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Procedia CIRP 00 (2019) 000–000

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29th CIRP Design 2019 (CIRP Design 2019)

Automated Learning of User Preferences for Selection of High Quality 3D Designs

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Abstract

3D object design is one of the most sought-after topics due to its application in many domains including Medical imaging, Virtual Reality, Computer Graphics, Animation etc. Manual 3D object design is inherently an expensive and labour intensive task. Several techniques such as GAN (Generative Adversarial Nets), SFM (Structure from Motion) and MVS (Multi-View Stereo) are employed to automate 3D design. 3D-GAN is one such method that allows the fully automated design of 3D objects using deep artificial neural networks. However, such generated 3D objects often suffer from distortions, obscure/missing parts, and other artefacts. For a large number of generated models, it becomes time-consuming for the human expert to select models of high quality among the set of generated ones. In this paper, we tackle this problem through machine learning powered 3D model quality assessment algorithm, that mimics the users preferences. For our experiments, we generate 3D objects using 3D-GAN and investigate several machine learning algorithms including Support Vector Machines, Gradient Boosting, Deep Neural Networks to classify generated models based on their visual appealability. We find that our model successfully mimics user choices with 90% accuracy, thus eliminating the need for human intervention in the subjective quality analysis, once user preferences have been learned. The proposed system can be seamlessly integrated into existing automated 3D design systems further augmenting the capabilities of human designers.

Keywords: Automated 3D Design, Artificial Intelligence, Quality Estimation, Machine Learning;

1. Introduction

The process of capturing shape of real or imaginary objects in a 3D setting is termed as 3D object design. More specifically, it is an intricate task of finding an objects 3D profile, as well as determining coordinate of every point on that profile. For the manual design, quite a few softwares such as Blender, Maya, FreeCAD are available at the designers disposal. These softwares provide tools for aiding design process and platform for seamless sharing of end designs. 3D designs find applications in a wide variety of fields including but not limited to Augmented and Virtual Reality, Computer Vision, Computer Graphics etc. Therefore, there is an overwhelming need to speed up design process to cater to ever growing demand from aforementioned fields. However, manual 3D design is intrinsically labour dependent, time consuming task and alone cannot address growing demand.

Creating 3D models of novel designs is an essential part of product development processes [15] [19]. The physical form of a product adds value to the product by increasing the quality of the usage experiences [10]. Product development process assume that the generation of product forms are constrained by conceptual product descriptions [19]. This stands in contrast to practical processes based on trial-and-error [28]. When distinguishing between the extreme poles between incremental designs and radical designs, creating product forms is the quest for a local maximum or a global maximum [16].

Artificial intelligence technologies are a means for supporting the creation of product forms by developing variations based on previous designs. For instance, convolutional neural networks (CNN) are used for applying extracted visual styles to images [21]. This approach supports finding incremental designs based on existing concepts and styles. Recently, generative approaches [22] have been applied to provide interactive support of novices during the creation process of product forms [29]. This approach potentially addresses semi-automatic creation of even radical design forms. In between incremental and radical product forms, machine learning technologies can be

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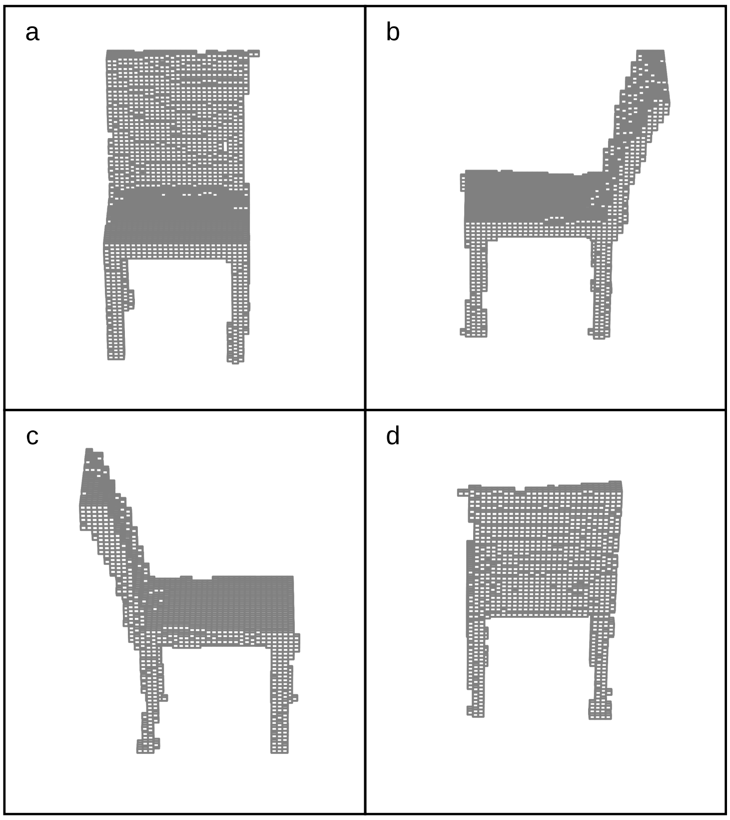

