Point Cloud Visualization Methods: a Study on Subjective Preferences

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***Abstract*—The availability of 3D range scanners and RGB-D cameras is pushing the spreading of point cloud-based applications. One of the main issues of this technology, in applications where the end user is a human observer, is the presentation of the data. Three-dimensional visual information represented as point clouds can be displayed in several ways, e.g. as sets of points with varying point size or as a surface rendered using one of several available methods, such as Poisson surface interpolation. Furthermore, to increase the feeling of presence, or immersiveness, novel hardware can be used such as 3D displays and head mounted devices. However, even if 3D-able visualization devices are available, common users are more accustomed to observing visual information displayed on a 2D screen and it is not clear which combination of presentation method and device are preferred by the users. In this contribution we assess the user preference of visualization of point clouds in terms of different rendering devices and methods. A set of subjective experiments is performed, involving point clouds presented as points or rendered surfaces displayed in 2D and 3D displays. The results obtained were analysed to measure user preferences.**

***Index Terms*—Point Clouds, Subjective Quality, Rendering, 3D visual representation, Immersiveness**

I. Introduction

A point cloud (PC) is a set of points in a given coordinate system representing information about a scene or an object often complemented with per-point attributes. This set of points may define the shape of real or computer-generated objects or even complex scenes. Point clouds are extensively used in 3D modeling for several applications including medical imaging, architecture, 3D printing, manufacturing, 3D gaming, as well as in virtual reality applications [1] and, more recently, in autonomous vehicle systems [2].

Several easy-to-use capture frameworks ranging from high precision and costly systems to low resolution and cheap ones are available. Point clouds can be acquired by active or passive sensors like laser scanners or close-range photogrammetry techniques, respectively. In the first modality, the processing starts with range data acquisition (dense 3D point cloud), followed by editing, alignment, and surface generation. In the latter case, image data acquisition is followed by pre-processing, calibration, orientation, dense 3D point cloud generation, and mesh or surface generation. In both cases, applications may demand point cloud feature extraction, texture mapping, visualization, and cloud navigation.

Many efforts to define subjective and objective quality assessment measures for point cloud data have been proposed in the literature. In [3] an objective quality metric, based on the angular similarity between two point clouds, is presented. A test was performed by considering Gaussian noise and octree-based compression distortion. In [4] a metric for assessing the quality of voxelized point clouds is presented. The proposed measure exploits 2D objective quality metrics on the data obtained by voxelization and projection of the 3D point clouds onto 2D planes. Alexiou et al. in [5] analyze the performance of projection-based point cloud objective quality measures when using different numbers of projections exploiting per-projection/view weights derived from subjective studies. The proposed measure does consider background pixels in the per-projection quality computation. The results show that using more than six projections does not improve significantly the accuracy of the estimated quality, while the use of per-projection quality using weights improves the quality estimates. In [6] a subjective assessment study on the performances of denoising algorithms applied to point cloud data is presented. A machine learning approach for assessing the local quality of indoor mobile mapping point cloud data is proposed in [7]. In [8] a study on quality assessment of point clouds is described. Seven geometry-only point clouds were degraded by octree-based compression on 5 different levels. The point clouds were displayed using screened Poisson surface reconstruction, and rated by the observers by using a 2D video. The results obtained by subjective assessment tests, conducted in five laboratories, show high inter-laboratory correlation. Furthermore, the test performed with state-of-the-art objective measures demonstrate that visual quality cannot be predicted accurately for every type of content. In [9] the same point cloud set is used with Screened Poisson surface reconstruction. Different rendering methods and 3D visual representations have been used: stereoscopic and texture-plus-depth. Inter-laboratory scores, collected from experiments using 3D videos among three laboratories, as well as scores from 2D videos from [8], show high correlation. Low correlation is instead obtained by comparing subjective and objective scores. In [10] subjective and objective quality assessment of

We thank the support of FCT project UIDB/EEA/50008/2020.

