into steps of construction as shown in Figure 1. These two aspects are jointly learned using an end-to-end neural network, allowing the recovery of further information about the design history such as CAD sketches. The proposed method is evaluated on the publicly available Fusion360 dataset [41], and a newly introduced dataset that is closer to real-world challenges. The key contributions can be summarized as follows:

- A neural network, CADOps-Net, that operates on B-Reps is proposed to learn the segmentation of faces into CAD operation types and steps. We introduce a joint learning method within an end-to-end model.
- We create a novel dataset, CC3D-Ops, that builds on top of the existing CC3D dataset [5] by extending it with B-Reps and their corresponding per-face CAD operation type and step annotations. Compared to existing datasets [41, 24, 15], CC3D-Ops better reflects real-world industrial challenges thanks to the complexity of its CAD models. This dataset can be found at https://cvi2.uni.lu/cc3d-ops/.
- The proposed approach is evaluated on two datasets and compared to recent state-of-the-art methods. We further showcase some preliminary results on a possible downstream application consisting of CAD sketch recovery from B-Reps.

The rest of the paper is organized as follows: In Section 2 related works are discussed followed by the problem formulation in Section 3. Section 4 describes the proposed CADOps-Net. The proposed CC3D-Ops dataset is introduced in Section 5. The experimental results are reported and analyzed in Section 6. Finally, Section 7 concludes this work and presents directions for future work.

2. Related Works

Learning representations for 3D shape modeling [1] is an important research topic that aims at finding the best deep feature encoding method. For instance, while a group of works leverages feature embedding for unordered and irregular point clouds [4, 27, 40, 44, 20] or regular grids of voxels [23, 21, 5, 2, 39], another group of works [11, 10, 22] defines convolution kernels and feature embedding techniques for meshes and manifolds. Other works [7, 18, 13, 32] focused on learning from high-level 3D shape representations such as CAD models. These methods either assume that the CAD models are obtained using CSG or feature-based modeling. In particular, the recovery of the CAD design history considering these two types of modeling has attracted a lot of attention [41, 13, 18, 32, 7].

CSG-based Approaches. Several approaches [32, 28, 9, 42] attempt to infer the design history of CAD models using CSG representation. For instance, when the input shape is a 3D point cloud, [7] and [42] convert it to the CSG tree (mainly binary-tree) of solid bodies which is a volumetric representation of simple geometrical primitives. Similarly, when the input is a B-Rep or a solid body, [31] and [28] describe unique CSG conversion steps (or vice-versa in [9]). The conversion reveals hierarchical steps involved in modeling solid bodies, whereas CAD models appear more as connected surface patches than volumetric solids [29]. Therefore, predicting CSG construction history may not reveal the actual CAD construction steps used in modern CAD workflows [45]. The latter mostly consider B-Reps instead of CSG and rely on feature-based modeling, which is addressed in our work.

Feature-based Approaches. The methods that either directly learn the B-Rep structure of a CAD model [13, 18, 12, 45, 6] or predict sketches and CAD operations [43, 26, 30, 8] are closely related to our work. The works in [26, 8] propose generative models for CAD sketches with a focus on the constraints of sketch entities. Therefore, they do not consider the connection between constrained CAD sketches and operations. On the other hand, methods like SolidGen [12], BRepNet [18], UV-Net [13], CADNet [6] put more emphasis on how to use the B-Rep data structure to obtain face embeddings followed by face segmentation, but obscuring the relation between the segmented faces and design steps. DeepCAD [43], Fusion360 [41] and Zonegraph [45] are the first set of methods, to the best of our knowledge, that relate parametric sketches and CAD operations proposing a generative model for CAD design. How-
ever, their models were restricted to only one type of CAD operations, namely extrusion. Finally, Point2Cyl [38] operates on point clouds to detect 2D sketches but is also limited to the CAD extrusion operation.