Fig. 1. Multiview of an example 3D design generated from 3D-GAN (a) 0° view (b) 90° view (c) 180° view (d) 270° view

also used for finding design gaps between existing concept designs based on conceptual product features without using visual or 3D information [26].

With the advancement of machine learning and computer vision, efforts have been in place to automate 3D design process. Available techniques can be broadly categorised into active and passive methods [1]. Passive methods generally do not involve any interaction with the object while active methods use some form of projection such as light on the object. Structure from motion(SFM), Multi-view Stereo (MVS) and Generative Adversarial Nets (GANs) are one of the most prominent techniques in place today for automatic 3D design.

Machine learning and artificial intelligence has been at the forefront in bridging the gap between supply and demand in 3D design. 3D-GAN [2] is one such machine learning method born out of original GANs that effectively generates 3D designs in bulk. Although methods such as 3D-GAN ease burden on manual designers, they still suffer from number of shortcomings. Firstly, these methods suffer from mode collapse i.e variety in generated 3D designs is limited [8]. Secondly, large number of generated 3D designs suffer from artefacts, missing limbs etc [2]. Therefore, automating 3D design is not sufficient on its own unless it is augmented with a quality screener which can efficiently segregate good designs from the bad.

In this paper, we present how machine learning technologies can be used for fully automatic creation of 3D product forms focussing on the class of incremental designs tasks. We propose a machine learning powered 3D design quality estimator which efficiently picks good designs from a mixed lot. We generate 500 3D designs from 3D-GAN [2] and conduct a short survey to gauge user behaviour in choosing good and bad designs. With 90% accuracy, we simulate user preferences with the help of machine learning. Our proposed system can be seamlessly integrated into any existing automatic 3D design systems.

2. Literature Survey

Modelling and synthesizing 3D designs has been an prominent problem in computer vision community. Rise of automatic 3D design generators have increasingly constrained subjective visual quality assessment due to their large throughput. Alternative approach is to automate this process by simulating user preferences. In the literature such approaches are categorized into three categories: Full- reference (a 3D design is available

for comparison), reduced reference (partial information about 3D design is available) and no reference (no reference design is available) [3].
Visual quality metrics for 2D images are extremely matured over the years while same is not the case with 3D designs. To utilize existing 2D metrics, I. Abouelaziz et al., (2018) [4] proposed a blind (no reference) visual quality assessment metric based on the convolutional neural network. Given a 3D design, 2D images from multiple views are generated. Each of these images are split into small patches of size 32x32 and fed into a convolutional neural network. Coupled with feature learning and regression, this method produces results on par with the full and reduced reference methods. However, 2D metrics arent as effective since they do not take into account depth information inherent in the 3D designs [3]. A. Nouri et al., (2017) [5] proposed a slightly different but equally effective view independent blind quality assessment method. This method generates multi scale saliency map and roughness map from a given 3D design and extracts features from each superfacet. These features are then fed into a Support Vector Machine (SVM) regressor to predict the quality score. Although A. Nouri et al., [5] is view independent, both aforementioned approaches involve lengthy of preprocessing steps such as multiple view generation, image patch creation etc. With the help of 3D convolutions, our proposed method works directly on the generated 3D designs and extracts relevant features. These features are then fed to a classifier for evaluation. This eliminates the need for lengthy preprocessing. Full reference methods such as [3], [6] and reduced reference methods such as [7] require full / partial information about the 3D design before hand. This is not feasible in the design process since generated 3D designs have to be evaluated on their own merit.
Perceptual metrics for 3D designs can also be categorized into image-based and geometry-based metrics depending on the component considered for the quality assessment [30]. For the former case, Lindstrom and Turk [14] proposed to render the design being simplified from several viewpoints and use a fast image quality metric to evaluate the impact of the simplification. In the latter case, the perceptual metrics work by analyzing the geometry of the 3D designs to predict perceptual impairments or evaluate other perceptual quality aspects, making the evaluation view-independent [30].

