Polygons, Points, or Voxels? Stimuli Selection for Crowdsourcing Aesthetics Preferences of 3D Shape Pairs

Kapil Dev
Lancaster University

Nicolas Villar
Microsoft Research Cambridge

Manfred Lau
Lancaster University

ABSTRACT

Visual aesthetics is one of the fundamental perceptual properties of 3D shapes. Since the perception of shape aesthetics can be subjective, we take a data-driven approach and consider the human preferences of shape aesthetics. Previous work has considered a pairwise data collection approach, in which pairs of 3D shapes are shown to human participants and they are asked to choose one from each pair that they perceive to be more aesthetic. In this research, we study the question of whether the 3D modeling representation (e.g. polygon, points, or voxels) affects how people perceive the aesthetics of shape pairs. We find surprising results: for example the single-view and multi-view of shape pairs lead to similar user aesthetics choices; and a relatively low resolution of points or voxels is comparable to polygon meshes as they do not lead to significantly different user aesthetics choices. Our results has implications towards the data collection process of pairwise aesthetics data and the further use of such data in shape modeling problems.

CCS CONCEPTS

• **Computing methodologies** → *Perception*; *Shape modeling*;

KEYWORDS

perception, aesthetics, 3D modeling

ACM Reference format:
Kapil Dev, Nicolas Villar, and Manfred Lau. 2017. Polygons, Points, or Voxels? Stimuli Selection for Crowdsourcing Aesthetics Preferences of 3D Shape Pairs. In *Proceedings of CAe'17, Los Angeles, CA, USA, July 28-29, 2017,* 7 pages.
DOI: 10.1145/3092912.3092918

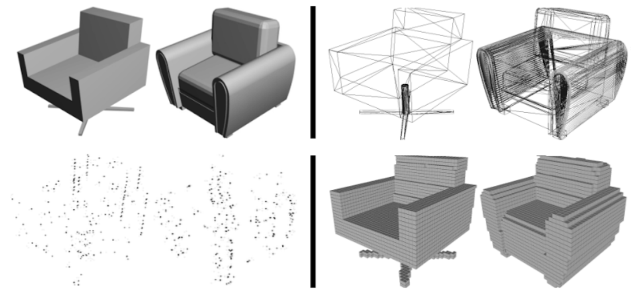

Figure 1: Example of a 3D shape pair of chairs in four shape modeling representations: polygon mesh, wireframe mesh, point cloud (250 points), and voxels (resolution of 32x32x32).

1 INTRODUCTION

In the past, researchers in diverse fields such as philosophy, psychology, and mathematics have explored the perception of beauty in different ways. More recently, the aesthetics of images [Leyvand et al. 2008; Liu et al. 2010] and 3D shapes [Bergen and Ross 2012; Gambino 2013; O'Toole et al. 1999; Séquin 2005] have been explored in computer graphics. The aesthetics of 3D shapes is a subjective concept, as whether a shape is aesthetic depends on an individual's preferences. Hence we take a data-driven approach in this work and consider the human preferences of shape aesthetics.

Designing experiments to collect data on the perceptual aesthetics of 3D shapes is a challenging task. One method is to show users a single shape and ask them to give an absolute aesthetics score. However, an absolute scale may not be consistent across individuals. One person might give a score of 0.95 to indicate an aesthetic shape while another might say that a score of 0.7 is already very aesthetic. Instead of an absolute scale, we choose a relative scale of scores. This is motivated by recent work in collecting crowdsourced data [Lau et al. 2016; Liu et al. 2015; Lun et al. 2015; O'Donovan et al. 2014] where triplets or pairs of media types (including fonts, 3D shapes, and 3D shape vertices) are shown to users. We collect aesthetics data by showing participants two shapes (or a shape pair) and asking them to choose one that they perceive to be more aesthetic. This is a "simple" task that fits well with crowdsourcing platforms as participants only need to provide a binary response for each question. Even though using shape pairs is a good way to collect data, there are still other parameters such as how the shapes are presented to the users that might affect their choice. In this paper, the key question we explore is whether the modeling representation of the 3D shapes affect the human aesthetic preferences of shape pairs (Figure 1).

This question is significant as the quality of data collected from humans is important towards the further study of shape aesthetics with such data. For example, if we use such data to study the features that make a shape aesthetic [Adkins and Norman 2016; Gambino 2013; O'Toole et al. 1999] or to learn measures of shape aesthetics [Dev et al. 2016], then the quality of the collected data is important. In addition, there is work in the analysis of 3D shapes that takes different 3D model representations (e.g. voxels [Wu et al. 2015] and point clouds [Qi et al. 2016]). An understanding of the effects of different representations would be useful for robust data collection for shape aesthetics and for general shape analysis problems.

One main use of the study presented in this paper is that we have attempted to predict shape aesthetics automatically by collecting

DOI: 10.1145/3092912.3092918

data of the aesthetics of shape pairs [Dev et al. 2016]. In this regard, it is not clear how we should present the shapes to the users, and whether the user perception may be significantly different if we change the modeling representation. The study in this paper is intended to offer insights for these, but we do not focus on the learning and prediction parts in this paper.

