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Semi-automated method for reviewing 3d printing datasets

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Abstract

There are many datasets available for various applications. Datasets, however, that consist of production data (such as Computer Aided Design, CAD) are scarce. There is no dataset that provides data for the whole process from engineering to production. Usually, production process data as well as design specifics are well kept secrets and may decide a company's success. With the wide spread of additive manufacturing machines such as fused deposition modeling (FDM) machines (3d printers), additive manufacturing has become broadly available. With additive manufacturing it is possible to manufacture arbitrary objects with machines that share a common toolset.

Thus, the goal of our research was to create a homogeneous 3d dataset that not only consists of the original 3d models, but also of the resulting production files (G-Codes).

To achieve this, we reviewed 12 different 3d datasets and examined a small-sized sample in respect of its suitability for 3d printing. We then developed a tool for semi-automated reviewing and editing of the dataset. After reviewing and editing the 3d dataset, production data was generated via slicing software. The whole research data can be accessed at the following repository: github.com/bbrosint/3dprintingdataset

Keywords

3d dataset, production data, FDM, 3d printing

1. Introduction

While there are numerous 3d datasets publicly available, there is no 3d dataset covering the whole production pipeline from design to production data, available. Thus, we want to generate a 3d dataset with reviewed designs and consistent production parameters for all designs.

In order to obtain a 3d dataset that is suitable for covering the processes from design to production, different criteria must be met. While any kinds of parts and shapes may be manufactured with additive manufacturing, certain geometric features pose challenges to any FDM process. These challenges are, for example overhangs, scale of geometric features and surface areas on printing beds. During this research, constraints of 3 axis FDM machines are considered.

To acquire a suitable 3d dataset in the domain of FDM production, a variety of different 3d datasets is analyzed by experts and rated according to the following criteria: a) dataset size describing the amount of items in the dataset, b) variety describing the different item classes / domains and c) quality describing the expected 3d model quality. These criteria are used to check if the 3d models are suitable for FDM production and how much heterogeneity, like varying transformations of same 3d model type and mesh quality (open / closed mesh loops) among the 3d dataset is to be expected.

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In the following section, 12 different 3d datasets are described and compared considering the criteria mentioned above. The domains of the 3d datasets range from general objects to machine elements.

2. Available 3d datasets

In this section, publicly available 3d datasets are presented. The applications of publicly available 3d datasets range from object recognition, reconstruction to surface algorithms for meshing and even pose recognition. Therefore, a pre-selection on 3d datasets which consist of 3d models that could be used for production is made. These 3d datasets are either derived by gathering 3d models from online portals, by recording sensor data or by using asset libraries from CAD software. The 3d datasets reviewed were preselected for 3d models with polygon-based surface representation, since sensor data or point cloud formats are not suitable for a FDM process without significant pre-processing.

Shilane et al. published one of the first 3d datasets in the year 2004. The 3d dataset consists of n = 1,814 3d models of n = 90 different object classes. The object classes range from everyday items such as tables, chairs and cars to humanoid characters [1].

The IKEA 3d model dataset published by Lim et al. in 2013 consists of n = 219 3d models representing furniture objects [2].

Starting in 2015, ModelNet has been published with a base dataset of n = 127,915 3d models in n = 620 object classes. With ModelNet 40 and ModelNet 10 subsets with n = 40 and n = 10, object classes have been published. The latter two datasets are reviewed for correct alignment and correct classification of the 3d models [3].

n = 3,000,000 3d models were made available by Chang et al. as the ShapeNet dataset in 2015. The dataset consists of 3d models representing everyday items which are categorized into n = 3,100 object classes. Additionally, subsets, such as ShapeNet Core, are available, where a reduced number of 3d models were manually reviewed and provided with further annotations by the authors [4].

Choi et al. reconstruct sensor data of depth camera scans. They gather n = 398 3d models from recorded point-clouds that meet their quality criteria. The resulting dataset consists of various 3d models that can be categorized into n = 9 classes [5].

Thingi10k is a 3d dataset by Zhou et Jacobson in the domain of 3d printing, introduced in 2016. The 3d models were gathered from an internet platform for display and exchange of 3d models. The 3d dataset consists of n = 10,000 3d models meant for 3d printing of various categories [6].

The ABC dataset consists of n = 1,000,000 CAD models and was introduced by Koch et al. in 2019. The CAD models represent mainly mechanical components, such as fasteners, gears, construction profiles but also assembled plant components and peripherals such as displays. The 3d data is available in STEP as well as in a polygon-based format [7].