3. Method

In this section, we describe the experimental setup and the methodology used for simulating homogenous user preferences in selecting high quality 3D designs.

3.1. 3D Design Generation

We use 3D-GAN [2] for generating 3D designs. 3D GAN uses a combination of volumetric convolutional neural networks and generative adversarial nets to generate 3D designs from a probabilistic space. Reasons behind choice of 3D-GAN are multifold:

- The architecture of 3D-GAN substantially uses neural networks which makes our integration easy in the end.
- Quality of generated 3D designs were much better than other 3D design generators.
- No reference image / object is involved since 3D designs are sampled from a low dimensional probabilistic space
- By changing mapping probabilistic space, wide variety of 3D designs can be generated
- Adversarial criteria over traditional heuristic criteria enables 3D-GAN to capture 3D designs without supervision.

We set up 3D-GAN on a local machine. 3D-GAN provides possibility to generate 5 different categories of 3D designs namely: Car, Chair, Desk, Gun, sofa. Number of 3D designs to be generated can also be controlled using sample size parameter. Due to its simplicity and universality , we chose Chair class and generated 500 different 3D designs. Figure 1 shows an example 3D design generated from 3D-GAN. As expected, many of these designs suffered from slight noise to extreme distortions. Figure 2 shows an example of good design and a bad design generated by 3D-GAN.

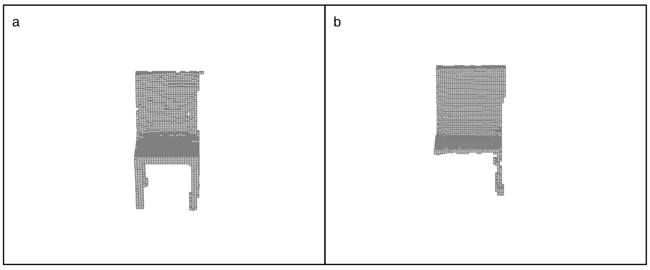

Fig. 2. Sample 3D designs where users had unanimous agreement on quality. (a) Good design (b) Bad design

3.2. User Survey

To comprehend user preferences in selection of high quality 3D designs, we conducted a survey among a homogenous group. 500 3D designs of Chair were generated using 3D-GAN. To bring uniformity and ease of use in the survey, multiple 2D projections were rendered from 4 views for each 3D design. 2D projections were generated from 4 different angles namely 0, 90, 180 and 270 degrees. Figure 1 shows an example of rendered 2D projections from a 3D design. Survey required the participants to go through all 4 2D projections and rate the design as good or bad based on the perceived quality. Participants had no time constraint and were in fact encouraged examine the 2D rendering in full detail. Survey consisted of two stages:

- Selecting a homogenous user group
  Participants of the survey were first briefed about the intricacies of 3D-GAN, 3D design generation and how automation can revolutionize this field. We showed a glimpse of few of the designs to familiarise them to the task at hand. Our primary goal is to simulate perceived quality of the 3D designs. Therefore, it is pertinent to consider homogeneous users who have similar quality perception of the 3D designs. We conducted a pre-test to gauge preference pattern of the user group. We then selected top 10 users who have high correlation in their preferences. These 10 users, though they belonged to different background, age group etc, had a similar understanding about quality of 3D designs. Since 3D designs are generated automatically from 3D-GAN without any human intervention, their visual quality cannot be compared with those designed manually. Therefore, participants need to be made aware of the best and worst designs in the survey. Added advantage of the pre-test was that users got acquainted with the process and took cognisance of the best and the worst 3D designs in the survey.
- Collecting preferences from the homogeneous group
  Participants from the homogeneous group were provided with 500 3D designs of chair, consequently 500x4 2D projections. Each participant took 50 minutes on an average to complete the survey.

