Towards Automatic CAD Modeling from 3D Scan Sketch based Representation

Abd El Rahman Shabayek[1], Djamila Aouada[1], Kseniya Cherenkova[1,2] and Gleb Gusev[2]
[1]*CVI*[2]*, Interdisciplinary Centre for Security, Reliability, and Trust, University of Luxembourg, Luxembourg*
[2]*Artec 3D, Luxembourg*

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Abstract: This paper proposes a novel approach to convert a 3D scan to its CAD counterpart. The objective is to extract intermediate sketch planes that well represent the input scan and are close enough to the original design intent. These sketches can then be easily converted into CAD models automatically due to their faithful representation of the input geometry. One objective is to avoid incorporating user/company dependent content in the CAD reconstruction process. The intermediate representation shall be directly supported in any CAD environment to boost the designer's work without the need of supplementary (model conversion, automatic feature recognition) steps. Nowadays, it is common to digitize an object and reconstruct its geometric primitives. However, this reconstruction contains only geometry. In literature, the final goal might be met by recovering the modeling tree itself, by means of automatic feature recognition, and converting to the proper format of a specific CAD software package. However, the constructed tree and its conversion introduce issues in the reconstruction process. The definition of an exact modeling tree, and the production of a meaningful final CAD model are rather hard to obtain. This imposes a rather inefficient working method, thereby heavily impacting the designer's modeling skills.

1 INTRODUCTION

Converting an input 3D scan to a Computer Aided Design (CAD) model involves extracting enough information to reproduce that scan. It can be applied to any scanned object like manufactured, chemical or biological products. There are various reasons to reverse engineer a scan such as developing interfaces for system interoperability, developing stricter security protocols, fixing product flaws, reducing costs, etc. There is no single process to reverse a scan to its original CAD (Barh and Azevedo, 2018).

Existing methods tend to tackle the scan to CAD conversion problem from a primitive fitting point of view (Kaiser et al., 2019; Buonamici and Carfagni, 2016). This approach is a natural consequence of the designers' community common practice in designing their products where basic geometric primitives (such as planes, spheres, cylinders and cones) are at the heart of it. These methods can be classified into constrained primitive fitting (Kaiser et al., 2019; Patil et al., 2017; Kovács et al., 2015) and learning-based primitive fitting (Li et al., 2019; Ranftl and Koltun, 2018; Brachmann et al., 2017). There are also recent learning-based approaches that look for the similarity between scans and CADs to finally retrieve the appropriate CAD model (Dahnert et al., 2019; Avetisyan et al., 2019) or look for specific feature or repetition patterns (Gauthier et al., 2019).

The constrained fitting approaches have to deal with complexities of geometrical constraints, correct boundary representations and accurate parametrization. Besides that, free-form surfaces are not well addressed or constrained (Kaiser et al., 2019) while for learning-based approaches, the basic assumption is the existence of a large database of scans and/or CADs which is not always available.

This paper addresses the problem from a different point of view; the scan can be converted to a set of one or more reference sketches that originate a CAD model. This point of view is closer to the design intent of an object modeled in terms of its 2D profile(s). This paper targets objects rather than complete scenes. The core idea is to have an intermediate standard representation which 1) preserves (to some extent) the design intent and 2) is understood by any CAD modeling software without any conversion requirement. This paper proposes an efficient

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approach to extract reference sketches that enable automating the modeling process. The work is further validated by demonstrating a semi automated conversion process from an input 3D scan to its CAD model. Although the current work assumes a possible human intervention to decide on the selected modeling sketches, it is foreseen to fully automate this step.

This paper is organised as follows; Section 2 presents the existing literature. Section 3 explains the proposed approach. The validation of the automated modeling experiments and their discussion are given in Section 4. Finally, the work is concluded in Section 5.

2 RELATED WORK

In the literature, there are numerous methods available that propose different solutions to convert from an input scan to a CAD model. Although there are many successful attempts, they are still limited to a certain category of objects or are practically difficult to be implemented in a general sense. These existing methods can be classified into: 1) learning-based approaches that either try to directly retrieve the most relevant CAD model from a database or learn the best fitting parameters of the object's geometric primitives, 2) constrained fitting based approaches that aim to segment the input scan and find the most appropriate geometrical primitive that fits it in a dedicated optimization framework, and 3) hybrid methods that learn to classify segments in order to apply constrained primitive fitting on them.