In 2020, Kim et al. introduced the Mechanical Components Benchmark dataset composed of n = 58,696 3d models. The 3d models are divided into n = 68 classes which can be attributed to the area of construction elements or standard parts. The majority of these are fasteners, i. e. various types of pins, bolts and nuts. Furthermore, various types of bearings, hinges, springs and transmission elements such as wheels and gears are available in the 3d dataset [8].

Fu et al. introduced the 3d Future dataset consisting of n = 9,992 high quality 3d models in 2020. The 3d models are from the domain of product representation for the sale of furniture objects. The industry usage of the 3d models results in a high visual quality. The 3d models do not only have clean mesh topology but also surface textures making them suitable for rendering [9].

Publishing under the name Fusion 360 Gallery Dataset, Willis et al. and Lambourne et al. present a collection of three 3d datasets with different objectives in 2020 and 2021. The different 3d datasets are aimed at segmentation, reconstruction of the construction sequence and assembly of CAD models. The segmentation 3d dataset consists of n = 35,858 CAD models which are segmented according to their construction sequence. The reconstruction dataset consists of n = 8,625 CAD models and their model operations, i. e. base sketch, extrusion, intersect, join etc. The assembly dataset consists of n = 8,251 assemblies which are composed of n = 154,468 separate parts [10, 11, 12].

3. Selection of a 3d dataset for further processing

By examining the 3d datasets, a trend towards specialization can be observed: While early 3d datasets consist of everyday items and general objects, later 3d datasets contain domain specific 3d models such as machine components. While generally any 3d model is suited for the FDM process, certain requirements should be met to enhance printing time and results.

A 3d model with applied transformations can result in a significantly different machined product. Certain transformations may lead to lost details and needless generation of support material during the FDM process. Poor mesh topology, i. e. open mesh loops or nested meshes, may even result in errors in the processing pipeline eventually leading to non-printable objects. In figure 1, effects of simple transformations on FDM parts are shown. While a simple rotational transformation as seen in figure 1 b) leads to the generation of excess support material, a scale transformation (figure 1 c)) results in a completely different part because details are lost due to the restrictions of the FDM process.

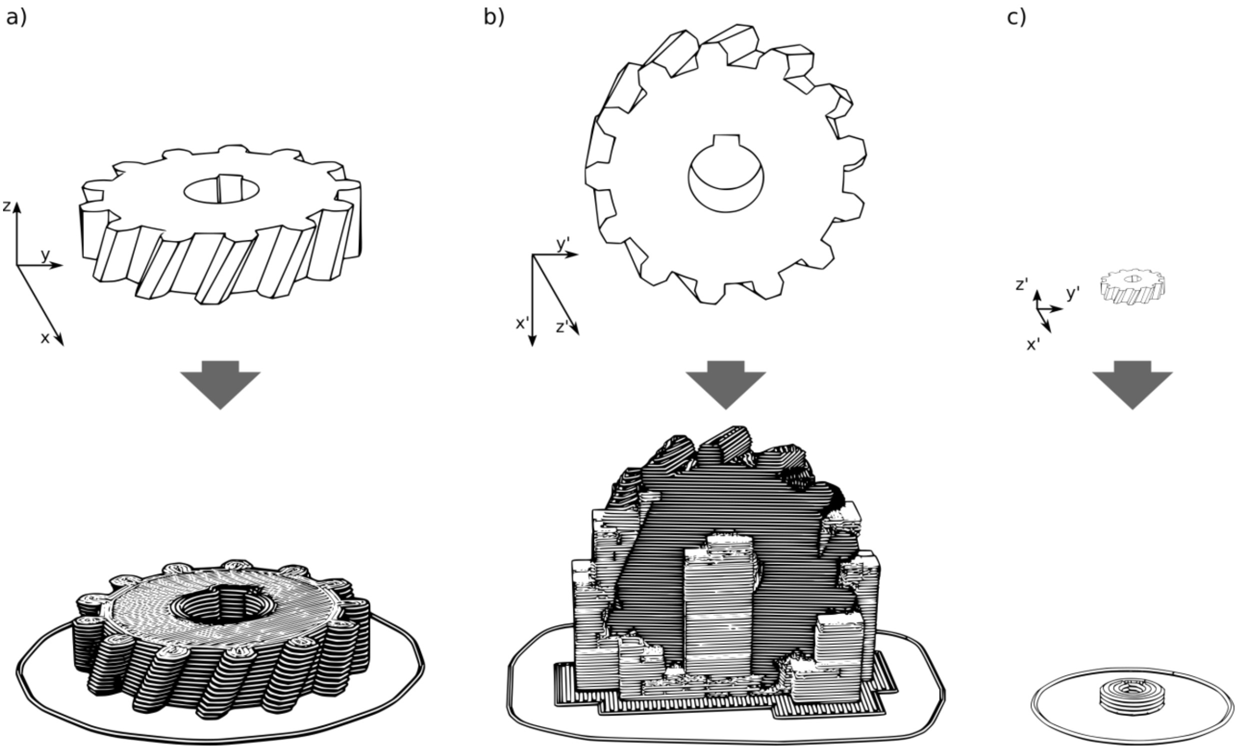

Figure 1: Effects of transformation on slicing for FDM process. a) original 3d model, b) rotational transformation, c) scale transformation