We first compare between single-view and multi-view representations of 3D shapes and investigate whether there is a difference between them towards the human aesthetics preferences of shape pairs. Similarly, we then compare between the polygon mesh and wireframe mesh representations, between the polygon mesh and point cloud (for various numbers of points) representations, and between the polygon mesh and voxel (for various voxel resolutions) representations. The basic experiment we perform is to take a shape pair (shapes A and B), generate different 3D modeling representations of them, render them side-by-side, and ask humans whether they perceive A or B to be more aesthetic. For example, to compare between polygon meshes and voxels, we take the polygon mesh renderings of A and B and collect the preferences for a number of participants. We also take the voxel (at some resolution) renderings of A and B and collect the preferences for the same number of participants. For each shape pair, we see whether the human preferences between polygons and voxels match. As this data may contain small numbers, we use Fisher's exact test to test the null hypothesis that there is no difference in the proportions of preferences (of A and B) between the polygon and voxel representations. We perform this test for many shape pairs to compare between the two representations.

Our key contribution is in comparing between various types of stimuli for collecting the aesthetics preferences of 3D shape pairs. We find results that are surprising and not expected. For example, we find that between single-view and multi-view representations, there is no significant differences in the human aesthetics preferences. We also find unexpectedly that a small number of points and a low voxel resolution are already comparable to the polygon mesh, when using them to collect data for the aesthetics preferences of shape pairs. For example, there are no significant differences in using a low voxel resolution of 32x32x32 compared to the polygon mesh. This implies that humans need not observe the details to form opinions on shape aesthetics and high resolution representations of shapes may not be necessary for analyzing these shapes.

2 RELATED WORK

2.1 Aesthetics of 3D Shapes

There is much previous work in 3D shape aesthetics. These can be for various types of shapes and for finding aspects of a shape that makes it visually appealing. For example, previous research has found that average faces are more attractive [O'Toole et al. 1999], humans prefer curves in abstract artistic shapes [Gambino 2013], and shape complexity is one criteria towards the perceived beauty of snowflakes [Adkins and Norman 2016]. There has also been work in creating aesthetic shapes [Bergen and Ross 2012; Séquin 2005; Wyvill et al. 2012]. In this paper, we do not have any predefined criterias of aesthetics but instead take a data-driven approach. We collect data for pairs of 3D shapes and study the effect of modeling representations on the human aesthetics preferences of shape pairs.

2.2 Effect of Rendering Method or Style on Perceived Shape

There exists work in the perception of shapes based on their rendering methods or styles. DeCarlo et al. [2003] introduce a non-photorealistic rendering method to convey a shape based on suggestive contours. Todd et al. [2004] study different sources of information (e.g. shading, texture, contours) that humans can use to visually perceive 3D shapes. Ferwerda et al. [2004] find that rendering methods (such as global illumination) and viewpoint have a significant effect on the ability to discriminate shape differences. McDonnell et al. [2012] study the effect of different rendering styles on the perception of virtual humans. Zell et al. [2015] study how shape and material stylization affect the perception of characters and facial expressions. In this paper, we study whether rendering shapes in different fundamental 3D modeling representations (e.g. polygon mesh, point cloud, voxels) can affect the human preferences of shape aesthetics.

2.3 Perception of Shapes

Shape perception is a large area and a complete review of work in this area is beyond the scope of this paper. One related work predicts the salient features of 3D models [Howlett et al. 2005]. Another related work determines perceptually good views of 3D models based on data collected on people's preferred views [Secord et al. 2011]. There is also work that learns semantic attributes of shapes and demonstrates an interface for creating new shapes with the desired strength of attributes [Chaudhuri et al. 2013]. While there is much work in the visual perception of shapes in general, we focus on shape aesthetics.

2.4 Crowdsourcing

Recent work in collecting crowdsourced data based on data triplets [Liu et al. 2015; Lun et al. 2015; O'Donovan et al. 2014] and pairs [Lau et al. 2016] gave us the original inspiration to collect aesthetics data in the simplest way of shape pairs. With the shape pairs, we then considered whether different 3D modeling representations would affect the user choice.

Crowdsourcing approaches to measure image quality are common. Researchers have explored different experimental methods for perceptually measuring image quality [Keelan and Urabe 2003]. A binary like/dislike rating and a numerical 10-point scale [Agrawal et al. 2014] have been tested with crowdsourced voters to understand image aesthetics. Different experimental setups to collect data to assess image quality have been compared [Mantiuk et al. 2012], and they find that a forced-choice pairwise comparison method gives the most accurate result. In our experiments, we use the forced-choice pairwise comparison method for 3D shapes, where we take two shapes and ask which is more aesthetic.

3 EXPERIMENTAL DESIGN

The purpose of our experiments is to explore whether the methods (in terms of 3D modeling representations) used to display the shapes to participants affect the human aesthetics preferences of shape pairs. In this section, we describe the 3D shapes we used, the 3D modeling representations, the crowdsourced data collection, and the method used to compare whether different modeling representations give significantly different user aesthetic responses.