2.1 Learning-based Approaches

learning-based approaches aim to learn the similarity between a set of CAD models and their corresponding scans. This learning enables to retrieve the closest available CAD model to the input scan and fit the best geometric primitive(s) to the input scan or recognize geometric patterns that enable model reconstruction. The main limitation is that possibly a large number of both scans and their corresponding CAD models shall be available for any new application domain.

(Dahnert et al., 2019) proposed to learn a joint embedding space of 3D scans and their CAD objects geometry. The work assumes that semantically similar objects shall be neighbours in the embedding space even if there is a clear difference in their geometric characteristics. The learned space is then used to retrieve the closest CAD model to the input scan. (Avetisyan et al., 2019) assumed that there is a predefined set of clean CAD models that can be aligned to a noisy input scan. Using a 3D Convolutional Neural Network, they predict a heatmap that links between the scan and the closest CAD model. Using this heatmap, the 9 DoF CAD pose is estimated to be aligned to the scan.

Primitive fitting from a learning perspective can be viewed as model prediction by regressing the parameters using a neural network. However, the regression loss based on measuring the parameter difference does not represent the real fitting error. Such erroneous loss can seriously limit prediction accuracy. (Brachmann et al., 2017) faced that by integrating a Random sample consensus (RANSAC) pipeline (Schnabel et al., 2007) into a deep neural network where differentiable routine replaces the hypothesis selection step in RANSAC. (Ranftl and Koltun, 2018) also introduced a deep learning network for model fitting to predict inlier weights while (Li et al., 2019) extended (Ranftl and Koltun, 2018) to predict weights representing point membership for multiple primitive models. Only cuboids are predicted in (Tulsiani et al., 2017; Zou et al., 2017), hence, the proposed methods can only act as a rough abstraction of the input scan. A more general method called Constructive Solid Geometry Network (CSGNet) (Sharma et al., 2018) is able to predict more types of primitives but with less accuracy due to limitation in their parameter space classification (Li et al., 2019). Moreover, it is computational expensive as a Constructive Solid Geometry (CSG) model shall be rendered to get visual feedback for each training iteration. These primitive fitting methods are limited in accuracy with a restricted number of supported primitive types.

Rule-based learning methods (Gauthier et al., 2019) focus on the recognition of two geometric features and their repetition patterns: counterboared and countersunk holes which require recognition of parallelism and concentricity relations. The recgonition rules are defined based on geometrical relations between primitives. The objective is to ease the model reconstruction process given these patterns.

2.2 Constrained Fitting Approaches

In the core of scan to CAD conversion comes the primitive fitting step in most existing literature. The abstraction of 3D shapes by simple parametrization enables geometry simplification while keeping acceptable representation of the input scan. However, this simplification has consequences on both performance and the ability to perform high level tasks. For a more comprehensive review, see (Kaiser et al., 2019).

Constrained fitting enforces dimensions and/or geometric constraints between input features during the fitting process (Werghi et al., 1999; Benkö et al., 2002; Kovács et al., 2015; Kaiser et al., 2019). This approach is meant to restore as mush design intent as possible that possibly models the target object. There are constrained fitting methods which are very specific to their domains like (Patil et al., 2017). They modify the existing Hough transform to automatically detect cylinder parameters in point clouds where a cylinder's radius is estimated using a circle fitting algorithm. However, there are more general and popular primitive detection approaches which are based on RANSAC (Fischler and Bolles, 1981) such as (Schnabel et al., 2007; Chum and Matas, 2005; Li et al., 2011; Kang and Li, 2015; Wu et al., 2018; Du et al., 2018). (Li et al., 2011) refines the extracted primitives by (Schnabel et al., 2007) by optimizing the relations between them. (Wu et al., 2018) and (Du et al., 2018) introduced a method to reverse a CSG model from an input scan. The performance of these RANSAC-based methods mainly depends on careful parameter tuning for each shape category and the availability of points normals. The need for careful parametrization is limiting as minor errors due to noisy input scans may lead to over/under segmentation. This careful control requirement may block the scale up of RANSAC-based methods to diverse shapes as it needs to be repeated for each of them.