**CAD Modeling Datasets.** Besides Fusion360 [41], there are no datasets that provide both B-Reps and fully explicit construction history in standard format. For example, the ABC dataset [15] provides $1M+$ CAD models with sparse construction history provided in Onshape proprietary format [41]. On the other hand, the SketchGraphs dataset [30] contains a large number of sketch construction sequences but not the B-Reps. Both MFCAD [24] and MFCAD++ [6] datasets contain B-Reps and machining feature labels. However, the samples are synthetic models and too simple to consider for industrial modeling tasks. CC3D dataset [5] offers $50k+$ pairs of industrial CAD models as triangular meshes and their corresponding 3D scans, but without construction steps and B-Reps. CC3D-Ops supplements the CC3D dataset with these elements.

### 3. Problem Statement

A B-Rep $B$ can be defined as a tuple of three sets of entities — i.e., a set of $N_f$ faces $\{f_1, f_2, \ldots, f_{N_f}\}$, a set of $N_e$ edges $\{e_1, e_2, \ldots, e_{N_e}\}$, and a set of $N_c$ co-edges (also known as directed half-edges) $\{c_1, c_2, \ldots, c_{N_c}\}$. Our main goal is to relate each face $f$ in $B$ with its construction history using three different types of features $F \in \mathbb{R}^{N_f \times d_f}$, $E \in \mathbb{R}^{N_e \times d_e}$, and $C \in \mathbb{R}^{N_c \times d_c}$ extracted for the three entities, namely, faces, edges, and co-edges, respectively\(^1\). The CAD construction history is defined as a sequential combination of sketches followed by some CAD operations. In this work, we are interested in learning (1) the type of CAD operations through the segmentation of each face that allowed for its creation, and (2) the CAD operation step to which the segmented face belongs.

### 3.1. CAD Operation Types

The choice of CAD operation types is crucial for constructing CAD models. For notation simplicity, let us denote them as $\text{op.types}$. The geometry of the final CAD model, usually stored as a B-Rep, is obtained through these operations, which makes each face of the B-Rep directly related to a type of operation. In Figure 1c, we show some intermediate steps of CAD construction and how the faces of the corresponding B-Rep are obtained using different $\text{op.types}$. For example, the B-Rep of a cube that was obtained by sketching a 2D square and applying an extrusion operation, as in Figure 1a, would result in two faces with ‘extrude end’ labels and four faces with ‘extrude side’ labels. The ability to automatically infer the $\text{op.type}$ that allowed for the creation of each face of the B-Rep constitutes a first, yet essential, step towards relating the geometry of the CAD model to its construction history. Recently introduced models [18, 13] proposed to learn the segmentation of B-Rep faces into $\text{op.types}$.

Formally, let us consider a B-Rep $B$ labelled with the surface $\text{op.types}$ $T = \{t_1, t_2, \ldots, t_{N_f}\} \in \{0, 1\}^{N_f \times k_t}$, where $k_t$ is the number of possible $\text{op.types}$. Here, $T \in \{0, 1\}^{N_f \times k_t}$ is an $N_f \times k_t$ matrix with binary entries, where each row $t_j \in \{0, 1\}^{k_t}$ can have only one element as 1 representing the $\text{op.type}$ of the face $f_j$. The task of $\text{op.type}$ segmentation consists of learning a mapping $\Phi$, such that,

$$\Phi : \mathbb{R}^{N_f \times d_f} \times \mathbb{R}^{N_e \times d_e} \times \mathbb{R}^{N_c \times d_c} \rightarrow \{0, 1\}^{N_f \times k_t}, \quad (1)$$

$$\Phi(F, E, C) = T. \quad (2)$$

It is important to highlight that the segmentation task of $\text{op.types}$ uses the features of faces, edges and co-edges, but assigns a unique $\text{op.type}$, among a fixed number of possible types, to each face of the B-Rep. Despite its usefulness for reconstructing the CAD construction history of B-Reps, the segmentation into $\text{op.types}$ is not sufficient as it does not describe the relationship between the faces nor the steps of the construction.

