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PHYSICALLY BASED IMAGE SYNTHESIS OF MATERIALS : A METHODOLOGY TOWARDS THE VISUAL COMPARISON OF PHYSICAL VS. VIRTUAL SAMPLES.

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Abstract—The assessment of images of complex materials on an absolute scale is difficult for a human observer. Comparing physical and virtual samples side-by-side simplifies the task by introducing a reference. The goal of this article is to study the influence of image exposure on the perception of realism on images of paint materials containing sparkling metallic flakes. We use a radiometrically calibrated DSLR camera to acquire high resolution raw photographs of our physical samples which provide us with radiometric information from the samples. This is combined with the data obtained from the calibration of a stereoscopic display and shutter glasses to transform the raw photographs into images that can be shown by the display, controlling the colorimetric output signal. This ensures that we can transform our data back and forth between a radiometric and a colorimetric representation, minimizing the loss of information throughout the chain of acquisition and visualization. In this article we propose a paired comparison scenario that improves the results from our previous work, focusing on three main aspects: stereoscopy, exposure time, and dynamic range. Our results show that observers consider stereoscopy as the most important factor of the three for judging the similarity of these images to the reference, followed by exposure time and dynamic range, which supports our claims from previous research.

Keywords—Human visual system, Texture perception, Paired comparison, Physically-based rendering, Perceptual quality metrics.

I. INTRODUCTION

This research takes place in the context of perceptually realistic simulation of sparkling metallic paint materials for industrial product design applications. Such applications rely strongly on the aspect of the product, and so it is paramount to ensure that a human observer perceives both the simulated and the physical product as equal. Stereoscopy is used to provide a more accurate simulation of the sparkling effect as explained by Da Graça et al [1].

Physically-based image rendering (PBR)¹ is a process that implies reproducing on a computer the exact aspect of a real object according to the laws of physics. Typically, the goal of PBR is to produce physico-realistic images which, in our context, means that the signal emitted by a screen displaying

a virtual representation of a given scene is radiometrically identical to that emitted by the real (physical) scene itself. We use a PBR rendering engine to create computer-generated (CG) simulations of the materials from a series of chemical, mathematical, and optical models of their composition and structure, and models of their interaction with the light.

The images generated by the rendering engine are expressed in terms of device-independent radiometric values for each pixel in the image. Since they will ultimately be shown on a computer display, those radiometric values must be transformed into some device-dependent colorimetric space before they can be visualized. The stereoscopic visualization pipeline is formed by a series of different elements, namely the computer display, the stereoscopic viewing device, and finally the human visual system (HVS).

The amount of factors to take into account to obtain a perfect PBR, along with the constraints and complexity of the visualization pipeline, make difficult to render true physically realistic images. An alternative approach is selective rendering (SR), which uses human visual perception principles to render images realistically from a perceptual point of view [3], [4]; it is at this point that the perceptual validation of the rendering engine becomes important. We know that the capabilities of the HVS to perceive visual information depend on many factors such as contrast, frequency, shape, or illuminant [5] [6] [7] [8] [9]; the perceptual validation stage helps us to improve the results in several ways. We can identify and resolve aspects of the rendering process that are not properly dealt with by the rendering engine, find perceptually superfluous information that may be removed from the computation—reducing the amount of image information and the computation times—and assign weights to relevant perceptual information in the images.

To study visual perception in our specific context of car paint materials with sparkling metallic particles we have designed a series of observation experiments under a controlled environment. We have taken photographs of a reference paint plate using different exposure times—resulting in a series of images with known characteristics—to analyze the effect of three main image aspects: stereoscopy, exposure time, and dynamic range. Human observers were asked to look

¹Here, we understand PBR in the sense of *predictive rendering* [2].

at randomly-arranged pairs of these images and rate their similarity to the physical reference paint plate, located beside them.

In the following sections we describe the preparations required prior to the actual experimentation (subsection II-A), and present three possible scenarios to perform side-by-side tests within our context of complex paint sample comparisons (subsection II-B). We then show that our preferred choice — consisting on using independent illuminations for the reference and sample images— provides meaningful information about the effect of the selected parameters in the perception of this type of material images (section III), allowing us to sort them by level of perceptual relevance. Finally, we discuss the results (section IV) and propose some future work directions (section V).

II. METHODOLOGY

Before designing the visualization experiments it is important to analyze the characteristics of the devices involved in the acquisition and visualization chain. The colorimetric signal emitted by the display, the spectral power distribution of the illuminant, or the luminance at each point on the surface of the display are factors to be considered since they can determine different aspects of the visualization such as the positioning of the virtual samples on the display, the distance between the two samples and the observer, or the ambient illumination in the room.