2.3 Hybrid Partial Learning and Fitting Approaches

Hybrid approaches are very common in reverse engineering of mechanical parts (Buonamici and Carfagni, 2016). A typical framework (Várady et al., 1997; Werghi et al., 1999; Benkö et al., 2002; Buonamici and Carfagni, 2016) would 1) generate a mesh from a point cloud, 2) pre-process the input scan, 3) segment the scan, 4) classify its regions to be linked to geometric features or primitives, 5) fit geometric primitives, 6) post-process (e.g merging into a solid model and filleting). The learning aspect is region based where the objective is to map the region to a known geometric primitive to further continue with the fitting process. The fitting step can be accomplished by any existing method (Kaiser et al., 2019). (Jia, 2017) fits multiple parametric models to an input point cloud. The assumption is that there is a priori knowledge of the correspondences between points and the geometric primitives. After associating the points with any component, the model parameters are searched in a minimization step. If there is no a priori knowlege of the correspondences, an initialization and classification algorithm is applied. Once the initial configuration is close enough to the point cloud, the technique provides very satisfactory results. However, it fails when the initial configuration parameters are far from the point cloud.

There are also hybrid approaches introduced for specific domains of use. (Yi et al., 2017) decomposes a large scale LiDAR data point cloud or urban building into individual ones. Each building is further partitioned into a set of consecutive blocks. The primitive elements in the block contours are extracted by employing spectral residual clustering. Constrained fitting is then applied on the extracted primitives to get an accurate contour. Finally, a union operation is applied on a set of extrusion operations that generated each block.

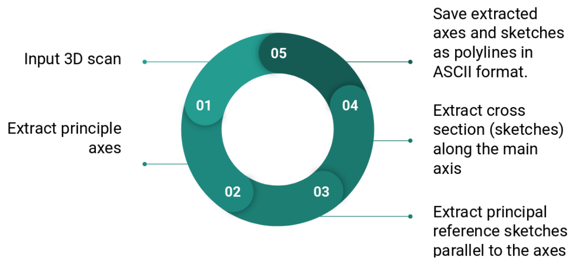
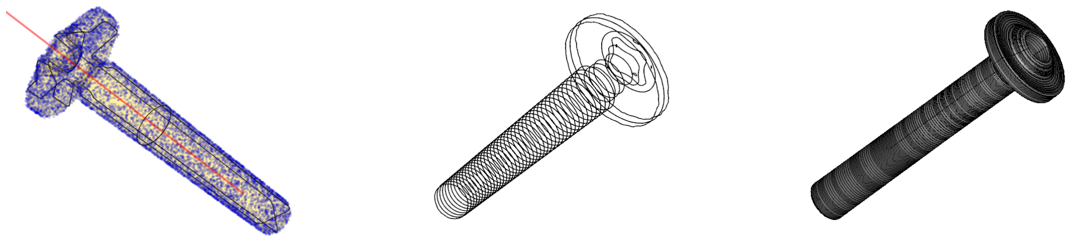


Figure 1: Proposed approach to extract reference sketch planes from an input 3D scan.

3 SKETCH BASED MODEL RECONSTRUCTION

In the literature, the modeling tree automatically retrieved by different software tools rarely corresponds to the real procedure used by the designer which makes it very difficult to modify. The proposed approach in this work has a different perspective on the conversion process and requirements. It takes a 3D mesh as an input. If the input is a 3D point cloud, it can be meshed using any standard algorithm (Berger et al., 2017). Afterwards, the principle axes of the input object are extracted using principle component analysis (Botsch et al., 2011). Then, the sketch planes parallel to each of the principle axes are also extracted by means of mesh slicing (Botsch et al., 2011). One of the principle axes shall be selected to extract the sketch planes across it (Botsch et al., 2011). By default, the main axis is used for this purpose. Finally, the extracted principle axes and sketch planes are represented as polylines and saved in ASCII format. The proposed approach is depicted in Figure 1 and described in Algorithm 1.