### 3.2. CAD Operation Steps

In addition to the operation types that are assigned to the faces of the B-Reps, our aim is to relate them further to the construction history. Accordingly, we propose a novel task consisting of segmenting the faces of B-Reps into CAD operation steps. For notation simplicity, they will be denoted as $\text{op.steps}$ in what follows. While the segmentation into $\text{op.types}$ aims at identifying the operation that was used to create each face, the purpose of the segmentation into $\text{op.steps}$ is to group faces that were created at the same time step. An example is shown in Figure 1b.

Formally, let us consider a B-Rep $B$ labelled with the surface $\text{op.steps}$ $S \in \{0, 1\}^{N_f \times k_s}$, where $k_s$ denotes the number of $\text{op.steps}$ in $B$. Similarly to the $\text{op.types}$ $T$, the $\text{op.steps}$ are represented by an $N_f \times k_s$ binary matrix $S = [s_1; s_2; \ldots; s_{N_f}] \in \{0, 1\}^{N_f \times k_s}$. Each row of this matrix, $s_j \in \{0, 1\}^{k_s}$, can have only one element equal to 1 denoting the $\text{op.step}$ for the face $f_j$. Segmenting the faces of B-Reps into $\text{op.steps}$, would require learning a mapping $\Psi$.

$$\Psi : \mathbb{R}^{N_f \times d_f} \times \mathbb{R}^{N_e \times d_e} \times \mathbb{R}^{N_c \times d_c} \rightarrow \{0, 1\}^{N_f \times k_s}, \quad (3)$$

$$\Psi(F, E, C) = S. \quad (4)$$

The proposed segmentation into $\text{op.steps}$ is a challenging task for two main reasons: (1) unlike the $\text{op.type}$ segmentation where the possible types are predefined, the labels of $\text{op.steps} S$ are arbitrary and any combination of labels, in which faces belonging to the same step have identical labels, can be considered as correct; (2) predicting

\(^1\)The considered features are described in Section 6.1.
op.steps aims at grouping B-Rep faces according to the design history. Therefore, it requires learning the relationship between the different faces of the B-Rep in addition to its geometry and topology.

4. Proposed CADOps-Net

The proposed CADOps-Net jointly learns the op.type and op.step segmentation within the same model. In practice, the mappings \( \Psi \) and \( \Phi \), introduced in Section 3, are learnt using an end-to-end neural network. BRepNet [18] is used as the backbone of our model, as it has been shown to effectively operate on B-Reps. BRepNet uses the face, edge, and co-edge features \((F, E, C)\) of a B-Rep \( B \) to learn per-face embeddings using a succession of convolutions defined through specific topological walks and Multilayer Perceptron (MLP) layers. For more details about this backbone, readers are referred to [18]. In what follows, the BRepNet backbone will be denoted by \( \Delta : \mathbb{R}^{N_f \times d_f} \times \mathbb{R}^{N_e \times d_e} \times \mathbb{R}^{N_c \times d_c} \rightarrow \mathbb{R}^{N_f \times 2d_{emb}} \) and \( F^\Delta \) will be used as a notation for the embedding extracted using this backbone from a face \( f \) of a B-Rep \( B \). The proposed network is composed of two modules that are described below.

4.1. CAD Operation Step Segmentation

The CAD operation step module has two roles. Firstly, it predicts the per-face op.step labels. Secondly, it is used to aggregate the embeddings of faces belonging to the same step and produce embeddings for each group of faces obtained in a single op.step.