A. Calibration

When we observe a sample, we perceive a series of radiometric signals emitted by the object, which hit the receptors in our eyes. We can simulate the behavior of the HVS and measure the signals arriving onto the receptors by replacing the human observer with a DSLR (Digital Single-Lens Reflex) camera. If we measure the radiance and color tristimulus values for a large enough number of color samples —such as a color chart— under some observation conditions, we can estimate a transfer function that gives us the radiometric value for any color pixel captured by the camera and vice versa; this is known as radiometric calibration. We used a 24-patch Macbeth color chart to calibrate a Nikon D800 camera. Fig. 1 shows the correlation between radiometric values measured directly over the sample and the values obtained with the estimated transfer function; we can see that the resulting graph is almost a straight line, which means that there is a very good correlation between both values.

Since we want to analyze the effect of different exposure times, it is important to calibrate for each exposure value that we want to study. However, we must keep in mind that the illumination intensity must be reduced or increased according to the exposure duration to avoid oversaturation or undersaturation, respectively.

In order to control the radiometric output of the display we must know its transfer function, which gives us the colorimetric input values (typically in the RGB color space) that must be input to the display to produce the desired output signal. The process required to obtain said transfer function is known as colorimetric display calibration, and can be used to convert RAW photographs obtained with the DSLR camera into images

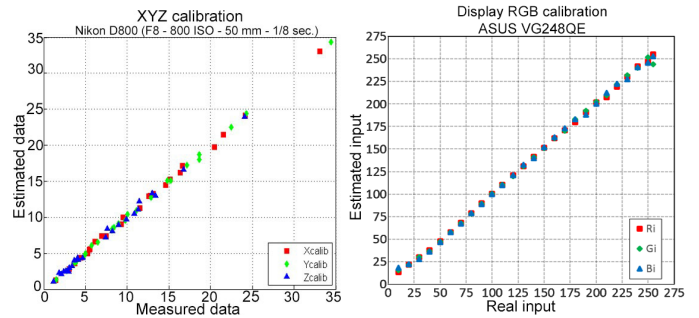


Fig. 1. [a,b] Left (a): Correlation curve between measured and estimated XYZ values using the camera calibration model for a exposure time of 1/8 seconds: The horizontal axis represents radiometric values computed directly from the sample with a spectroradiometer; the vertical axis represents radiometric values computed using the estimated transfer function. The coefficient of determination R^2 for channels X, Y and Z is, respectively, 0.999, 0.999, and 0.998. Right (b): Correlation curve between real RGB values and those estimated with the colorimetric calibration of the display using a gain-offset-gamma (GOG) model. The coefficient of determination R^2 for channels R, G and B is, respectively, 0.999, 0.998, and 0.998.

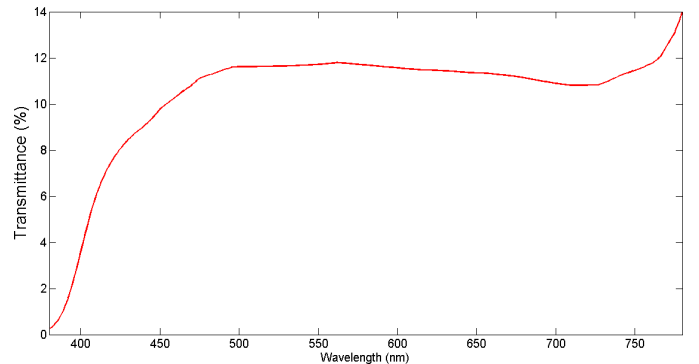


Fig. 2. Spectral transmittance (expressed as a percentage) of the Nvidia 3D Vision shutter glasses.

within the color gamut of the display that are perceptually equivalent to the photographed scene. Two display calibrations were performed: in stereoscopic mode and monoscopic mode. The stereoscopic calibration is performed similarly to the monoscopic one, but enabling the stereoscopic mode in the display and placing a pair of stereoscopic shutter glasses before the spectroradiometer while measuring the color samples on the display; this is important so that we can account for the effect of visualizing the samples with stereoscopic glasses, since not only do the filters on the glasses reduce drastically the overall luminance, but they also modify the perceived color by adding an overall greenish tint (see Fig. 2).

Typical LCD displays do not produce a very large color gamut due to the technology used; for that reason we chose the ASUS VG248QE given its relatively high colorimetric performance in benchmarks [10]. Fig. 3 shows the gamut obtained for the settings used in our calibration, which were chosen experimentally to obtain the largest color gamut. This gamut was built measuring each primary color on the display with an Xrite i1Display colorimeter and representing their xy coordinates on the CIE 1931 color space chromaticity diagram. Although the chosen settings do indeed provide a large enough color gamut, initial results showed that they also create some additional problems. Fig. 4 shows the spectral

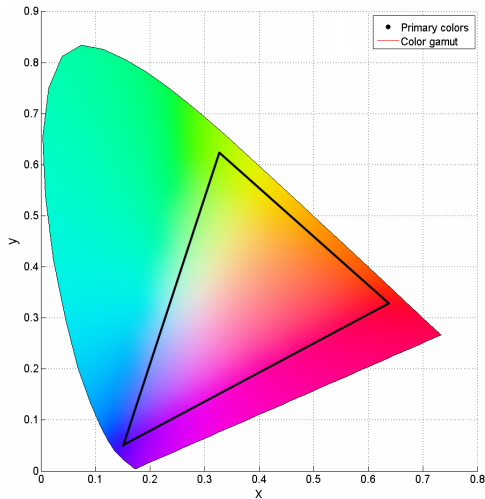


Fig. 3. Color gamut of the display obtained with an Xrite i1Display colorimeter. The display is a stereoscopic LCD ASUS VG248QE with White LED Backlight.