3.1 3D Shapes

We collect a variety 3D shapes from ShapeNet [Chang et al. 2015]. These shapes belong to three categories: chairs, lamps, and tables. We consider the shape geometry and not the color and texture information. The shapes are already oriented and scaled.

We generate pairs of shapes, where each pair comes from the same category. It makes more intuitive sense to compare a chair against another chair, rather than a chair against a lamp. For each category, we have a set of 30 shapes and we generate 60 shape pairs randomly. The total number of shape pairs is 180.

3.2 3D Modeling Representations

We convert each shape into these 3D modeling representations before using them in our data collection process: single-view polygon mesh, multi-view polygon mesh, wireframe mesh, point clouds with various number of points, and voxels for various resolutions.

For single-view polygon mesh (or just "single-view"), we create a single-view image that shows a representative forward-facing viewpoint of the polygon mesh. The viewpoints are chosen by us and the shapes are consistently rendered in the same way. For multi-view polygon mesh (or just "multi-view"), we rotate the mesh along the up-axis and have a slightly slanted up-direction to better show the 3D shape. We choose to take three seconds for each complete rotation followed by half a second of pause at the same representative viewpoint for single-view. These are then repeated continuously as a *gif* image and rendered with the same shading parameters as the single-view case. The video shows examples of these images.

For "polygon mesh", the meshes are as originally downloaded. These are in multi-view, as we prefer to truly show the 3D aspects of a mesh from multiple views. So these are the same as the multi-view case above, except we use the term "polygon mesh" whenever we directly compare the polygon representation with the other 3D representations below (which are also rendered in multi-view). The "wireframe mesh" either shows the "original" mesh or a "re-meshed" case. We convert the mesh into voxels (at a high resolution to minimize jagged artifacts) and then use marching cubes to convert back into a mesh that has a large number of polygons that are more uniform in size. We then apply a quadric-based edge collapse method to reduce the number of polygons to a desired number while maintaining the shape. For "point clouds", we use the same approach as the one for wireframe mesh to first convert into a mesh with a large and more uniform number of polygons and then reduce this mesh to the desired number of points. We tested various cases and eventually used meshes with 125, 250, and 500 points. For "voxels", we tested various cases and took voxel resolutions of 16x16x16 and 32x32x32. The voxels are rendered as small cubes. Figure 1 shows examples of these modeling representations.

3.3 Crowdsourced Data Collection

We use crowdsourcing as a method to collect data. We collect data for: 60 shape pairs x 3 shape categories x 9 modeling representations x 25 participants. Each HIT (Human Intelligence Task) or each set of questions on Amazon Mechanical Turk has 30 shape pairs. Hence there were 54 HITs x 25 participants. Note that each participant can only do each unique HIT once, but they can do any number of the different HITs if they wish. Each shape can repeat within the same HIT, but the 30 shape pairs are different. Each shape pair is posted as a question on Amazon (Figure 2 shows some examples), where we asked participants to choose which shape is more aesthetic. The order of shapes in each appearance of a shape pair is randomized. We filter out "bad" participants by allowing those whose approval rate of previous questions they have done is 95% or higher. This is a constraint that can be set within the Amazon system. We paid \$0.05 to \$0.10 for each HIT, which typically took participants approximately a few minutes to complete.

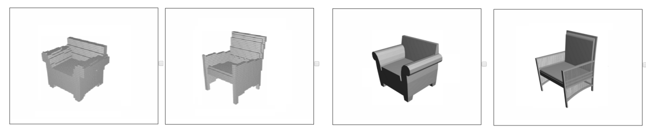

Figure 2: The interface on Amazon Mechanical Turk allows users to click anywhere on the image or the small box to the right to indicate the one they perceive to be more aesthetic. The left pair is for voxel resolution of 32x32x32 and the right pair is for polygon meshes.

3.4 Comparing 3D Modeling Representations

Using the collected data, we wish to study the effect of the modeling representation on participant choice, by comparing the results of two modeling representations each time. At a high level, if most people choose shape A for one representation of the pair (A,B), while most people choose shape B for another representation, then these two modeling representations lead to a significantly different user choice. We describe the modeling representations that we compare against, and the method to compare the data collected for two modeling representations to decide whether they lead to significantly different user responses.

We compare the data collected for two modeling representations separately each time. First, we compare between single-view and multi-view (of polygon meshes). We then use polygon mesh as a basis to compare between: polygon mesh and wireframe mesh (original and re-meshed wireframe), polygon mesh and point cloud (125, 250, and 500 points), and polygon mesh and voxels (16x16x16 and 32x32x32 resolutions).

We compare between two modeling representations by using Fisher's exact test. This test tells us whether any differences that we observe in the proportions of (A,B) choices between two modeling representations is significant. As the number of responses for a particular choice can be small or even be zero, we choose Fisher's exact test which can handle these cases. The null hypothesis for each of the comparisons above is that the two modeling representations are equally likely to have the same proportions of choices.