Learning CAD operation steps: The mapping \( \Psi \) introduced in Section 3.2 consists of two components, i.e., \( \Psi := \sigma \circ \Delta \), where \( \Delta \) uses the features of the B-Rep \( (F, E, C) \) and extracts per-face embeddings \( F^\Delta = [f_1^\Delta ; f_2^\Delta ; \ldots ; f_j^\Delta] \in \mathbb{R}^{N_f \times 2d_{emb}} \). \( \sigma \) is an MLP followed by softmax that maps the face embeddings \( F^\Delta \) into probabilities of predicted op.steps \( \hat{s} \). Using these predictions, the face embeddings, \( F^\Delta \), are aggregated with a function \( \mathcal{A} \) into step embeddings \( S^\Delta \). Finally the concatenation, \( \circ \), of the face embeddings, \( F^\Delta \), and their corresponding step embeddings, \( S^\Delta \), are passed through an MLP layer, \( \rho \) to predict the op.type face labels.

\[
\mathcal{L}_{step} = \frac{1}{N_f} \sum_{j=1}^{N_f} \left(1 - \text{RlIoU}(s_j, \hat{s}_j)\right).
\]

For inference, the Hungarian matching is not used and the predicted op.steps are given by taking the maximum probability over each \( \hat{s} \).
CAD operation step embedding: In addition to predicting the per-face \( op.steps \) given a B-Rep, the same module is used to extract CAD step embeddings \( \{s_1^A, s_2^A, \ldots, s_k^A\} \). This is achieved by aggregating the embeddings of faces predicted to belong to the same \( op.step \). Specifically, each \( op.step \) \( \varphi \) would have an embedding \( s_\varphi^A \in \mathbb{R}^{d_{emb}} \), such that

\[
s_\varphi^A = \mathcal{A} \left( \arg \max_{j} \mathcal{S}_{j, \varphi} \right),
\]

where \( \mathcal{S}_{j, \varphi} \) denotes the per-face predicted \( op.step \) labels for \( \varphi \), and \( \mathcal{A} \) is an aggregation function that preserves the dimension of the input embeddings such as average or maximum. Finally, each face of the B-Rep will have the corresponding \( op.step \) embedding \( s^A \) according to the predicted \( op.step \) label. These embeddings are finally stacked in a matrix \( \mathbf{S}^A \in \mathbb{R}^{N_f \times d_{emb}} \).

4.2. CAD Operation Type Segmentation

The introduced mapping \( \Phi \) to obtain the \( op.type \) segmentation from an input B-Rep shares the same BRRepNet backbone \( \Delta \) used by the module of \( op.type \) segmentation. Moreover, it uses two other mappings, \( \gamma \) and \( \rho \), where \( \Phi := \rho \circ \gamma \circ \Delta \). The mapping \( \gamma : \mathbb{R}^{N_f \times d_{emb}} \times \mathbb{R}^{N_f \times d_{emb}} \to \mathbb{R}^{N_f \times 2d_{emb}} \) takes as input the face embeddings \( \mathbf{F}^\Delta \) and outputs their concatenation with the corresponding step embeddings \( \mathbf{S}^A \). These concatenated embeddings are fed to an MLP with softmax which are represented by \( \rho : \mathbb{R}^{N_f \times 2d_{emb}} \to \{0, 1\}^{N_f \times k_s} \). The final \( op.types \) \( \mathbf{T} \) can be obtained following,

\[
\mathbf{T} = \rho(\mathbf{F}^\Delta \oplus \mathbf{S}^A),
\]

where \( \oplus \) is the column-wise concatenation operation. The loss function for the \( op.type \) segmentation is computed using the cross-entropy \( \mathcal{H} \) between the predicted per-face \( op.types \) \( \hat{t} \) and the ground truth labels \( t \),

\[
\mathcal{L}_{type} = \frac{1}{N_f} \sum_{j=1}^{N_f} \sum_{i=1}^{N_f} \mathcal{H}(t_j, \hat{t}_j).
\]

The total loss function is the sum of the \( op.step \) and \( op.type \) losses,

\[
\mathcal{L}_{total} = \mathcal{L}_{step} + \mathcal{L}_{type}.
\]

The model jointly learns to predict the per-face \( op.type \) and \( op.step \) labels of a CAD model given its B-Rep, with the \( op.type \) being conditioned on the \( op.step \).