Therefore, the "quality" criterion is not only assessed by general mesh quality but also by whether the 3d models are homogeneous as a whole and suitable for FDM process. The different item classes as well as the domains are evaluated with the criterion "variety". 3d dataset size is considered as a third criterion. A comparison of the presented 3d datasets can be seen in table 1. Except for three of the 3d datasets, the 3d dataset sizes can be described as large. Only the 3d datasets of Shilane et al., Lim et al. and Choi et al. consist of less than n = 2 000 3d models. Variety is spread among the 3d datasets although earlier 3d datasets with more generic classes have been observed to be more diverse. Quality is different and the method how a 3d dataset was collected is possibly affecting this criterion. 3d datasets only consisting of randomly downloaded, generic 3d models are expected to have a huge variety of quality. While more domain specific 3d datasets are expected to be of more consistent quality. Considering the 3d dataset selection, only the Thingi10k 3d dataset consists of 3d models which are specifically prepared for FDM processing, not all examined 3d models were of consistent quality.

Table 1: Comparison of different 3d datasets

3d dataset	Ref	Size	Variety	Quality	Domain
Princeton Shape Benchmark	[1]	○	◗	◗	generic
ModelNet	[3]	◕	◕	◔	generic
IKEAObjects	[2]	○	◔	◗	furniture
ShapeNet	[4]	●	●	◔	generic
Large Dataset of Object Scans	[5]	○	◔	◗	generic
Thingi10K	[6]	◗	◕	◕	3d printing
ABC Dataset	[7]	●	◗	◔	construction elements
Mechanical Components Benchmark	[8]	◕	◔	◗	construction elements
3D Future	[9]	◗	◗	◕	furniture
Fusion 360 Gallery Dataset	[10,11,12]	◕	◗	◗	Constructions

For further analysis, the Thingi10k 3d dataset was chosen. While the 3d dataset is FDM process specific, it contains 3d models of a wide variety. Furthermore, the 3d models of Thingi10k are mainly prepared for FDM processing.

4. 3d dataset preliminary analysis

We conducted a preliminary analysis before processing the 3d dataset. Therefor a random sample of n = 100 3d models of the Thingi10k dataset is analyzed for disadvantageous rotational transforms and mesh quality.

While translational errors (the 3d model is not centered, meaning the 3d model's origin is not at [0,0,0]) may be automatically corrected by a simple transformation, automatically correcting rotation cannot be easily done.

During our analysis, the optimal FDM processing orientation was determined by expert opinion as to what orientation would result in minimum requirement of support structures and therefore result in the shortest production times. Any preferred FDM processing orientation to affect the produced part's strength is not accounted for. The only factor considered in alignment rating is minimal production time.

4.1 Coordinate system convention

For FDM processing, a 3d model needs to be aligned according to the FDM machine's axis. Therefore, the following conventions are made: The X-Y plane is aligned with the FDM machine's hotbed. The Z axis acts as the resulting normal and is positive regarding FDM process direction. Resulting from this, a 3d model should be oriented in a way that the "Z-", meaning the direction pointing to the hotbed (bottom), acts as a base for the FDM process. The resulting FDM process direction is then defined as “Z+”. Orthogonal to these are the “X+”, “X-” and “Y+”, “Y-” directions. The signs refer to a positive or negative direction.

The research’s underlying coordinate system convention is based on the import convention of the open source 3d modeling program Blender3d [13]. The files are imported into Blender3d with the common presets of the Blender3d STL importer; the scale is set at 1.0, “Y+” is defined as forward direction, “Z+” is defined as up direction.