As an example of this test, to compare between polygon mesh and voxels (at a specific resolution), we take each shape pair (A,B) and observe the choices of 25 participants. For polygon mesh, we may have 18 participants choosing A and 7 choosing B. For voxels,

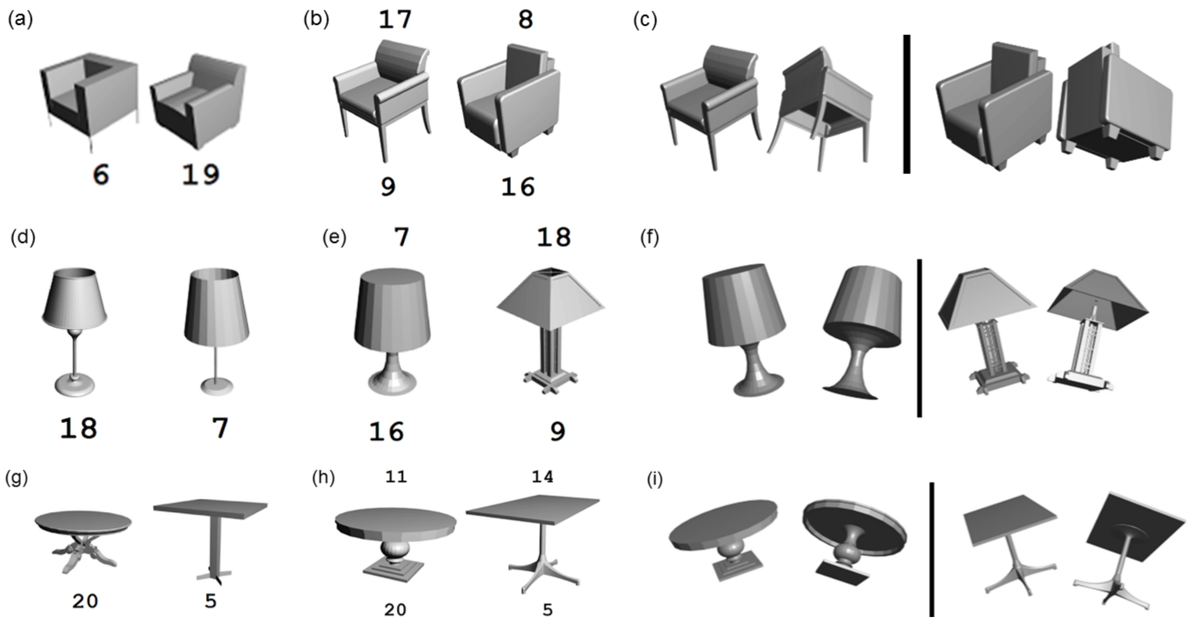

Figure 3: Single-View vs. Multi-View: Examples of shape pairs with user (A,B) responses. (a) A shape pair of chairs with the same (A,B) responses (numbers below shapes) for both single-view and multi-view. (b) A shape pair of chairs with quite different responses between single-view (numbers above shapes) and multi-view (numbers below shapes). (c) Two views for each of the shapes in (b). Second row shows the same type of examples as in first row but for lamps, and third row is for tables.

we may have 9 choosing A and 16 choosing B. Intuitively (18,7) and (9,16) are quite different. Fisher's exact test gives a p-value of 0.022. Since the p-value is less than 0.05, this provides evidence to reject the null hypothesis at the 5% significance level or that the two modeling representations lead to significantly different proportions of responses (note that this was just an example to illustrate the process). We perform Fisher's exact test with the data for each shape pair. Then for all shape pairs for each shape category, we note the percentage of pairs where the null hypothesis is rejected or where the two modeling representations lead to different responses. The results in the next section show these percentages.

4 RESULTS

We show and analyze the results to give insights into whether the modeling representation of 3D shapes affects the human aesthetic preferences of shape pairs.

4.1 Single-View vs. Multi-View

We compare between the single-view and multi-view representations with the method described in the previous section. The percentages of shape pairs where we observe significant differences (according to Fisher's exact test at 5% significance level) in the proportions of (A,B) aesthetic choices between single-view and multi-view are 1.7% for chairs, 6.7% for lamps, and 1.7% for tables. The overall percentage for all shape pairs is 3.3%. These are the percentages of shape pairs where the null hypothesis is rejected. Figure 3 shows examples of shape pairs where the single-view and multi-view cases give either the same or quite different (A,B) responses.

The results provide some initial evidence that the single-view polygon mesh and multi-view polygon mesh have similar proportions of aesthetic responses. The implication is that having a single-view is enough even though the shapes are in 3D, at least for the shape categories we tested.

4.2 Polygon Mesh vs. Wireframe Mesh

We compare between the polygon mesh and wireframe mesh representations. The percentages of shape pairs where we observe significant differences (according to Fisher's exact test at 5% significance level) in the proportions of (A,B) aesthetic choices between polygon mesh and "original" wireframe are 8.3% for chairs, 5.0% for lamps, and 10.0% for tables. The overall percentage for all shape pairs is 7.8%. The percentages between polygon mesh and "re-meshed" wireframe are 5.0% of chairs, 1.7% for lamps, and 5.0% for tables. The overall percentage for all shape pairs is 3.9%. Figure 4 shows examples of shape pairs where the polygon mesh and wireframe mesh cases give either the same or quite different (A,B) responses.

