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Estimating Appearance Differences of 3D Objects with an RGB Camera

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Abstract

The paper present a method to estimate appearance difference of two 3D objects, such as 3D prints, using an RGB camera under controlled lighting environment. It consists of three parts. Firstly, calculating image color differences after geometry alignment under different light sources. Secondly, estimating glossiness of the objects with a movable light source. And finally, psychophysical data are used to determine the parameters for estimating appearance differences of 3D prints.

Introduction

3D printing is widespread in recent years. Color 3D printers are also available in the market now for rapid prototyping and small amount productions. The quality of 3D prints is not good in common. To achieve better quality in its production, most of them needs some sort of post-production such as de-powdering, coating and polishing. The manual post-productions result in unstable of quality in roughness, color appearance and color uniformity. How to assess its quality in terms of visual differences is an unsolved issue to be studied. CIE recently lists 3D printing is one of ten major applications in the future. Related standards must be established for the new applications.

The present study is our initial attempt on measuring 3D appearance differences. It consists of camera calibration, image alignment, image color differences evaluation, glossiness estimation and finally determine a single index for related applications.

The methods will be introduced in the following sections.

Apparatus

In this study, an X-rite Spectralight III viewing booth was used for providing uniform standard lighting. As white LED is more and more popular, a handheld white LED matrix was used as movable light source for color differences and glossiness estimation. A 3D Systems ProJet 460 Plus color 3D printer was used to print 3D models with different gamut mapping algorithms. A Canon 5D Mark II digital camera was used to capture the images of 3D models under the viewing booth and movable light source. All programs were written using Matlab.

Color Characterization of an RGB Camera

The aims of the study is to develop a method to measure appearance of 3D objects with an RGB camera. As the spectral response functions of the RGB camera is different from CIE 1931 color matching functions, it might have observer metamerism problem between the camera and human eyes. It means a camera color match in certain illuminant might look differently in the human eyes. On the other hand, illuminant metamerism would cause color mismatch in some lighting conditions. To minimize these problem, the RGB camera is characterized using ColorChecker Passport under more than one light source. The image color differences of two objects are estimated under multiple important light sources such as D65, A, CWF, TL84 and white LED. The light sources are covered by a large diffuser so as to reduce specular effects on the objects.

To characterize the camera colorimetrically, 2nd order and 3rd order polynomial regression recommended by Hong *et. al.*, [1] were tested. The input variables for the 2nd order polynomial and he 3rd order polynomial are [$R^2, G^2, B^2, RG, GB, BR, RGB, R, G, B, 1$] and [$R^3, G^3, B^3, R^2G, G^2B, B^2R, RG^2, GB^2, BR^2, R^2, G^2, B^2, RG, GB, BR, RGB, R, G, B, 1$] respectively. The RGB values were taken in 14-bit rawRGB image format and read the files using **dcraw** in linear RGB space with 16-bit TIFF. The characterization results are shown in Table 1. The 3rd order regression are used in the later steps as it is slightly better than the 2nd order regression.

Table 1: Accuracy of camera characterization

Unit: ΔE_{00}		D65	A	TL84	WLED	CWF
2nd Ploy. Regression	Mean	1.59	1.59	2.28	1.93	1.35
	Max	3.90	4.27	5.90	5.09	3.74
3rd Ploy. Regression	Mean	0.96	0.58	0.55	0.56	0.73
	Max	2.99	2.01	2.61	2.31	1.88

Image Alignment

The 2D images for the two objects must be geometrically aligned before the comparsion. SURF algorithm [2] is applied to search the feature points of the objects for the image registration.

Figure 1 used the same image with 5 degree rotation. We use SURF features to do cross-image matching and take out unreasonable long matched point-pairs. Leave short matched pairs to create a projection matrix for rectifying the rotated image. As can be seen in Figure 2, they have perfect match using the method (Figure 2) except some edges.

Figure 1. Left: Source image (a 3D print), Middle: 5 degree rotation, Right: image differences with matched points.