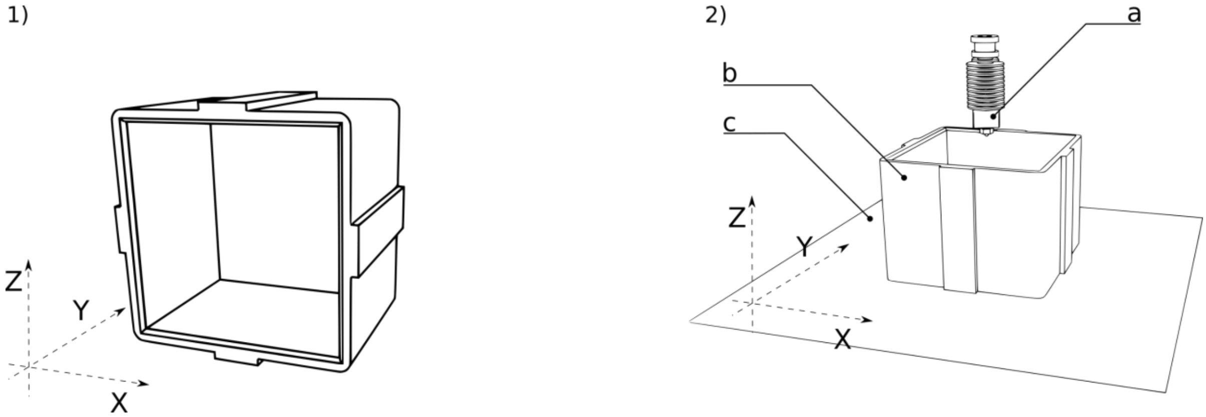

Figure 2: 3d model No. 368890 of the Thingi10k 3d dataset; 1) 3d model as imported by Blender3d, 2) adjusted rotation for FDM process; a) hotend, b) product, c) hotbed

In figure 2 a 3d model within the defined coordinate system can be seen. While on the left side, the 3d model has a rotational transformation that will result in excess overhangs and generated support structures, the adjusted 3d model on the right can be processed without the need of any support structures. With the defined coordinate system conventions, it is now possible to analyze the Thingi10k subset on suitability for FDM processing.

4.2 Preliminary analysis results

For assessing the quantity of 3d models that need adjustments or further editing, the optimal process orientations for the 3d models are noted by an FDM process expert. For the ease of interpretation, if a 3d model has two equally possible 3d printing orientations, i. e., a “Z-” and a “Y+” orientation, only the “Z-“ orientation is included in the data because this would mean no realignment of the 3d model is required.

If there is no ideal FDM processing direction to be found for a particular 3d model by the expert, i. e., if the 3d model has no preferred direction for FDM processing by design, the 3d model is categorized as “None”. A 3d model is also categorized as “None” if its preferred FDM processing direction is skewed in space. Therefore, needing a transformation along an axis that is not a principal axis.

In figure 3 the results of the Thingi10k subset analysis are presented. It can be seen, that p = 80 % of the 3d models are aligned for the FDM process. p = 20 % of the 3d models are not oriented in a suitable manner, as can be observed in figure 3 a). Additionally, the count of other prevalent orientations is included in part b) of figure 3. It is noticeable that the majority of misaligned 3d models can be categorized as being fixable by a rotational transformation around one of their main axes. Only a minor fraction (n = 2) of the misaligned 3d models is categorized by the “None” category. With these results, an interim summary of the Thingi10k dataset can be made: While the Thingi10k dataset mainly consists of 3d models which are suited for FDM processing, a non-negligible portion of the 3d models needs further editing prior to any further progressing in the FDM production chain.

Transferring the subset’s results of misaligned 3d models (p = 20 %) to the main Thingi10k 3d dataset allows recognizing that a program for easing the 3d model’s processing is needed.