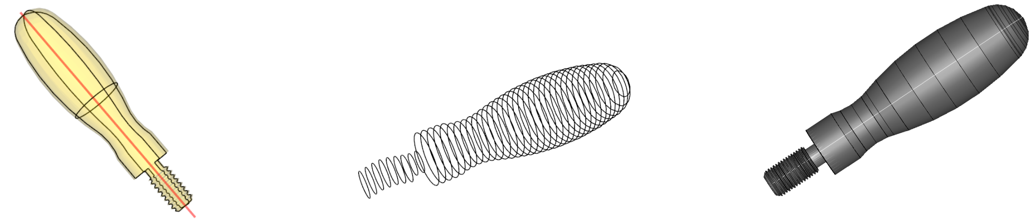
The perspective of this work is that the CAD re-



(a) Input point cloud (blue), reconstructed mesh (yellow), principal axis (red) and principal 3D profiles (black).

(b) Principal 3D profiles (cross sections) extracted along the principal axis.

(c) Output 3D model using SALOME.



(d) Input mesh (yellow), principal axis (red) and principal 3D profiles (black).

(e) Principal 3D profiles (cross sections) extracted along the principal axis.

(f) Output 3D model using SALOME.

Figure 2: Top row: from a 3D point cloud of a screw to 3D CAD model. Bottom row: from a 3D mesh of door handle to a 3D CAD model.

construction shall avoid incorporating user/company dependent content. Hence, given an input 3D scan (point cloud or mesh), the algorithm extracts reference sketch planes required to produce a feature-based CAD model (i.e. a model produced by applying a sequence of operations like revolution, extrusion and sweep). The need for constrained fitting is relaxed, hence providing explicit geometric constraints is relaxed too. The geometric constrains are generally related to a set of predefined parameters that define generated surfaces. Such solutions make heavy assumptions on the knowledge of each segmented region/part thanks to the classification step of the input segments.

The proposed algorithm is general enough to provide 2D/3D contours and the main direction axes required for standard modeling operations (CAD features) that together provide a meaningful design intent bases for the designer to further create the model. This representation (main axis and meaningful 2D/3D profiles) in essence covers basic geometric primitives (planes, spheres, cylinders, cones and cuboids) as they can be directly generated using a rotation/directional extracted axis and a generating polyline (an extracted 2D/3D profile). Moreover, many free-form shapes can be well reconstructed by applying standard CAD modeling operations like revolution, extrusion and sweep using a 2D/3D profile and a rotational/directional axis or path.

Algorithm 1: Sketch planes extraction algorithm.

1. Input: 3D mesh (if a point cloud then reconstruct a surface mesh using any standard algorithm (Berger et al., 2017))
2. Extract the principle axes of the input object using principle component analysis (Botsch et al., 2011)
3. Extract the sketch planes parallel to each of the principle axes by means of mesh slicing (Botsch et al., 2011)
4. Extract the sketch planes across a selected principle axis (the main axis by default) by means of mesh slicing
5. Save extracted principle axes and sketch planes represented as polylines

The benefits of the proposed approach can be seen in: a) being able to handle complete objects or segmented parts rather than being applicable to segmented regions only as in constrained primitive fitting based approaches, b) no need for a large number of prior scans and their CAD models as in learning-based approaches c) having no obligation to have a priori knowledge about the input scan, hence, not forcing certain geometric constraints, d) geometric constraints are implicitly imposed thanks to the sketch extraction process which is done either parallel (as in 1 - 3) or perpendicular (as in 1 - 4) to the principle axes and e) sketches representation as polylines in ASCII format is supported by any CAD engine. The proposed approach is validated by (semi) automating the modeling process applied to the extracted intermediate representation as explained in Algorithm 2 in Section 4.

4 AUTOMATED MODELING AND DISCUSSION

The proposed sketch extraction approach to create an intermediate representation is tested on PartNet (Mo et al., 2019), TraceParts (TraceParts S.A.S., 2019) and implemented using Trimesh (Trimesh, 2019) and vtkplotter (Musy et al., 2019). It is validated by writing generic automation Python scripts in SALOME 9.3.0 CAD modeling platform (Ribes and Caremoli, 2007) to construct the corresponding CAD models of the input scans given the intermediate representation only.