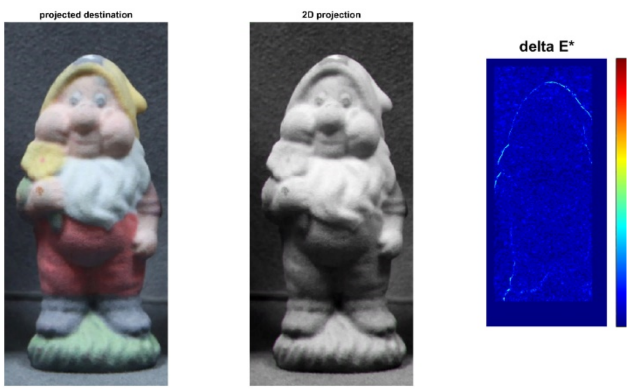


Figure 2. Left: rectified image. Middle: Image differences (No color indicates no difference). Right: △E map (only edges have some differences).*

Figure 3 used two different 3D prints with 5 degree rotation for test. As can be seen in Figure 4-middle, the color edges indicate that the matching is not good enough. It can be further improved by 2D SAD (sum of absolute difference) matching [3] in LAB space. The SAD matching technique was frequently used for stereo correspondence of left- and right-view images. We regard the rest of image differences which cannot be matched by 2D projection are stereo differences. Therefore, we match each of 8x8 patches with 32 pixel range locally. It also is similar to motion compensation technique in MPEG format.

As some micro differences across the two objects cannot be seen, Spatial-CIELAB filters [4] are applied in an opponent color space to simulate visual blur of luminance and chromatic channels. After the viewing distance-dependent image blurring, we can generate color difference map as Figure 5.

We notice that edges of the images cannot match perfectly. It would generate huge color differences. The color differences cannot be perceived by human eyes, therefore, we reduce the weightings of color differences near edges. Referring to Figure 6, it is done by Sobel edge detection [5], followed by edge dilation and blurring. The blurred edges are weighting values for reducing color differences near the edges.

Figure 3. Left: object 1, Middle: object 2, Right: image differences with matched points.

Figure 4. Left: rectified image. Middle: Image differences (No color indicates no difference). Right: Additional SAD matching.

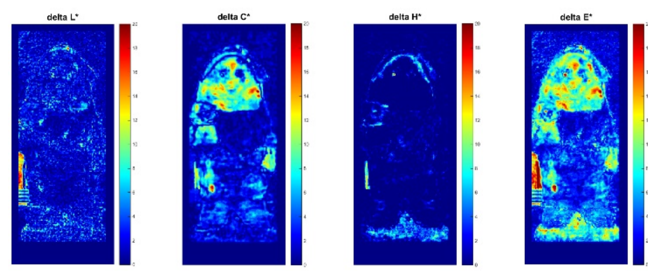


Figure 5. Color difference map in CIELCH space.

Figure 7 estimated image differences between the high chroma ceramic original and its low chroma 3D print. As can be seen, the proposed approach can estimate the color differences without problem. The next question is how to determine a perceptually meaningful index from the color difference map.

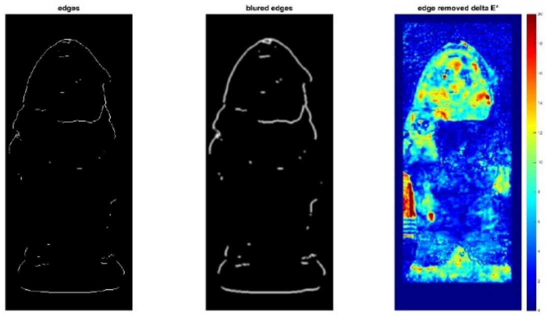


Figure 6. Left: Sobel edge detection for the source image. Middle: blurred mask. Right: △E map with edge removal.*