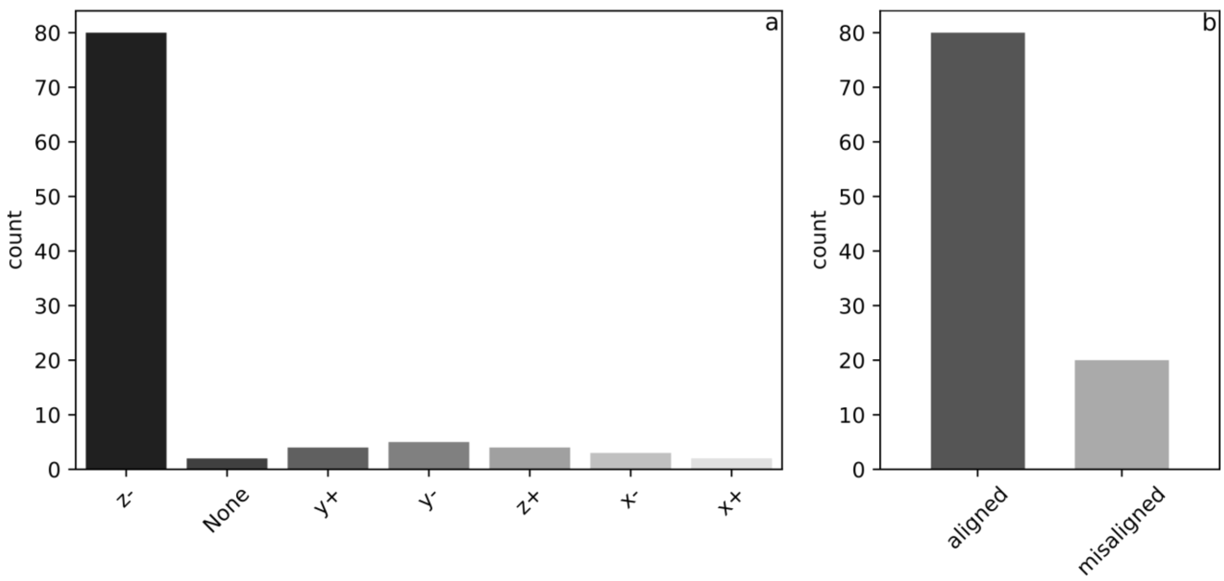

Figure 3: Results of preliminary analysis of Thingi10k 3d dataset; a) count plot of prevalent FDM process directions, b) conclusive count plot

5. Development of a semi-automated tool for 3d model review and alignment

To enhance processing the Thingi10k 3d dataset, the user should have minimal interaction with file operations. Therefore, a software tool should iterate over the 3d models and do input / output operations automatically. Additionally, the program should aid fast 3d model transformations and ideally provide a means to offer a shortcut for manually editing of 3d models.

5.1 Orientation criterion for FDM processing

With the data gathered from the subset mentioned above, exploratory data analysis was undertaken. We hypothesize that the ratio between largest extreme surface area for a given principal axis [A_{max}] and total surface area [A_{tot}] of a 3d model may be suitable for determining a base surface for FDM processing (see equation 1). The outermost surface areas are represented by a 3d model's outermost vertex location and all neighboring surfaces within a given relative tolerance in the same direction.

$$oc = \frac{A_{max}}{A_{tot}} \tag{1}$$

In figure 4 the visualization of said method can be seen. The outermost surfaces in each principal axis' direction are displayed in a unique hatched style. The area of the hatched surfaces is then used for calculating the orientation criterion mentioned earlier.

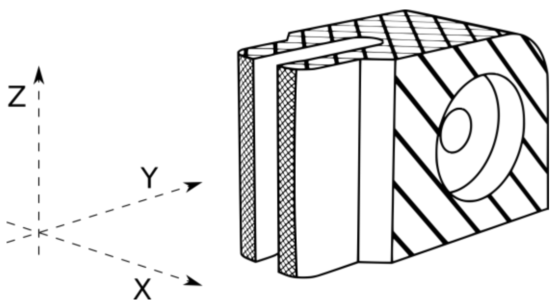

Figure 4: 3d model No. 1307396 of the Thingi10k 3d dataset with visualization of base alignment method

During the subset analysis, a value for the orientation criterion of $oc = 0.2$ is observed to be suitable for automated determination of the FDM process direction.

5.2 Software tool conception

A flowchart of the program's proposed software concept is visualized in figure 5. At the start of the program, a list of all 3d models is created, then this list is processed subsequently: Each 3d model is loaded sequentially and presented to the expert. During this process, the orientation criterion for automatically determining FDM process direction is calculated.