The results provide some initial evidence that the polygon mesh and re-meshed wireframe representations have similar proportions of aesthetic responses.

4.3 Polygon Mesh vs. Point Clouds

We compare between the polygon mesh and point cloud representations. The percentages of shape pairs where we observe significant differences (according to Fisher's exact test at 5% significance level) in the proportions of (A,B) aesthetic choices between polygon mesh and point clouds (for 125, 250, and 500 points respectively) are 26.7%, 10.0%, and 6.7% for chairs, 5.0%, 6.7%, and 6.7% for lamps,

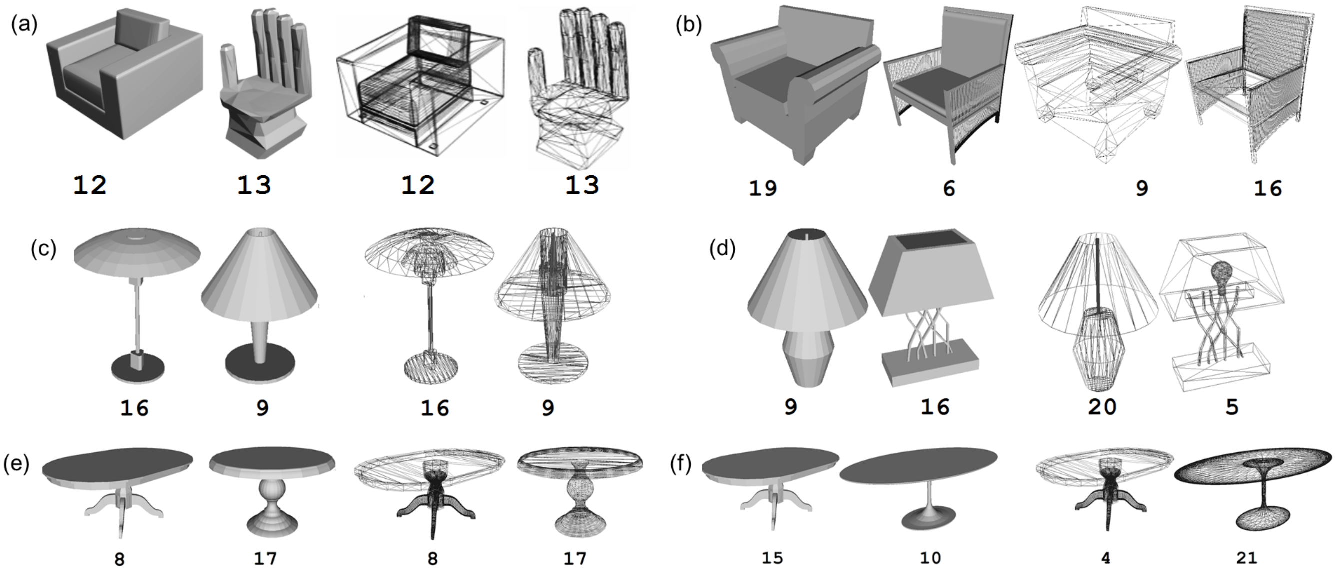

Figure 4: Polygon Mesh vs. Wireframe Mesh (original mesh): Examples of shape pairs with user (A,B) responses (numbers below shapes). (a) A shape pair of chairs with the same (A,B) responses for both polygon mesh and wireframe mesh. (b) A shape pair of chairs with quite different responses between polygon mesh and wireframe mesh. Second row shows the same type of examples as in first row but for lamps, and third row is for tables.