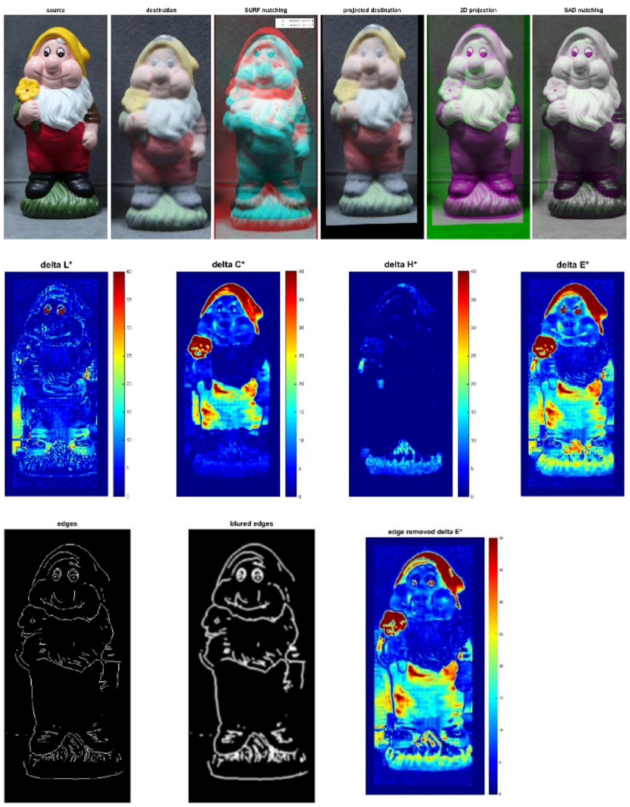


Figure 7. Estimation of image differences between the high chroma ceramic original and its low chroma 3D print.

Glossiness

Glossiness can be estimated by puting the same polarizers onto light source and camera lens. And then compare a pair of images with different filter rotation angles which induce maximum and minimum glossiness on object surface. Figure 8 and Figure 9 show the comparison of a glossy ceramic object and a matte 3D print. The glossiness can be rightly estimated by standard deviation of the △L* or △E* maps.

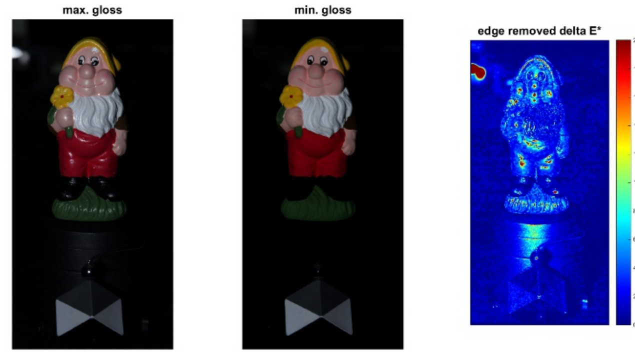


Figure 8. Polarization based glossiness estimation for a glossy sample. Left: max. gloss. Middle: min. gloss. Right: △E map with edge removal.*

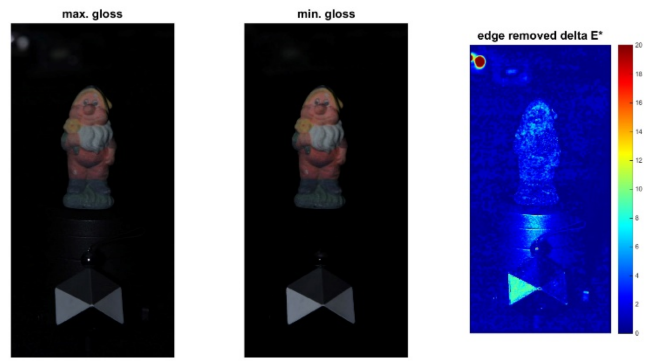


Figure 9. Polarization based glossiness estimation for a matte sample. Left: max. gloss. Middle: min. gloss. Right: △E map with edge removal.*

The glossiness of the object surface can also be roughly estimated by a movable point source. The camera takes a video of the object when the source is doing systematic moving by one hand. In Figure 8, a small mirror ball in front of the test sample can record the lighting direction. The glossiness can be estimated by the lightness standard deviations divided by the mean lightness. The estimation values for Figure 10 and Figure 11 are 0.983 (glossy) and 0.699 (matte) respectively.