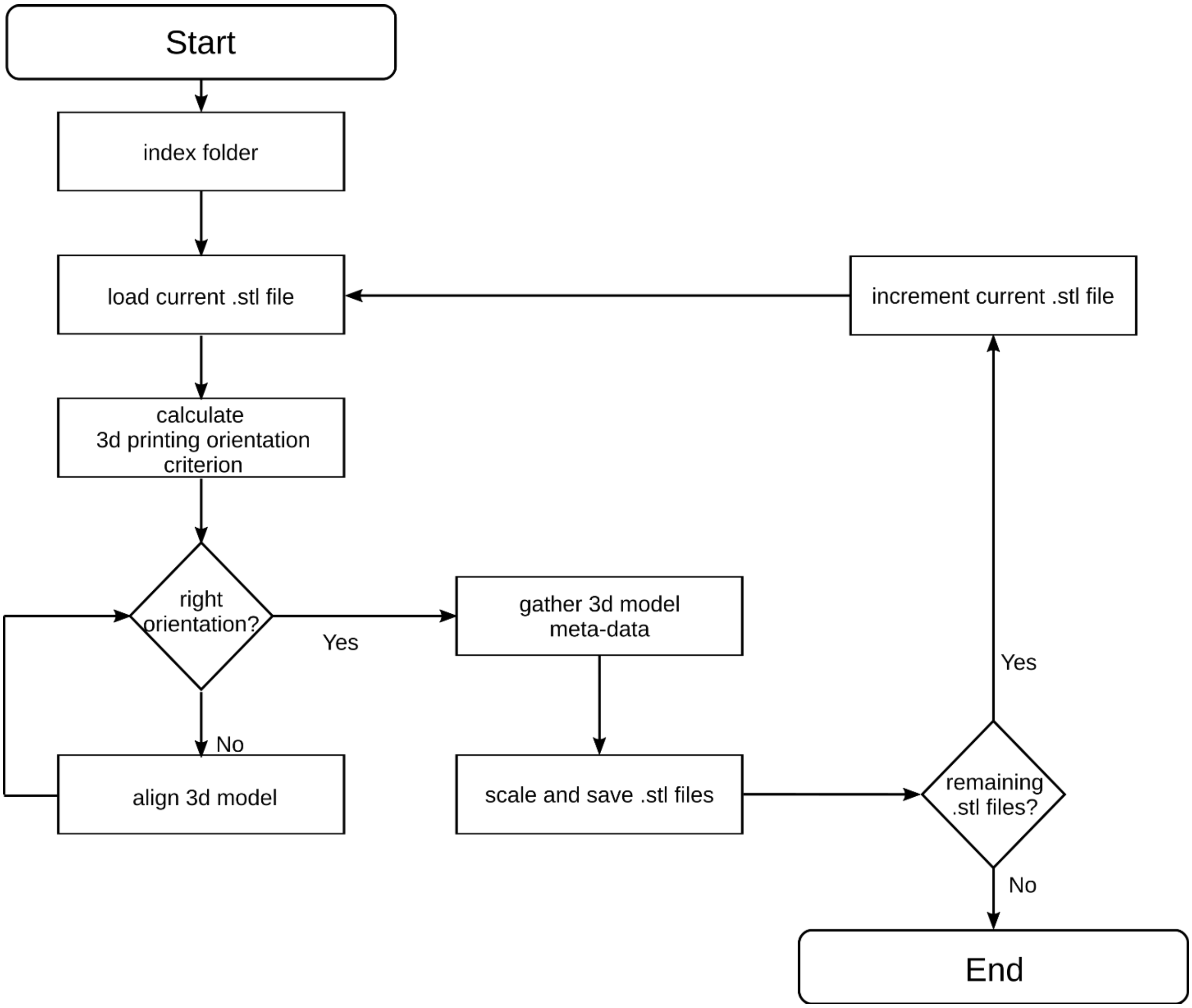

Figure 5: Conceptual flowchart of proposed program to assess the Thingi10k 3d dataset

The expert then decides on the 3d model's orientation: Whether any transformation should be applied or if the 3d model can be saved as it is. When the 3d models' orientation is right, the program saves three instances of the 3d model, in three different sizes, together with meta-data.

The different sizes [100 mm, 150 mm, 200 mm] of the 3d model are scaled to fit common FDM machine dimensions. The scale transformations of the 3d models are calculated by normalizing the 3d model to its largest dimension and multiplying by the output size.

To ease any further necessary editing, the software tool is projected to be developed inside a 3d modeling program that can handle various formats.

5.3 Software tool implementation

The software tool is implemented as an add-on in the Blender3d program with the python 3 scripting language. A screenshot of the program can be seen in figure 6. After launching the software tool, a menu appears in Blender3d's main window, together with an STL file in the 3d view. The expert reviewing the 3d dataset may then inspect the 3d model for FDM process orientation. Minor errors (like a non-closed mesh) as well as 3d model realignment are mendable with the Blender3d mesh editing mode. To speed up the rotational transformation around the 3d model's main axes, two automated methods for fast rotational transform are implemented:

The first method is based on the criterion mentioned above (see section 5.1). The method is suitable for basic alignment of the 3d model. If the criterion is satisfied or the expert sees the method suggesting the right FDM process orientation, a rotational transformation can be applied automatically. The alignment method can be invoked by pressing the button "Base Alignment" as shown in figure 6 f).

The second method is the implementation of a Continuous Principal Component Analysis (CPCA) with