point clouds was performed. Point clouds were degraded by compression artifacts and the correlation between the most popular objective quality metrics and human judgement is reported. In [11] a state-of-the art review of subjective and objective quality measures for point cloud is presented. In [12] a study on point cloud quality evaluation, conducted in the context of JPEG Pleno is presented. A heterogeneous set of 8 static point clouds, both small-scale and large-scale contents, with geometry and texture information were selected and compressed using octree-pruning and a projection-based method, with three different levels of degradation. Subjective assessment was performed in three laboratories, with high inter-laboratory correlation. In [13] the subjective and objective quality assessment results for volumetric video compression are presented. The state-of-the-art compression algorithm, MPEG Point Cloud Compression Test Model Category 2 (TMC2), is used. In [14] the entire set of encoders developed in the MPEG framework (V-PCC, Video-based Point Cloud Compression, and G-PCC, Geometry-based Point Cloud Compression) are assessed through an extensive and rigorous analysis of quality. Those schemes take into account two main features: the compression rate and the quality of the decoded data. One of the main problems in understanding the quality perceived by a human when looking at an image (video or point cloud) depends on the objective quality of the data as well as on the viewing condition and modalities. In particular, the problem of how to present these data to the user arises. In fact, when dealing with 2D image or video, the use of Tv or monitor is straightforward. The point cloud media allows more freedom: several algorithms can be used for rendering and different viewing modalities can be employed, such as still image, pseudo-video, 2D, or 3D.

In this contribution, we investigate the user preference of point clouds (some with only geometry information and other with both geometry and texture information), displayed as rendered video with respect to different rendering devices (2D and stereo 3D) and methods (raw and after surface reconstruction). The outcome of these experiments may be used as guidelines for applications involving point cloud visualization in which the human judgment is required.

The rest of the paper is organized as follows. In Section II the details of the stimuli used in the experiment are reported while in Section III the experimental setup is described. In Section IV the collected results are discussed and in Section V the conclusions are drawn.

II. Test Stimuli Preparation

In this study, a dataset of 9 PCs with geometry and texture information is used. For 5 PCs (i.e., *bunny*, *cube*, *dragon*, *torus*, and *vase*) only the geometry information is provided while for the other 4 (i.e., *bumbameuboi*, *longdress*, *loot*, and *romanoillamp*) both texture and geometry information are provided. PCs *bunny* and *dragon* are selected from the Stanford 3D Scanning repository; they represent real objects acquired using a Cyberware 3030 MS scanner [15]. *Bumbameuboi* and *romanoillamp* are selected form the São Paulo subset of the JPEG Pleno repository [16], and *longdress* and *loot* are part of the 8i point clouds available in the JPEG Pleno database [17]. *Vase* is an object captured using an Intel RealSense R200 scanner as described in [18]. *Cube* and *torus* are computer-generated PCs (the latter is created by using MeshLab) [8]. The main features of PCs are listed in Table I.

Figure 1 shows a view of each selected point cloud, represented as raw points, i.e., without any surface rendering. Figure 2 shows views of rendered versions of point clouds,

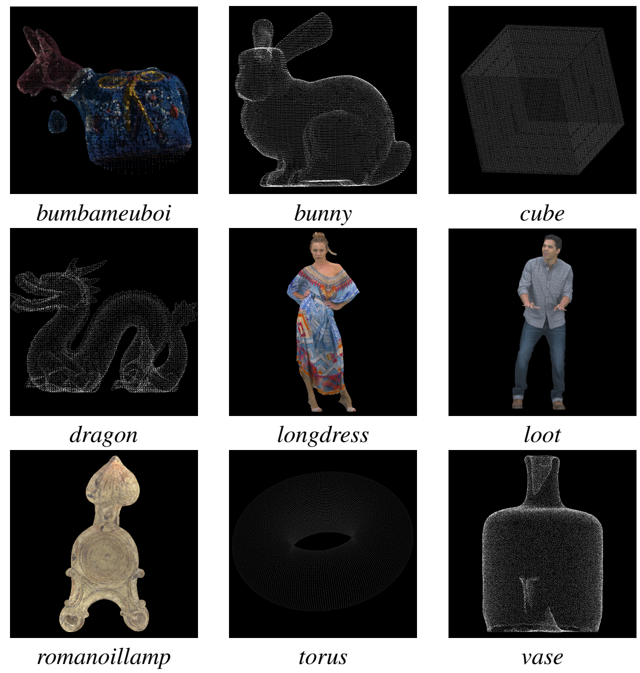

Fig. 1. Raw point clouds.

obtained by using screened Poisson surface reconstruction [19] and CloudCompare v.2.9.1 from [20]. Raw point clouds are presented using default point size 1 and default type (square) in CloudCompare, while surface reconstruction was performed with an octree depth of 12 and default parameters. Normal vectors were estimated using CloudCompare with default settings: the radius to identify nearest neighbors was selected automatically and a plane was used as the surface approximation model. Shades were rendered using sun light for all point clouds, with normals turned on. For geometry-only point clouds grayscale colorization was added, also using CloudCompare.