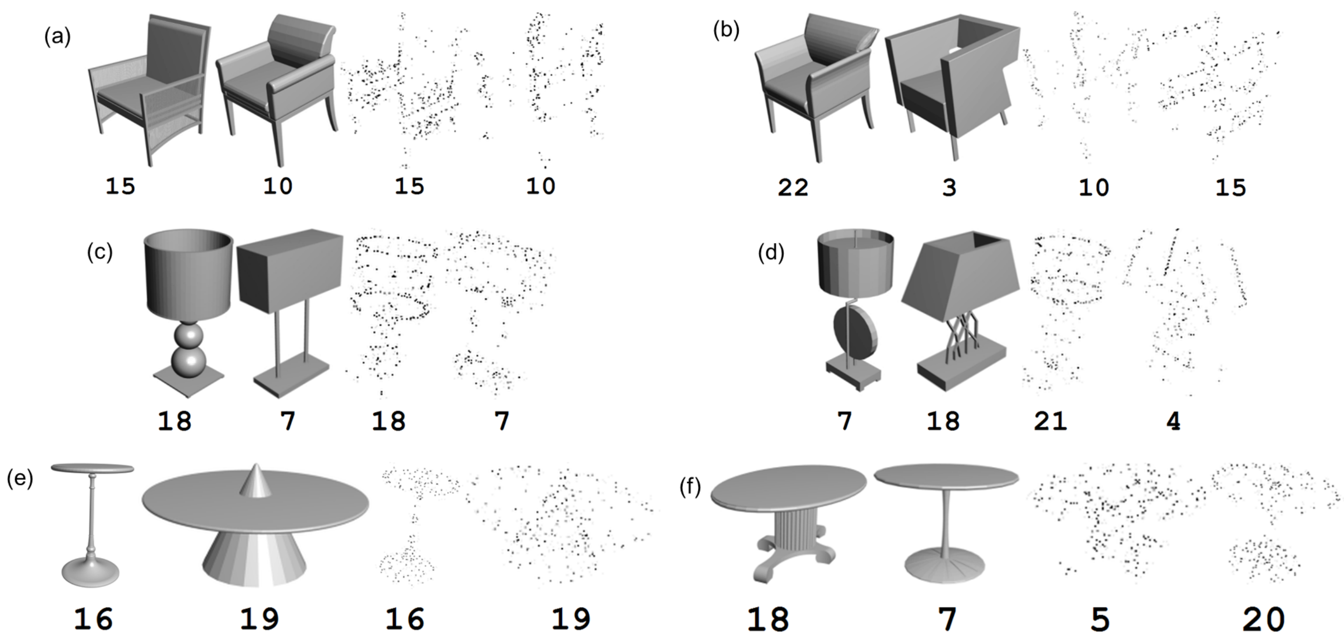

Figure 5: Polygon Mesh vs. Point Clouds (250 points): Examples of shape pairs with user (A,B) responses (numbers below shapes). (a) A shape pair of chairs with the same (A,B) responses for both polygon mesh and point clouds. (b) A shape pair of chairs with quite different responses between polygon mesh and point clouds. Second row shows the same type of examples as in first row but for lamps, and third row is for tables.

and 16.7%, 18.3%, and 8.3% for tables. The overall percentages for all shape pairs are 16.1%, 11.7%, and 7.2%. Figure 5 shows examples of shape pairs where the polygon mesh and point cloud cases give either the same or quite different (A,B) responses.

The results provide some initial evidence that a relatively small number of points is enough to represent each shape, compared to the thousands of vertices that these models typically have (in their original mesh form). In some cases, the point representation

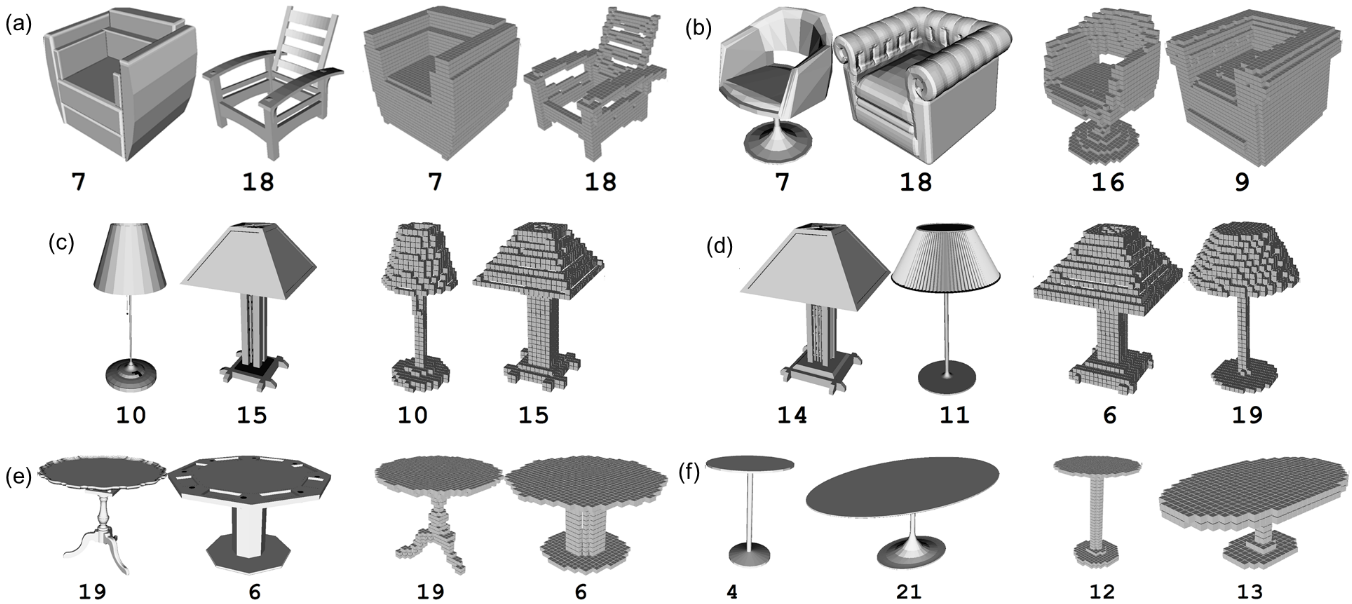

Figure 6: Polygon Mesh vs. Voxels (resolution of 32x32x32): Examples of shape pairs with user (A,B) responses (numbers below shapes). (a) A shape pair of chairs with the same (A,B) responses for both polygon mesh and voxels. (b) A shape pair of chairs with quite different responses between polygon mesh and voxels. Second row shows the same type of examples as in first row but for lamps, and third row is for tables.

can miss some shape details or even parts of the shape (e.g. the lamp pole). This implies that participants typically do not need to observe the details of a shape to make the aesthetics choices.