Figure 2a and Figure 2d show an input 3D point cloud and a mesh respectively with the principal axis and 3D principal profiles overlaid on them. The automatically extracted cross sections are shown in Figure 2b and Figure 2e and the automatically produced models are shown in Figure 2c and Figure 2f. A more complex input mesh (a Faucet) is shown in Figure 3a and its extracted principal profiles in Figure 3b, its extracted cross sections through principal axes in Figure 3c and the semi-automatically produced model in Figure 3d.

The automated CAD modeling scripts load the ASCII files and produce revolution and generalized sweep surfaces. Please note that automated extrusion scripts can be easily similarly produced. These scripts scan the input files for the principle axes, the principle sketches and the sketches extracted across the main principle axis. The (semi) automated modeling process is explained in Algorithm 2.

The proposed modeling algorithm covers 1) revolutions which are very common and fully represent the objects in many cases, 2) generalized sweep through directed cross sections (along an autogenerated path) which can reproduce the output of one or more extrusion, revolution and sweep operations. It is straightforward to write a similar script dedicated to extrusion. Given the output of the automated modeling script, the designer may intervene to check the produced models and keep the most relevant one(s) for further modification.

The sketch based representation would enable a broader representation of objects which are not directly interpreted as geometric primitives. It supports

Algorithm 2: Automated modeling algorithm.

1. load the ASCII formatted files in the CAD environment
2. Apply revolutions corresponding to the principal profiles around their parallel axes in Algorithm 1 - 3
3. Apply a generalized sweep on the sketch planes extracted through the (default) main principal axis in Algorithm 1 - 4
4. The sweep path is automatically constructed by computing the 3D path through the 3D sketches
5. The designer may interactively:
   (a) keep the generated features of interest
   (b) change the default principal axes for revolution and sweeping

the generalization of the CAD modeling process eliminating the complexity of detecting geometric primitives and computing their intersections to construct accurate boundary representation.

The main limitation is that the current approach is not fully automatic in some cases where the designer may interfere to reject one or more extracted features like the model shown in Figure 3d. The top part is generated by an automated generalized sweep while the bottom part is generated with automated revolutions. Another limitation is that fine details are not considered in this work yet. The output shown of a revolved input screw in Figure 2c has its internal head hole circular rather than being shaped with sharp internal edges as its original form in Figure 2a. Although the model automatically generated in Figure 2f faithfully represent its input mesh in Figure 2d, the automatically generated cross sections in the lower part do not fit well the handle thread. It needs more dense sections extracted, however the dense versus sparse sections extraction needs to be fully automated. Currently, an equidistant number of sections is extracted relative to the input scan height. Future work, will consider fully automating cross sections density, sketches filtering and mixed modeling to decide on the most relevant operation given the input sketches and axes.

5 CONCLUSIONS

This paper proposes a novel approach to convert an input 3D scan to a CAD model. The core idea is to extract reference sketches which act as an intermediate representation between the input scan and the

(a) Input 3D mesh.

(b) Principal 3D profiles (sketch planes).

(c) Principal 3D profiles (cross sections) extracted along the principal axis.

(d) Output 3D model using SALOME.

Figure 3: Complex Faucet example: from 3D mesh to 3D CAD model.

final model. They keep, to certain extent, the original design intent. This eases the designer interaction with the automatically generated models wherever required. The automation of the modeling step is straight forward using these sketches. The benefits of the proposed approach can be seen in relaxing the need to extract specific geometric primitives which remove the complexity of carefully designing well constrained optimization problems. There is no need to have a priori knowledge of every single segmented region or provide a large database of scans and CADs for learning. The proposed approach implicitly imposes geometric constraints like parallelism on subsequent extracted sections and perpendicularity constraints between the sweep axis and base sketch plane(s). The intermediate sketches are saved in ASCII format which naturally supports any available CAD software packages. The proposed method is validated by automating the modeling process for simple and complex objects.

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