Figure 2 shows the sample designs where users had unanimous agreement on their quality. Out of 500 desings, 11 designs were ranked good and 165 designs were ranked bad unanimously. Krippendorffs alpha coefficient is a statistical measure persistently used by researchers to gauge extent of agreement among the users in the survey [24]. The alpha is given by

$$\alpha = 1 - \frac{D_o}{D_e} \quad (1)$$

where D_o is the disagreement observed and D_e is the disagreement expected by chance. Krippendorffs alpha coefficient for the user group is found to be 0.44357 when computed using R package *irr* [25].

3.3. User Preference Simulation

We then combined user ratings by way of maximum approval. A 3D design is rated as good if maximum number of users voted it as good and same is the case for bad designs.
We formulate our approach as a supervised learning problem. 3D designs generated from 3D-GAN are essentially 3-dimensional in nature. Hence they can not be used directly for two reasons: first, They are bulky i.e they consume lot of memory and hence slow down the whole process; second, existing machine learning libraries are not well equipped to handle 3D data directly. Therefore, feature extraction is necessary to speed up learning process without compromising performance of a learning algorithm. To make most of available infrastructure, 3D designs need to be converted to into 1D before they can be used in machine learning algorithms. 3D designs are first fed into a 3D convolutional neural network and thereby transformed into 1D vectors. These feature vectors are used as an input while consolidated user preferences are used as output for training machine learning algorithm. Figure 3 shows our proposed system.
With the combined data in hand, machine learning offers several avenues to simulate user preferences. In a crude sense, machine learning algorithms tries to establish a relationship between input and output which could then be generalised to any arbitrary input. In this case, we investigate several machine learning algorithms and compare their effectiveness. Generally termed as No Free Lunch algorithm, Law of Conservation for Generalization performance(LCG) states that generalization performance of any lerner sums to 0 across datasets [13]. There is not one algorithm which works best for all datasets. Therefore, it is essential to consider a mix of machine learning algorithms when dealing with a new dataset.
Linear Support Vector Machines (SVM) [27] are one of the learning algorithm classes we considered in our implementation. SVM is a discriminative classifier which outputs an optimal hyperplane separating classes by the highest margin. The output of a binary Linear SVM is a sign of weighted sum of input features plus bias; Thus only linear relationships can be modelled. Because of this specific form, Linear SVM can be trained efficiently on datasets of our scale.
Another class of models considered are Decision Trees [11].

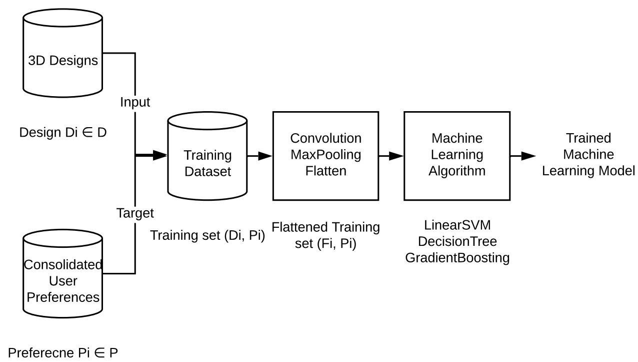

Fig. 3. Machine learning pipeline for simulation of the perceived quality of 3D designs.