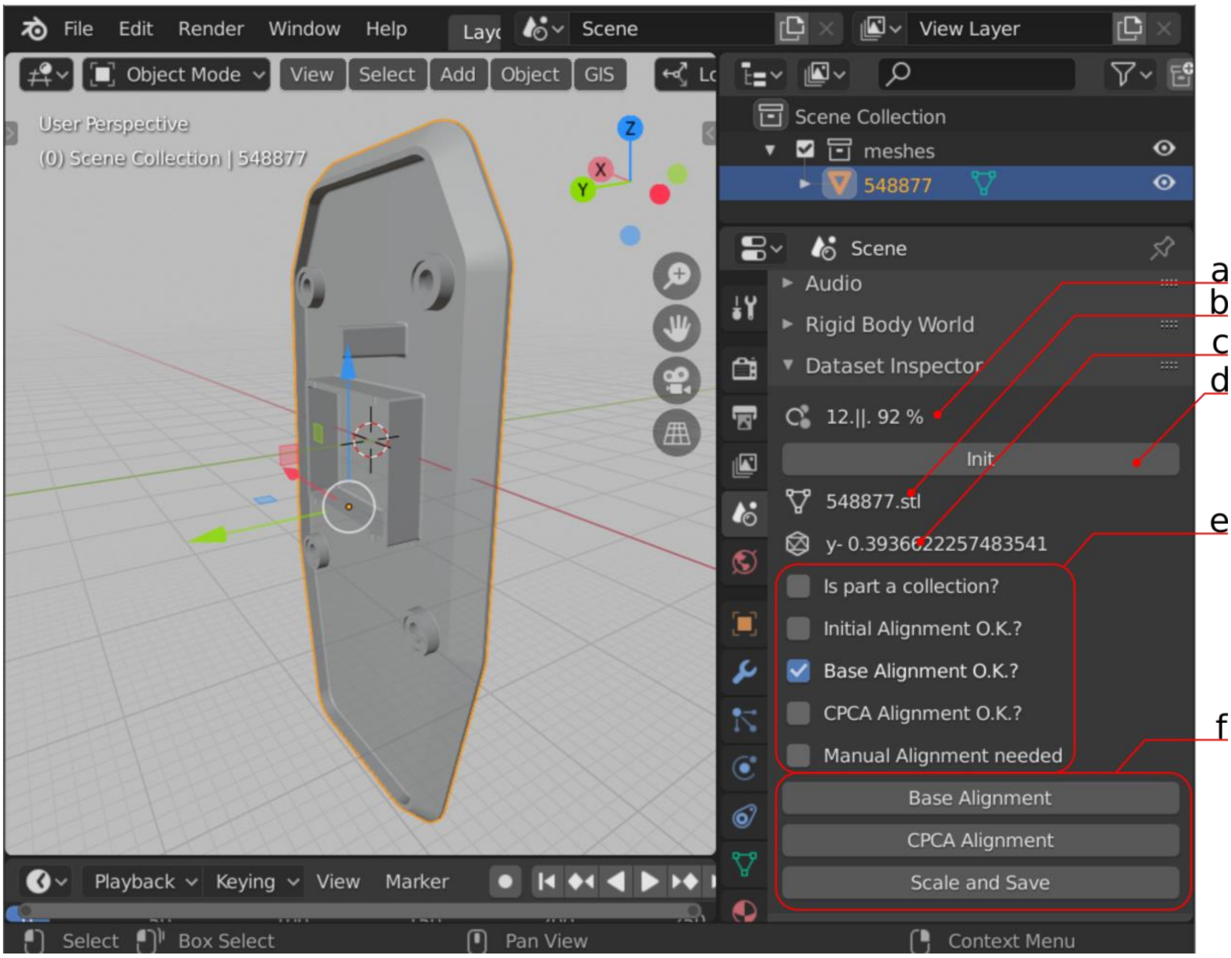

Figure 6: Software tool for reviewing 3d datasets in Blender3d. a) progress indicator, b) filename, c) value of orientation criterion and proposed FDM process direction, d) index files, e) meta-data gathering, f) operator buttons

which a 3d model can be aligned along the axis with the biggest variance [14], thereby, theoretically transforming a 3d model in an optimal way for additive manufacturing. The implementation is done with the means of python 3 package numpy [15]. The CPCA method should be applied if the 3d model is not misaligned with a rotation around a principal axis.

If the automated methods mentioned above do fail, the expert has the option to correct the 3d model alignment manually with the editing tools of the Blender3d program.

Additionally meta-data (figure 6 e) is collected during the review process. It is recorded whether the part is a collection, i. e. more than two separate, non-connected meshes on the “XY”-plane and if the alignment methods mentioned before are able to appropriately align the 3d model. The “Scale and Save” button (figure 6 f)) invokes the scaling transformation as described in section 5.2.

5.4 FDM process preparation

To simulate FDM processing, the 3d models must be sliced. Therefore, automated slicing by calling Slic3r 1.30 via python 3 script [16]. Simulation of FDM processing times as well as the amount of filament spent is done with the gcoder module of Printrun 2.0.0 [17]. Standard parameters of an FDM machine with a hotbed of $A_{hotbed} = 200 \cdot 200\ mm^2$ are used for slicing.

6. Resulting dataset

Of the initial n = 10,000 3d models, n = 9,911 are evaluated by an expert to be suited for FDM processing. The loss of 3d models can be attributed to three different types of defects: A 3d model has large open unfixable mesh loops, it is a non- or semi-processed point cloud, or it is of the collection type where the single meshes are spread in every spatial direction. In these cases, a correctional editing cannot be performed in a manner recognized by the expert.