To allow the inspection of objects from different viewpoints, the (static) point cloud objects are presented as 24 second, 30 fps, movies showing the object being rotated around the Y axis for the first 12 seconds and afterwards around the Z axis, for the remaining 12 seconds, at a rate of 1 degree per frame. Since we want to understand the impact of the rendering device, (i.e., 2D and 3D monitors) two versions of each PC are produced: a single view movie to be displayed in monoscopic monitors and a stereoscopic two-view version for presentation in 3D stereo monitors (see Table II for details about equipment). The animations are performed with CloudCompare [20], which

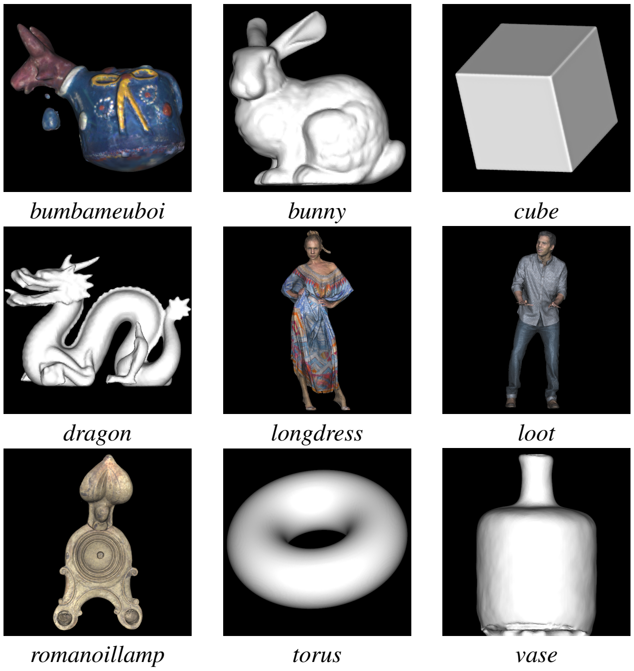

Fig. 2. Views of the rendered point clouds.

TABLE I
RAW POINT CLOUDS CHARACTERISTICS.

Point Cloud	Information	Number of Points
bumbameuboi	geometry + color	150,388
bunny	geometry	35,947
cube	geometry	30,246
dragon	geometry	22,998
longdress	geometry + color	857,966
loot	geometry + color	805,285
romanoillamp	geometry + color	1,286,052
torus	geometry	31,250
vase	geometry	36,022

has been configured to encode the final movies at very high quality and resolution. Figure 3 shows stereo anaglyph output image from *cube* point cloud after surface reconstruction, rendered with CloudCompare and converged pair of stereo cameras: both positive and negative disparities are present in stereoscopic presentation.

III. Setup for Subjective Assessment

The subjective experiments were conducted in 3 laboratories: University of Coimbra (UC), Coimbra, Portugal, University North (UNIN), Varaždin, Croatia and Roma Tre University (UNIROMA3), Rome, Italy. The conditions of every test environment were adjusted to follow the ITU-R Recommendation BT.500-13 [21], while the equipment used in each laboratory was as described in Table II. A passive subjective methodology was applied, with the subjects visualizing the generated 2D and 3D video sequences in customized video players, and providing their scores using a customized interface, either during or after the completion of each movie playback. Subjective evaluation was performed by using a single stimulus Absolute Category Rating (ACR) protocol,

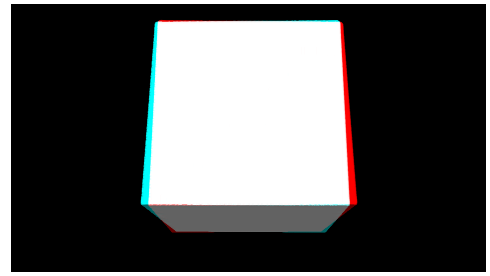

Fig. 3. Anaglyph from *cube* point cloud after surface reconstruction.

according to the ITU-R Recommendation BT.500-13 [21]. Grading was done on a 1-5 scale, where grade 1 represents ”bad”, while 5 represents ”excellent”.