5. CC3D-Ops dataset

We introduce the CC3D-Ops dataset that contains 37k+ B-Reps with the corresponding per-face \( op.type \) and \( op.step \) annotations. These labels were extracted using the Solidworks API [34]. The B-Reps and their corresponding annotations constitute an extension of the CC3D dataset [5]. While the Fusion360 dataset [41] contains a similar number of B-Reps (35k+) with the corresponding \( op.type \) labels, it does not provide \( op.step \) labels and it includes relatively simple CAD models. The proposed CC3D-Ops dataset comes with more complex models that are closer to real-world industrial challenges. In Figure 3, we illustrate the distribution of \( op.step \) number per model as a box plot for both Fusion360 and CC3D-Ops datasets. It can be clearly observed that the distribution of CC3D-Ops is more skewed towards a higher number of \( op.steps \) than the one of Fusion360. Specifically, ~48% of the Fusion360 models are made of only one \( op.step \) and ~80% of them are constructed by 3 or less \( op.steps \). On the other hand, only ~20% of the CC3D-Ops models are built with a single \( op.step \) and ~44% of them with 3 or less \( op.steps \). Moreover, the maximum number of \( op.steps \) per model, \( k_s \), is 50 for Fusion360 and 202 for CC3D-Ops. Finally, the CC3D-Ops dataset introduces three new \( op.types \) to the eight present in Fusion360 which consists of, ‘cut revolve side’, ‘cut revolve end’, and ‘others’. More details about the dataset can be found in the supplementary material.

6. Experiments

6.1. Experimental Setup

Input Features: The input features of CADOps-Net are face, edge and co-edge features \( (\mathbf{F}, \mathbf{E}, \mathbf{C}) \) extracted from the B-Rep, \( \mathbf{B} \). Following [18], the face type \( (e.g. \) plane, cylinder, sphere) and area are encoded in a single vector. 3D points are further sampled on each face using the UV-grid of the B-Rep and encoded as described in [13]. These two features are concatenated and used as face features. The features of the B-Rep faces are then concatenated in a row-wise fashion to form the matrix \( \mathbf{F} \). For edge features, a similar approach is taken by considering the type, convexity, closeness, length of the edge as in [18], and encoded sampled 3D points as done in [13]. The result is concatenated in an edge feature matrix \( \mathbf{E} \). The co-edge features, \( \mathbf{C} \), are simple flags to represent the direction of the corresponding edges [18].

Network Architecture: The input features are passed through a BRRepNet backbone, \( \Delta \), with the same parameters as in [18] using the wing-edge kernel. The dimension of the face embedding, \( \mathbf{f}^\Delta \), is \( d_{emb} = 64 \). These embeddings...
are fed to an MLP followed by softmax, $\sigma$, to predict the $op.step$. The aggregation function used to compute the step embedding, $S^d$, is the average function. Each $op.step$ embedding $s^d$ has the same dimension as $f^d$. The final face embedding, $f^\Delta \oplus s^d$, are 128-dimensional. Lastly, the $op.type$ is estimated by passing these embeddings through an MLP followed by softmax, $\rho$. In our experiments, the number of layers of the employed MLPs is 1.

**Datasets:** CADOps-Net is evaluated on the Fusion360 dataset [41] and the novel CC3D-Ops dataset described in Section 5. Note that in Fusion360, the $op.step$ annotations were derived from the $op.type$ annotations as they were implicitly provided. The train, validation, and test sets for the Fusion360 dataset are the same as in [18]. For the CC3D-Ops dataset, the splitting ratios are approximately 65%, 15%, and 20% for the train, validation, and test sets.

**Training details:** The training was conducted for 200 epochs with a batch size of 100 using an NVIDIA RTX A6000 GPU. Adam optimizer is employed with a learning rate of 0.001 and beta parameters of 0.9 and 0.99.