Gamut Mapping for 3D Prints

In color rendering index and color gamut mapping researches, rendering intent plays a very important role. A 3D object reproduction also can be divided as perceptual, colorimetric, even preferred or accurate reproduction. We have done a psychophysical study on gamut mapping algorithms in perceptual rendering intent between 3D scan model (on LCD) and its color 3D prints.

Most of 3D color printer cannot print 3D objects in wide color gamut. And current ICC based color management system has not yet applied to the 3D printing systems. The color of 3D prints are therefore unpredictable to designers. The designers want to have a What You Got Is What You See 3D display and printing environment. However, it is not possible as the color gamut of the 3D printers are much smaller than any LCD displays. As color match is nearly impossible, the next best thing is to make the color appearance of the prints perceptually similar to the original 3D model displayed on a color calibrated LCD. To minimize the gap between the original 3D model and its 3D print, ICC color management system was applied and a psych-visual experiment was conducted to compare six rendering approaches.

Figure 10. A glossy sample with a movable light source.

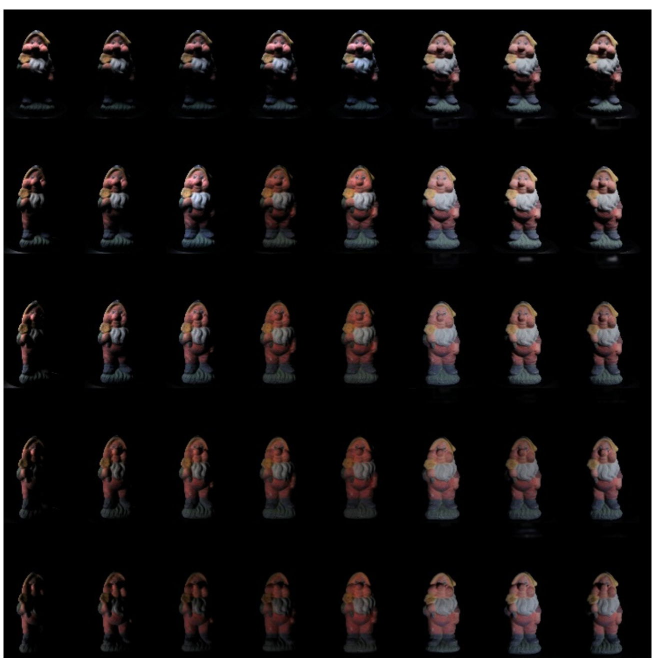


Figure 11. A matte sample with a movable light source.

This study used a 24” EIZO ColorEdge CG241W LCD as source device and 3D Systems ProJet 460 Plus as destination device for gamut mapping in CIELAB color space. The LCD display were calibrated to sRGB standard with 100 nit white point. The gamut boundary descriptors of the 3D printer were estimated by a segment maxima method. Three representative gamut mapping algorithms (GMAs) - minimum ∆E clipping, hue-preserved minimum ∆E clipping and sigmoid Gaussian cusp knee (SGCK) were implemented [6]. The impact of unsharp masking (USM) also was tested. The test objects thus were processed in 6 different ways (3 GMAs x 2 level USM). Four different 3D models in different colors were tested to make sure the best method is robust to different conditions.

To follow the ICC profile format, we derived B2A0 color LUTs for the printer which separates the CIELAB color space into 33x33x33 segments. L* form 0 to 100, a* and b* axis from 128 to 127. The resolution of L*, a* and b* axis are 3, 7.5 and 7.5 respectively. The texture images of the 3D models were converted to color corrected RGB signals via sRGB profile and the gamut mapped printer profiles. The USM also applied to the texture images before the process.

12 color normal observers viewed the color 3D prints under a 500 lux D65 lightbooth (Figure 12). They were asked to compare each pair of the prints with its original displayed on the EIZO display in terms of preferred reproduction using a pair comparison method. The results show that all six color managed approaches are better than the one without color management. In terms of GMAs, SGCK is recommended (Figure 13).