After a screening step to remove candidates with vision problems (subjects were screened for visual acuity, color vision and stereo vision using Snellen chart, Ishihara chart and ”fly”/Randot tests), selected observers were asked to grade how well they recognized the object represented by the PC. At the beginning of each subjective session, an example PC, the *cube*, was presented to the observer so that he became acquainted with the aspect of the PCs presented during the evaluations. This example PC is excluded from the actual testing.

A total of 32 scores were obtained per evaluation session, considering that each subject assessed 8 test PCs, all in raw and rendered format, presented in 2D and stereoscopic 3D displays.

Two different assessment protocols were used. In the UC and UNIN laboratories, sessions were divided in 4 subsessions, where each subsession consists in 1 example PC, and 8 test PCs presented in random order. The 4 subsessions followed the order (raw, 2D), (raw, 3D), (rendered, 2D), and (rendered, 3D). In the UNIROMA3 laboratory, a slightly different approach was used. In order to avoid to the user the continuous change from 2D to 3D for each PC, sessions were divided in 2 subsessions. For each subject, first 2 example PCs were shown followed by the 16 test PCs mentioned earlier in random order. In this case the two subsessions showed first a specific PC in the (raw/rendered, 2D) and then (raw/rendered, 3D) formats. An outlier detection algorithm based on ITU-R Recommendation BT.500-13 was applied to the collected scores, and the ratings of the identified outliers were discarded. Then, the Mean Opinion Scores (MOS) were computed. Table III, reports some observer statistics and the number of outliers.

IV. Results and Analysis

After the screening procedure, a statistical analysis of the collected scores was performed. Tables IV, V and VI summarize the results reporting the difference between means of the sessions, computed using two-sample t-test, with 5% significance level, two-tailed test. The null hypothesis of the test was that samples being compared are independent random samples from normal distributions with equal means and equal but unknown variances, against the alternative that the means

TABLE II
EQUIPMENT SPECIFICATIONS AND VIEWING DISTANCES.

	UC	UNIN	UNIROMA3
Monitor	Asus VG278HR	Sony KD-55x8505	Panasonic Viera TX-P42VT30E
Screen Diagonal	27”	55”	42”
Resolution	1920x1080 pixels	1920x1080 pixels	1920x1080 pixels
3D render type	Active stereoscopic	Active stereoscopic	Active stereoscopic
Video Player	Nvidia 3D Vision	MPV	VLC
Viewing Distance	0.8 m ($\pm$20 cm)	2 m ($\pm$20 cm)	2 m ($\pm$20 cm)

TABLE III
OBSERVERS STATISTICS AND OUTLIERS.

	UC	UNIN	UNIROMA3
Male Observers	10	7	8
Female Observers	8	9	12
Age range (years)	20-55	20-59	21-22
Average age (years)	28.17	24.31	21.7
Number of outliers	0	0	2

are not equal. Normality of the samples was also tested using kurtosis: if it was between 2 and 4, it was assumed that the tested data had normal distribution. In cases where normality was not confirmed, t-test could give unreliable results, so additional Wilcoxon rank sum test was also performed, with 5% significance level, two-tailed test. The Wilcoxon rank sum test is a nonparametric test for equality of population medians of two independent samples.

For UC and UNIN grades, comparison was made between 2D and 3D view, for both raw and rendered PCs. In the case of UNIROMA3 laboratory, similar procedure was performed, but in this case comparison was performed between raw and rendered PCs, for both 2D and 3D views.

In the case of the UC data, it can be seen that both for raw and rendered PCs, it is not possible to reject the hypothesis that the 2D and 3D scores are Gaussian distributed with same mean and same variance. However in most cases the distributions are not Gaussian and so a strong conclusion for the equality of the means cannot be reached, although the tabled values show that for the samples collected during the experiment the 2D and 3D means are close. This is a weak indicator that both for raw and rendered PCs there is no preference for either 2D or 3D visualization of PCs. Wilcoxon rank sum test confirms this conclusion, but for the equality of medians. Analysis of the results from UNIN lead to similar conclusions, although the samples in this study show stronger Gaussian trend. Although neither of these two studies were meant to compare directly raw and rendered scores, a quick interpretation of the results shows that both UC and UNIN exhibit a very weak and not consistent preference for the rendered PCs.