Using the software tool results in n = 29,733 3d models that are generally suitable for FDM processing. Using the slicing software, the same amount of G-Codes is generated.

7. Concluding analysis

In this section, meta-data gathered during the 3d dataset's review is presented and discussed. In fig. 7 two bar plots are shown. In figure 7 a) an overall analysis of the alignment of the 3d models is shown. For $p = 84.8\ \%$ of the 3d models, the rotational alignment is suited for FDM processing, while for $p = 15.2\ \%$ realignment needs to be carried out. Compared with the initially analyzed, randomly sampled subset of the Thingi10k dataset, it can be seen, that the expected share of 3d models needing realignment is slightly ($\Delta p = 4.8\ \%$) lower for the complete Thingi10k dataset.

Figure 7 b) shows the alignment methods used for 3d model realignment. The share of 3d models that needed realignment and are processed with the developed base alignment method, is $p = 71.3\ \%$. The base alignment method’s applicability is observed to be $p = 86.8\ \%$ for the whole Thingi10k 3d dataset. The category ‘manual alignment’ in figure 7 b) means that either no automated realignment method was applicable or that the mesh had errors (i. e. open mesh loops that had to be manually closed) which had to be fixed manually for the 3d model to be 3d printable. Manual alignment is applied to $p = 26.4\%$ of all misaligned 3d models.

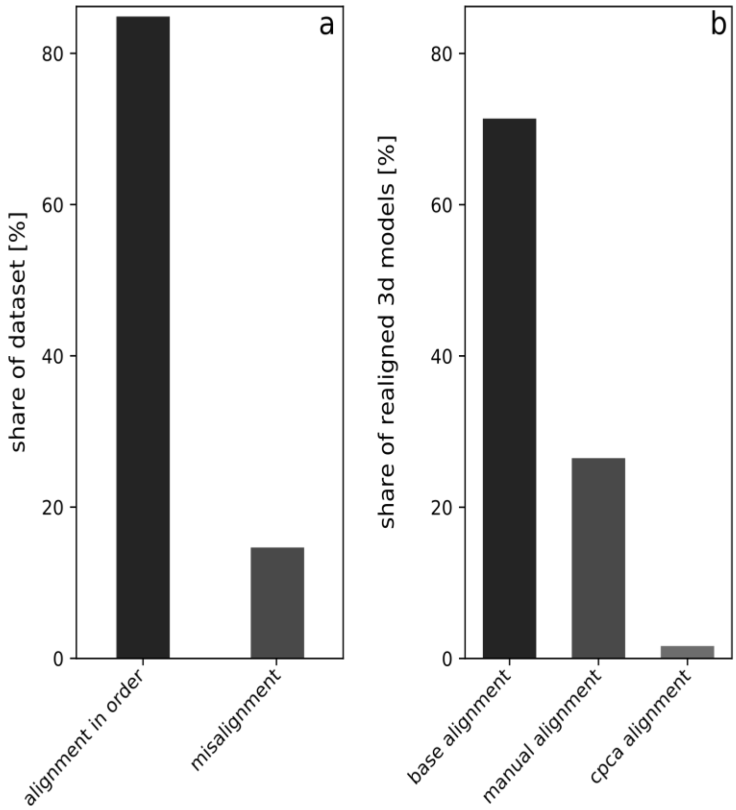

Figure 7: Results of Thingi10k analysis; a) aligned vs misaligned 3d models, b) necessary measures for alignment

Overall, it can be concluded that the majority of the Thingi10k 3d dataset is suitable for FDM processing. There is however an issue with uniform scale and rotation which is non negligible and which this research has tried to overcome through a revised 3d dataset.

8. Conclusion

During this research, various 3d datasets were evaluated for further processing into a production pipeline dataset. After preliminary assessment, Thingi10k dataset was chosen to be analyzed for FDM processing. After an initial manual analysis of a subset of the data, a semi-automated method based on a software tool was developed for processing of the Thingi10k 3d dataset. In this context, an orientation criterion was formulated for the automated alignment of the 3d models. This was applicable to $p = 86.8$ % of the 3d models and could be used for automating the additive manufacturing production pipeline, i. e. as a slicing software plugin. The complete 3d dataset was reviewed by a FDM processing expert and the 3d models were edited for FDM production. An FDM process was simulated for each 3d model and the resulting data has been combined into a new dataset covering the manufacturing chain from design stage to production. The resulting dataset could be used for analyzing the design to production process such as the relation between design and sliced 3d printing part. A further use case may be the training of models for pose estimation of 3d printed models. At last, an analysis of the gathered statistics during the review of the Thingi10k dataset was performed.

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