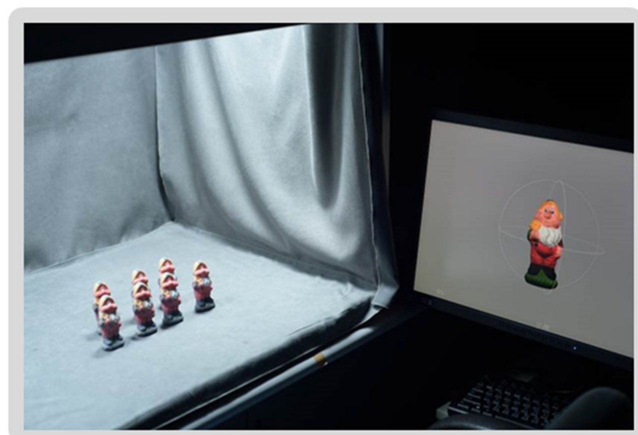


Figure 12. Experimental setup of the gamut mapping experiment.

Figure 13. Comparison: LCD image, Without CMS and apply SGCK GMA.

Integration

To link the visual experiment results with the color difference map. The correlation between different indices and the visual results were estimated and summarized as follows:

- The color mapping of SGCK model is close to CIEDE2000 [7] which compresses high chroma intensively but preserves low chroma. Therefore CIEDE2000 is recommended for generating color differences map.
- Human vision could discount luminance and contrast differences of 3D objects to some degree. Therefore, CIEDE2000(l:c) 1.5:1 is recommended.
- Observers dislike uneven color differences, the 90 percentile of image color differences have higher correlation to the visual data compared to mean color differences.
- The Pearson correlation of chroma between high saturation original and low saturation 3D print can be a weight for image preferences. Low correlation in high chroma (C*>40) indicates the color of 3D prints might not be uniform (Figure 15). [8] It is not acceptable.
- To reduce illuminant metamerism problem, it's better to average the 90 percentile CIEDE2000(l:c) errors under D65, A, TL84, white LED and CWF light sources (Figure 14).

Figure 14. Images are taken under 5 representative light sources.

- As the glossiness of a 3D print can be further enhanced by polishing, the glossiness estimation provide an optional scale for estimating appearance differences of the two objects.

Conclusions

The paper introduces methods for comparing appearance differences of 3D objects under control environment. A common digital camera is used for capturing the image of 3D objects under 5 representative light sources. 3rd order polynomial regression is recommended for covert linear RGB to XYZ. Image alignment is very important. SURF descriptors can be used to find paired point samples for creating 2D projection matrix. However, the 2D projection cannot match 2D different image well. A SAD matching method can be used to enhance the mapping.

The color differences of edge must be discounted. CIECAM02(l:c) is recommended for generating color difference map as the color weightings are similar to observer preferred SGCK gamut mapping algorithm. Uneven color differences are noticeable. Non-contact glossiness estimation can be done by either polarization approach or movable light source approach. More psychophysical experiment must be done in the future to bridge image-based measurement and the 3D visual appearance.

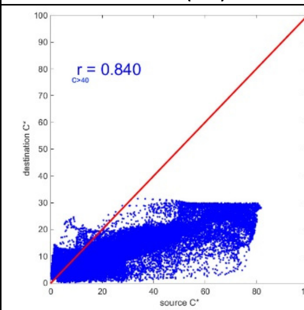
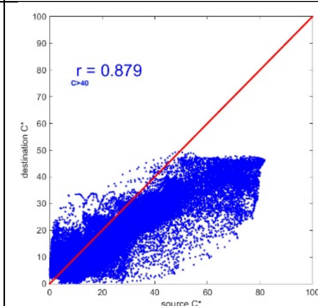
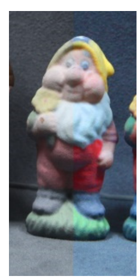
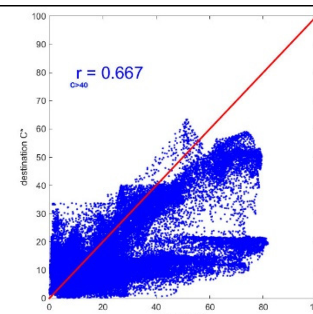
3D prints		Chorma (C*) ratio
Lower Chroma		
Higher Chroma		
Uneven Chroma		

Figure 15. A comparison of chroma ratio between a colorful original and its 3D prints.

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