As already stated, the protocol adopted in the UNIROMA3 tests was designed to present in the same session raw and rendered PCs (in 2D in the first session and in 3D in the second one). Therefore, it is not surprising that the scores show different trends from those observed in the UC and UNIN experiments. The first observable difference is that the null hypothesis, that the raw and rendered scores have same Gaussian distribution with same mean and variance, can now be reject for several PCs, both for the 2D and 3D presentations. That means that, in several cases, the observers have a preference for one of the PCs formats (raw or rendered). Wilcoxon rank sum test generally follows this conclusion, with one difference (*loot* point cloud, 2D view). The second and most striking result of this analysis is that UNIROMA3 observers actually prefer the raw PCs to the detriment of the rendered PCs, both for observations made in 2D and in 3D. A possible explanation, to be further investigated, is in the presence of memory-effect which may cause UNIROMA3 observers to directly compare the raw and rendered PCs (since unlike in the UC and UNIN cases here both formats are observed in the same session) and be more critical of the rendered surface quality.

V. CONCLUSIONS

In this contribution, an analysis of the user preference of point cloud rendered video with respect to different rendering devices and methods has been presented.

A subjective experiment has been performed in 3 laboratories in different countries for collecting data on point clouds presentation format and display type user preference. Although more extensive tests are needed, the obtained results indicate that there is no preference for viewing the point clouds in 3D displays over in 2D. A second conclusion, also in need of future confirmation, seems to be that when presented a mix of raw and rendered point clouds within a short time interval, the observers show preference for the raw format, irrespective of the type of display (2D or 3D). Different rendering procedure for 3D stereo (e.g. off-axis), as well as 3D texture-plus-depth rendering, might be also considered in the future.

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TABLE IV
UC LABORATORY: T-TEST AND WILCOXON TEST COMPARING 2D VS 3D VIEW. BOLD VALUES REPRESENT HIGHER MEAN GRADES.

Point cloud	t-test and Wilcoxon test comparing 2D vs 3D view, raw PCs						t-test and Wilcoxon test comparing 2D vs 3D view, rendered PCs					
	SMT (p)*	SMW (p)**	mean_2D	mean_3D	N_2D$^{\diamond}$	N_3D†	SMT (p)*	SMW (p)**	mean_2D	mean_3D	N_2D$^{\diamond}$	N_3D†
bumbameuboi⊕	Yes (0.87)	Yes (0.89)	**4.00**	3.94	Yes	Yes	Yes (0.21)	Yes (0.33)	4.39	**4.67**	Yes	No
bunny⊖	Yes (0.85)	Yes (0.78)	4.44	**4.50**	No	No	Yes (0.13)	Yes (0.18)	4.06	**4.50**	No	Yes
dragon⊖	Yes (0.65)	Yes (0.70)	4.28	**4.44**	No	No	Yes (0.30)	Yes (0.49)	4.22	**4.50**	No	Yes
longdress ⊕	Yes (1.00)	Yes (1.00)	**4.78**	**4.78**	No	No	Yes (0.20)	Yes (0.27)	3.89	**4.33**	Yes	No
loot ⊕	Yes (0.80)	Yes (1.00)	4.72	**4.78**	No	No	Yes (0.08)	Yes (0.09)	3.61	**4.22**	No	No
romanoillamp ⊕	Yes (0.21)	Yes (0.32)	4.33	**4.61**	Yes	No	Yes (1.00)	Yes (1.00)	**4.83**	**4.83**	No	No
torus⊖	Yes (0.77)	Yes (0.67)	**3.89**	3.78	Yes	Yes	Yes (1.00)	Yes (0.85)	**4.00**	**4.00**	No	No
vase⊖	Yes (0.37)	Yes (0.28)	3.61	**3.94**	Yes	No	Yes (1.00)	Yes (1.00)	**4.44**	**4.44**	Yes	Yes

⊖ - geometry; ⊕ - geometry and texture; * - same mean, t-test (p-value); ** - same mean, Wilcoxon test (p-value); $^{\diamond}$ - normal distribution of 2D grades; † - normal distribution of 3D grades

TABLE V
UNIN LABORATORY: T-TEST AND WILCOXON TEST COMPARING 2D VS 3D VIEW. BOLD VALUES REPRESENT HIGHER MEAN GRADES.