**Metrics:** The performance of the network is evaluated on $op.type$ and $op.step$ segmentation tasks. To evaluate the $op.type$ segmentation, we use the same metrics as in [18], namely, the mean accuracy (mAcc) and the mean Intersection over Union (mIoU). Note that we do not consider the mIoU for evaluating the $op.step$ as the labels represent membership sets rather than predefined classes. Furthermore, the consistency between the $op.type$ and $op.step$ predictions is considered. For this purpose, we group the sub-$op.types$, such that ‘extrude end’ and ‘extrude side’, into a single ‘extrude’ $op.type$. Similar grouping is done for ‘revolve’, ‘cut extrude’, and ‘cut revolve’. We define an $op.step$ prediction as consistent if all its faces have the same $op.type$ prediction. To evaluate this consistency, two metrics are computed: (1) the first one, $R_{C}$, quantifies the overall consistency as the ratio of consistent predicted $op.steps$; (2) the second one quantifies the amount of consistency of a model as $S_{C} = \sum_{i} \max(n_{(t_{i},s_{i})})$ where $n_{s_{i}}$ is the number of faces with $op.step$ label $s_{i}$ and $n_{(t_{j},s_{i})}$ the number of faces with $op.type$ label $t_{j}$ and $op.step$ label $s_{i}$. We then compute $MS_{C}$ as the average over all the models.

6.2. Results and Discussions

**Qualitative Evaluation:** In Figure 4, we illustrate the predictions obtained by CADOps-Net on five models from the CC3D-Ops dataset. More predictions are provided in the supplementary material. Despite the complexity of some models, it can be observed that most of the $op.type$ predictions (left panel) were correct except for very few faces. On the other hand, the segmentation into $op.steps$ (right panel) was more challenging for complex models (two last rows) as the segmentation into $op.steps$ requires the model to learn the relationship between the faces of the B-Rep according to the construction history. Such aspect is more challenging to capture for complex models than the $op.types$ which could be hypothetically learned from the geometry and topology of the B-Reps. This hypothesis is further discussed in the quantitative evaluation.

**Quantitative Evaluation:** In Table 1, we report the quantitative results of our approach compared to baselines. CADOps-Net (Ours w/JL+) is compared to the same model without the joint learning of $op.steps$ and $op.types$ (Ours w/o JL−). In the latter, the $op.type$ and $op.step$ segmentation modules are trained independently. In the following, we first analyze the results for the segmentation into $op.steps$ (column 5 of Table 1) and for the $op.type$ segmentation (columns 3 and 4), then we discuss the consistency.
Table 1: Results of the segmentation into CAD operation types and steps on the Fusion360 and CC3D-Ops datasets. All results are expressed as percentages. Ours w/o JL− denotes our method without joint learning. Ours w/ JL+ refers to the proposed CADOps-Net with joint learning.

| Model       | op.type | op.step | Consistency |
|-------------|---------|---------|-------------|
|             | mAcc    | mIoU    | RC | mSC |
| Fusion360   |         |         |    |     |
| CADNet [6]  | 88.9    | 67.9    | -  | -   |
| UV-Net [13] | 92.3    | 72.4    | -  | -   |
| BRepNet [18]| 94.3    | 81.4    | -  | -   |
| Ours w/o JL | 95.5    | 83.2    | 80.2| 87.1| 97.4|
| Ours w/ JL+ | 95.9    | 84.2    | 82.5| 93.3| 98.7|
| CC3D-Ops    |         |         |    |     |
| CADNet [6]  | 57.5    | 26.9    | -  | -   |
| BRepNet [18]| 71.4    | 35.9    | -  | -   |
| Ours w/o JL | 76.0    | 43.0    | 48.4| 40.7| 82.7|
| Ours w/ JL+ | 75.0    | 44.3    | 62.7| 82.4| 96.7|

Table 2: Ablation study on the aggregation function used in the joint learning of CADOps-Net. All results are expressed as percentages.