4.4 Polygon Mesh vs. Voxels

We compare between the polygon mesh and voxel representations. The percentages of shape pairs where we observe significant differences (according to Fisher's exact test at 5% significance level) in the proportions of (A,B) aesthetic choices between polygon mesh and voxels (for resolutions of 16x16x16 and 32x32x32 respectively) are 13.3% and 5.0% for chairs, 11.7% and 10.0% for lamps, and 11.7% and 1.7% for tables. The overall percentage for all shape pairs is 12.2% and 5.6%. Figure 6 shows examples of shape pairs where the polygon mesh and voxel cases give either the same or quite different (A,B) responses.

The results provide some initial evidence that the polygon mesh and a voxel resolution of 32x32x32 have similar proportions of aesthetic responses, while a resolution of 16x16x16 leads to higher percentages of "different" responses. This result is surprising as a resolution of 32x32x32 is quite coarse and in some cases can miss many details of the shape. Similar to the previous subsection for point clouds, this also provides evidence that participants typically do not need to observe the details of a shape to make their choices.

5 DISCUSSION

We have studied the effect of the 3D shape representation on the human aesthetics preferences of pairs of 3D shapes. The results are sometimes not expected and surprising. Our results have implications for further work that uses this kind of aesthetics data and 3D modeling problems that use this kind of data in general. For example, we find that a relatively low number of points and low resolution of voxels are comparable to polygon meshes when collecting aesthetics data of shape pairs. This implies that a coarse resolution of the shapes may be enough for some problems even if this reduces some shape details.

One limitation of our work is that the shapes that we considered are man-made and furniture objects, which in many cases are symmetric or have some almost-symmetric axes. Most man-made shapes available online have some symmetry though, so this is still a fair comparison. For future work, it would be interesting to perform our experiments for more abstract shapes.

We realize that voxelizing the models may cause thin structures to appear thicker. This is an artifact of the voxelization that may affect the aesthetics results. This is partially one of the purposes of our study in the sense that we wish to explore whether the voxelization affects the perception of shape aesthetics.

We find that a surprisingly low voxel resolution of 32x32x32 is enough for humans to detect aesthetic preferences as with the polygon mesh representation. A voxel resolution of 32x32x32 is quite coarse and we actually hypothesized that it would be too coarse to represent the details of the shapes. We thought that users would not be able to give the same aesthetics responses with such low voxel resolutions, but this is not true and may be counter-intuitive. It seems that humans can unconsciously perform some smoothing and interpolation, for example to visualize some jagged voxels and think of the overall smoothed surface rather than the jagged-ness of the voxels.

We believe that our work provides a good start to this problem. For future work, there are many possible ways to extend our experiments to explore the problem further. A limitation of our work is that we have only three man-made shape categories. We can extend this to a larger number of shape categories and shape pairs. We can also have shape pairs that crosses two categories to have one shape A from one category and the other shape B from another category.

Other good experiments to do for future work include: considering 3D shapes with color/texture/material, considering different rendering parameters such as non-photorealistic effects, having different multi-view parameters (how to rotate the shape, how long to rotate and pause, and/or even allow direct interactions from the users), performing the single-view vs. multi-view experiment for representations other than the polygon mesh (we decided not to be too exhaustive in this paper), and considering two or three static images instead of a continuous rotation to achieve the effect of multiple views.

ACKNOWLEDGMENTS

We thank the anonymous reviewers for their feedback. Kapil Dev is supported by the Microsoft Research Ph.D. program.

REFERENCES

Olivia C. Adkins and J. Farley Norman. 2016. The Visual Aesthetics of Snowflakes. *Perception* (July 2016).

Abhishek Agrawal, Vittal Premachandran, and Ramakrishna Kakarala. 2014. Rating Image Aesthetics Using a Crowd Sourcing Approach. *Pacific-Rim Symposium on Image and Video Technology 2013 Workshops - Volume 8334* (2014), 24–32.

Steve Bergen and Brian J. Ross. 2012. Aesthetic 3D Model Evolution. *International Conference on Evolutionary and Biologically Inspired Music, Sound, Art and Design* (2012), 11–22.

Angel X. Chang, Thomas A. Funkhouser, Leonidas J. Guibas, Pat Hanrahan, Qi-Xing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, Jianxiong Xiao, Li Yi, and Fisher Yu. 2015. ShapeNet: An Information-Rich 3D Model Repository. *CoRR* (2015).

Siddhartha Chaudhuri, Evangelos Kalogerakis, Stephen Giguere, , and Thomas Funkhouser. 2013. AttribIt: Content Creation with Semantic Attributes. *ACM Symposium on User Interface Software and Technology (UIST)* (Oct. 2013).