Point cloud	t-test and Wilcoxon test comparing 2D vs 3D view, raw PCs						t-test and Wilcoxon test comparing 2D vs 3D view, rendered PCs					
	SMT (p)*	SMW (p)**	mean_2D	mean_3D	N_2D$^{\diamond}$	N_3D†	SMT (p)*	SMW (p)**	mean_2D	mean_3D	N_2D$^{\diamond}$	N_3D†
bumbameuboi⊕	Yes (0.48)	Yes (0.57)	3.00	**3.19**	Yes	Yes	Yes (0.40)	Yes (0.35)	**4.56**	4.38	Yes	Yes
bunny⊖	Yes (0.55)	Yes (0.48)	3.56	**3.75**	Yes	Yes	Yes (0.27)	Yes (0.36)	**3.94**	3.62	No	Yes
dragon⊖	Yes (0.40)	Yes (0.50)	**3.94**	3.69	Yes	Yes	Yes (0.81)	Yes (0.82)	**4.06**	4.00	No	Yes
longdress⊕	Yes (0.81)	Yes (0.12)	4.06	**4.56**	Yes	No	Yes (0.38)	Yes (0.53)	3.50	**3.75**	Yes	No
loot⊕	Yes (0.84)	Yes (0.97)	4.25	**4.31**	Yes	No	Yes (0.21)	Yes (0.29)	3.31	**3.69**	No	Yes
romanoillamp⊕	Yes (0.52)	Yes (0.39)	**4.06**	3.81	No	No	Yes (0.46)	Yes (0.61)	**4.87**	4.75	No	No
torus⊖	Yes (0.24)	Yes (0.24)	2.81	**3.25**	Yes	No	Yes (0.86)	Yes (0.81)	**4.19**	4.12	No	Yes
vase⊖	Yes (0.69)	Yes (0.78)	**3.25**	3.12	No	No	Yes (0.53)	Yes (0.51)	**4.12**	3.94	No	Yes

⊖ - geometry; ⊕ - geometry and texture; * - same mean, t-test (p-value); ** - same mean, Wilcoxon test (p-value); $^{\diamond}$ - normal distribution of 2D grades; † - normal distribution of 3D grades

TABLE VI
UNIROMA3 LABORATORY: T-TEST AND WILCOXON TEST COMPARING RAW VS RENDERED PCS. BOLD VALUES REPRESENT HIGHER MEAN GRADES.

Point cloud	t-test and Wilcoxon test comparing raw vs rendered PCs, 2D view						t-test and Wilcoxon test comparing raw vs rendered PCs, 3D view					
	SMT (p)*	SMW (p)**	mean_raw	mean_rend	N_raw$^{\diamond}$	N_rend†	SMT (p)*	SMW (p)**	mean_raw	mean_rend	N_raw$^{\diamond}$	N_rend†
bumbameuboi⊕	Yes (0.16)	Yes (0.20)	**3.61**	3.00	Yes	No	Yes (0.34)	Yes (0.32)	**3.67**	3.33	Yes	No
bunny⊖	No (0.05)	No (0.00)	**3.50**	2.17	Yes	Yes	Yes (0.07)	Yes (0.11)	**3.83**	3.17	Yes	Yes
dragon⊖	No (0.00)	No (0.00)	**4.39**	2.72	Yes	Yes	No (0.01)	No (0.01)	**4.28**	3.44	Yes	Yes
longdress⊕	No (0.02)	No (0.02)	**3.61**	2.78	Yes	Yes	Yes (0.55)	Yes (0.52)	**3.39**	3.17	Yes	Yes
loot⊕	No (0.03)	Yes (0.05)	**3.05**	2.22	No	Yes	Yes (0.14)	Yes (0.10)	**3.06**	2.56	No	Yes
romanoillamp⊕	Yes (0.38)	Yes (0.42)	3.33	**3.67**	No	Yes	Yes (0.49)	Yes (0.52)	3.44	**3.67**	No	Yes
torus⊖	Yes (0.24)	Yes (0.24)	**3.39**	2.89	No	No	Yes (0.09)	Yes (0.12)	**3.56**	2.83	No	No
vase⊖	Yes (0.21)	Yes (0.27)	**3.17**	2.67	Yes	No	No (0.01)	No (0.01)	**3.72**	2.83	Yes	No

⊖ - geometry; ⊕ - geometry and texture; * - same mean, t-test (p-value); ** - same mean, Wilcoxon test (p-value); $^{\diamond}$ - normal distribution of raw grades; † - normal distribution of rendered grades

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