Decision trees can be represented in a form of a binary tree. Classification with such tree starts at the root node, which checks the value for one of the features in input. Depending on the value of feature, left or right child of the node is taken as root of tree, and the procedure repeats until a node without children is reached. Such node contains a value, which will be taken

as output. Despite their simplicity, decision trees can model arbitrary function. There exist efficient heuristic algorithms that extract decision trees from data, and scale linearly with size of the data. The resulting decision tree can be inspected; If the tree does not contain any rules regarding such feature, then effectively the tree discards some information, and hence it is not informative. Furthermore, Gini importance metric can be used as a proxy for how "important" a particular feature is.
Finally, Gradient Boosting Classifier [17] is a method where a number of different models, in our case decision trees, are combined to obtain a more expressive predictive model. The scalability w.r.t. size of data of the approach is same as that of its components, hence similar to that of a decision tree. Additionally, Gini Importance for every decision tree can be averaged, to obtain an average estimated importance measure for every feature of the input to the model.
In our experiemnt we restrict ourselves to aforementioned machine learning models due to computational simplicity. Advanced algorithms such as Deep neural Networks can also be tried in the future depending on the availability of computational power. Once the training process is over, our proposed system effectively learns to differentiate between good and bad 3D designs. Trained model can then be saved and reused across 3D designs.

3.4. System Integration

The end product our proposed method is a trained machine learning algorithm. We propose two ways to integrate our system into 3D design process. First, with the rise of sophistication in transfer learning, knowledge learnt in one task can be transferred to other similar tasks[12]. In a production scenario where 3D designs are similar to the ones considered in this paper, our trained model can be reused directly without any modifications. Python programming language offers various avenues to save, store and load trained machine learning models. Once trained, models can be reused across 3D designs. Second, as per [13], there is not one algorithm which works best for all datasets. In scenarios where 3D designs are contrastingly different from the ones used in this paper, models proposed need to be retrained on the new dataset.
Proposed method has virtually no dependency over 3D design generators. Therefore, any 3D design created either manually or through systems such as 3D-GAN can be evaluated qualitatively using our system.

4. Evaluation

4.1. Experimental Setup

We use Python programming language for evaluating our proposed method. Python has established itself as a major player in data analysis [18]. 500 3D designs are generated using 3D-GAN and corresponding 2D projections are captured using matplotlib, a python visualization library. We first transform 3D design to 1D feature vector using Tensorflow [23] and then model machine learning algorithms using Scikit-learn [20]. All of these libraries are free and open source, and are powered by thousands of programmers across the world. We conducted our experiment on a 8 core machine with 32GB RAM and with one Graphical Processing Unit (GPU) consisting of 8GB RAM.

4.2. Evaluation Results

Table 1. User preference simulation using various machine learning models

Algorithm	Accuracy	Precision	Recall
Linear SVM	0.900	0.790	0.755
Gradient Boosting	0.895	0.815	0.688
Decision Trees	0.851	0.674	0.644
Logistic Regression	0.905	0.795	0.744
Average	0.887	0.768	0.707

Table 1 compares the performance of different machine learning algorithms while keeping 3D design generation and feature extraction steps intact.
On an average, all algorithms considered in Table 1 could simulate user preferences by 88.7%. With 90.5% accuracy, Logistic regression performs better than all other algorithms considered. Since the dataset is highly biased towards bad designs, it is imperative to look at other metrics in addition to accuracy. Precision and Recall are a supplementary metrics that aid understanding of the algorithms performance. Precision represents the fraction of good 3D designs among those rated as good while Recall represents fraction of good 3D designs among all generated good 3D designs. Gradient Boosting has the highest precision while Linear SVM has the highest recall. Theres always a tradeoff between precision and recall as can be seen in Gradient Boosting.
Results show that it is possible to automate quality assessment and reduce burden from the designers shoulder. Further work is needed to explore other algorithms that might yield better results.

5. Conclusion and Future Work

In this paper, we presented a automatic 3D design quality estimator that effectively simulates user preferences of visual appealability and there by aiding design process. Proposed system is a powerful yet simple quality metric that can be seamlessly integrated into any 3D design generator. We argue that integration of our system reduces burden from designers shoulders by positively impacting design process. Proposed system is not intended to replace human workforce, rather work hand in hand with the designer to speed up design process. Machine learning powered automatic quality estimators are a step in the right direction to overhaul quality and throughput in the design process. Our proposed method can be extended to other design domains to reap benefits of automation in the long run.
At the moment, we consider chair as a model class. Future work could include extending our method to address various

3D design classes. A Generic quality estimator would be great to have but difficult to implement long term goal. More research is needed to understand user behaviour beyond the training set.

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