Doug DeCarlo, Adam Finkelstein, Szymon Rusinkiewicz, and Anthony Santella. 2003. Suggestive Contours for Conveying Shape. *ACM Transactions on Graphics (Proc. SIGGRAPH)* 22, 3 (July 2003), 848–855.

Kapil Dev, Manfred Lau, and Ligang Liu. 2016. A Perceptual Aesthetics Measure for 3D Shapes. *CoRR* (2016).

James A. Ferwerda, Stephen H. Westin, Randall C. Smith, and Richard Pawlicki. 2004. Effects of Rendering on Shape Perception in Automobile Design. *Proceedings of the 1st Symposium on Applied Perception in Graphics and Visualization* (2004), 107–114.

Megan Gambino. 2013. Do Our Brains Find Certain Shapes More Attractive Than Others? *Smithsonian.com* (Nov. 2013).

Sarah Howlett, John Hamill, and Carol O'Sullivan. 2005. Predicting and Evaluating Saliency for Simplified Polygonal Models. *ACM Trans. Appl. Percept.* 2, 3 (July 2005), 286–308.

B. W. Keelan and H. Urabe. 2003. ISO 20462: a psychophysical image quality measurement standard. *Proceedings of the SPIE* 5294 (Dec. 2003), 181–189.

Manfred Lau, Kapil Dev, Weiqi Shi, Julie Dorsey, and Holly Rushmeier. 2016. Tactile Mesh Saliency. *ACM Trans. Graph.* 35, 4, Article 52 (July 2016), 52:1–52:11 pages.

Tommer Leyvand, Daniel Cohen-Or, Gideon Dror, and Dani Lischinski. 2008. Data-driven Enhancement of Facial Attractiveness. *ACM Trans. Graph.* 27, 3 (Aug. 2008), 38:1–38:9.

Ligang Liu, Renjie Chen, Lior Wolf, and Daniel Cohen-Or. 2010. Optimizing Photo Composition. *Computer Graphics Forum* 29, 2 (2010), 469–478.

Tianqiang Liu, Aaron Hertzmann, Wilmot Li, and Thomas Funkhouser. 2015. Style Compatibility for 3D Furniture Models. *ACM Trans. Graph.* 34, 4, Article 85 (July 2015), 85:1–85:9 pages.

Zhaoliang Lun, Evangelos Kalogerakis, and Alla Sheffer. 2015. Elements of Style: Learning Perceptual Shape Style Similarity. *ACM Trans. Graph.* 34, 4 (July 2015), 84:1–84:14.

Rafal K. Mantiuk, Anna Tomaszewska, and Radoslaw Mantiuk. 2012. Comparison of Four Subjective Methods for Image Quality Assessment. *Comput. Graph. Forum* 31, 8 (Dec. 2012), 2478–2491.

Rachel McDonnell, Martin Breidt, and Heinrich H. Bülthoff. 2012. Render Me Real?: Investigating the Effect of Render Style on the Perception of Animated Virtual Humans. *ACM Trans. Graph.* 31, 4, Article 91 (July 2012), 11 pages.

Peter O'Donovan, Janis Libeks, Aseem Agarwala, and Aaron Hertzmann. 2014. Exploratory Font Selection Using Crowdsourced Attributes. *ACM Trans. Graph.* 33, 4, Article 92 (July 2014), 92:1–92:9 pages.

Alice J. O'Toole, Theodore Price, T. Vetter, James C. Bartlett, and V. Blanz. 1999. 3D shape and 2D surface textures of human faces: the role of averages in attractiveness and age. *Image and Vision Computing* 18, 1 (1999), 9–19.

Charles Ruizhongtai Qi, Hao Su, Kaichun Mo, and Leonidas J. Guibas. 2016. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. *CoRR* (2016).

Adrian Secord, Jingwan Lu, Adam Finkelstein, Manish Singh, and Andrew Nealen. 2011. Perceptual models of viewpoint preference. *ACM Transactions on Graphics* 30, 5 (Oct. 2011).

Carlo H. Séquin. 2005. CAD Tools for Aesthetic Engineering. *Computer-Aided Design* 37, 7 (June 2005), 737–750.

James T. Todd. 2004. The Visual Perception of 3D Shape. *Trends Cogn Sci.* 8, 3 (March 2004), 115–121.

Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and Jianxiong Xiao. 2015. 3D ShapeNets: A Deep Representation for Volumetric Shape Modeling. *CVPR* (2015).

Brian Wyvill, Paul G. Kry, Raimund Seidel, and David Mould. 2012. Determining an Aesthetic Inscribed Curve. *Symposium on Computational Aesthetics in Graphics, Visualization, and Imaging* (2012), 63–70.

Eduard Zell, Carlos Aliaga, Adrian Jarabo, Katja Zibrek, Diego Gutierrez, Rachel McDonnell, and Mario Botsch. 2015. To Stylize or Not to Stylize?: The Effect of Shape and Material Stylization on the Perception of Computer-generated Faces. *ACM Trans. Graph.* 34, 6, Article 184 (Oct. 2015), 12 pages.