| Agg. type   | op.type | op.step |
|-------------|---------|---------|
|             | mAcc    | mIoU    | mAcc |
| No agg.     | 73.0    | 40.2    | 61.5 |
| Soft labels | 73.4    | 40.0    | 59.7 |
| Sum         | 70.4    | 34.4    | 62.6 |
| Max         | 74.3    | 42.0    | 62.2 |
| Avg         | 75.0    | 44.3    | 62.7 |

In order to provide a deeper insight into the joint learning approach, we conduct an ablation study on the aggregation function $A$ of the face embeddings. Experiments are conducted with the following five scenarios: (1) the output face embeddings, $f^A$, from the BRepNet backbone are directly used to predict both the $op.type$ and $op.step$ without any aggregation (No agg.). (2) Another scenario concatenates the BRepNet face embeddings with the predicted soft labels of the $op.step$ (Soft labels) again without any aggregation. (3) The last three scenarios focus on the type of aggregation function used to obtain the $op.step$ embeddings, $S^A$, namely the maximum (Max), the average (Avg), and the sum of the embeddings combined with a softmax normalization (Sum).
Figure 6: Sketch recovery from predicted CAD operation types (op.types) and steps (op.steps). op.step 1 and 2 are colored in yellow and blue, respectively. Figure 4 defines the color codes used for different op.types.

Table 2 shows the ablation results for both op.type and op.step segmentation tasks on the CC3D-Ops dataset. The results show that aggregating the face embeddings using an Avg pooling leads to slightly better overall performance.

6.4. CAD Sketch Recovery

Figure 6 illustrates preliminary results on how CADOps-Net predictions can be used to retrieve the CAD sketches. A sketch $\hat{Q}$ of a B-Rep $B$ can be defined as a set of simple geometrical entities (e.g., straight lines, arcs). We consider a small subset of 20 models made of extrusions from the Fusion360 dataset. In the following, we describe the process for recovering the sketch corresponding to op.step 2 using the CADOps-Net predictions shown in Figure 6a. We first identify the faces for which the op.type was predicted as ‘extrude side’. Second, we cluster these faces according to their predicted op.step. Third, we store the face-normals ($\hat{n}_1, \ldots, \hat{n}_m$) and sample UV-grid points on the faces. This allows to derive a common axis of extrusion $\hat{a}$ and a projection center $\hat{o}$. Finally, the predicted sketch $\hat{Q}_2$ is obtained by projecting the sampled points along $\hat{a}$. (more details are in the supplementary material). Figure 6a and 6b show qualitative results of successful and failed sketch recoveries from correctly and incorrectly predicted op.types. These preliminary results on sketch recovery illustrate the relevance of op.step prediction in the context of 3D reverse engineering.

6.5. Limitations

In CAD modeling, designers may opt for different design solutions. Consequently, the segmentation into op.type and op.step is not necessarily unique. An example for which the op.step prediction is valid despite not matching the ground truth can be found in Figure 7a. The letters were predicted as part of the same op.step, which could be a valid design approach. However, these letters were extruded with separate op.steps in the ground truth. In Figure 7b, an example with valid predictions of op.types not matching the ground truth is depicted. Here, the hole in the center of the shape was predicted as a ‘cut’ type operation, while being an ‘extrude’ in the ground truth. In general, CAD designers follow good practices so that the final model reflects the design intent [25]. However, different designers might have their own set of good practices, making it difficult for a learning-based model to capture all the different design intents.

7. Conclusion

In this work, CADOps-Net, a neural network that jointly learns the CAD operation type and step segmentation of B-Rep faces is presented. The joint learning strategy leads to significantly better results for the challenging task of CAD operation step segmentation, while achieving state-of-the-art results on the CAD operation type segmentation task. Moreover, we showed the potential of combining these two segmentations for recovering further information of the construction history such as sketches. Finally, the CC3D-Ops dataset is introduced with its operation type and step annotations. We believe that this dataset will help in advancing research on CAD modeling thanks to the complexity of the CAD models. As future work, an investigation of the ordering of the construction steps while maintaining various types of CAD operations would allow for the recovery of a more complete construction history.

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