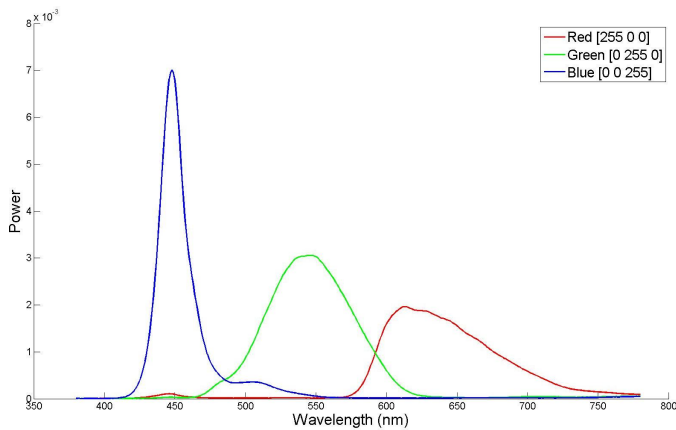


Fig. 4. Spectral distribution curves of the three primaries of the display.

power distribution (SPD) of the three primaries measured with a spectroradiometer under the same illumination conditions used in our experiments. If we look at the graphs, we can see there is a very large peak in the blue component that also affects the green and red channels (see the small blue peak around 450 nm).

Indeed, the occurrence of such peaks complicates the estimation of the transfer function. To characterize the response of the display we estimated three parametric models (one for each color channel) from a set of 119 color samples, which were then validated against the Macbeth color chart. These parametric models were estimated by fitting the obtained channel curves to a gain-offset-gamma (GOG) characterization model and solving a nonlinear least squares regression, obtaining a high coefficient of determination R^2 of 0.999, 0.998, and 0.998, for the estimation of channels red, green and blue, respectively.

B. Exposure-time paired comparisons

We are interested in obtaining perceptually realistic results, and paired comparisons are a good way to assess the aspect of

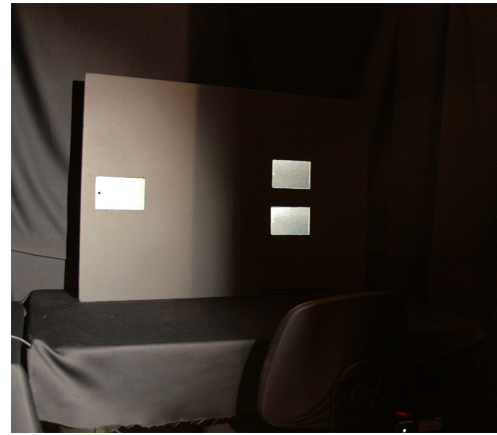


Fig. 6. Photograph of the experimentation room. We can see that the illumination only affects the left side of the panel (reference plate).

these sparkling metallic paint textures. Given the complexity of the sparkling effect, it is difficult for an observer to visually assess these images on an absolute scale, so introducing a reference that acts as ground truth simplifies the evaluation task. At the same time, comparing the images side-by-side reduces the time to move the eyes from the test image to the reference and, therefore, the effects of low visual memory persistence times in the comparisons.

In order for the photographs to be comparable to the physical reference we must bare in mind three important constraints: firstly, the photographs must be taken under the same illumination conditions as those in the visualization experiment; secondly, given the effect of contrast and luminance on perception in general [7] and material texture perception in particular [11], we must ensure similar contrast levels in both the images and the physical samples; finally, if we want to include both stereoscopic and monoscopic images in the comparisons, observers must keep the stereoscopic glasses on at all times, regardless of the type of image they are looking at, to ensure similar colorimetric conditions.

The most straightforward scenario to compare a physical and virtual sample under the same observation conditions is to visualize the photographs and the physical reference together, under the same illuminant (Figure 5.a). The idea behind this test scenario is to equalize as much as possible the observation conditions so that, if we hide everything outside the samples, we can somehow make the observers forget that they are looking at two samples on different supports (physical and digital). However this solution has an important downside to it: the display is an emissive surface and, as such, it introduces additional light into the virtual sample—the illumination already present in the photograph, plus the one in the visualization environment, plus that of the black point of the display. While we can correct for some of the additional lighting, it is impossible to obtain similar luminance levels on both samples because there will always be a common factor, the ambient illumination in the visualization environment, which will remain constant for both samples.

A possible workaround to this scenario, which should resolve the problem with the additional lightness on the virtual sample, is to take the photographs of the samples with a

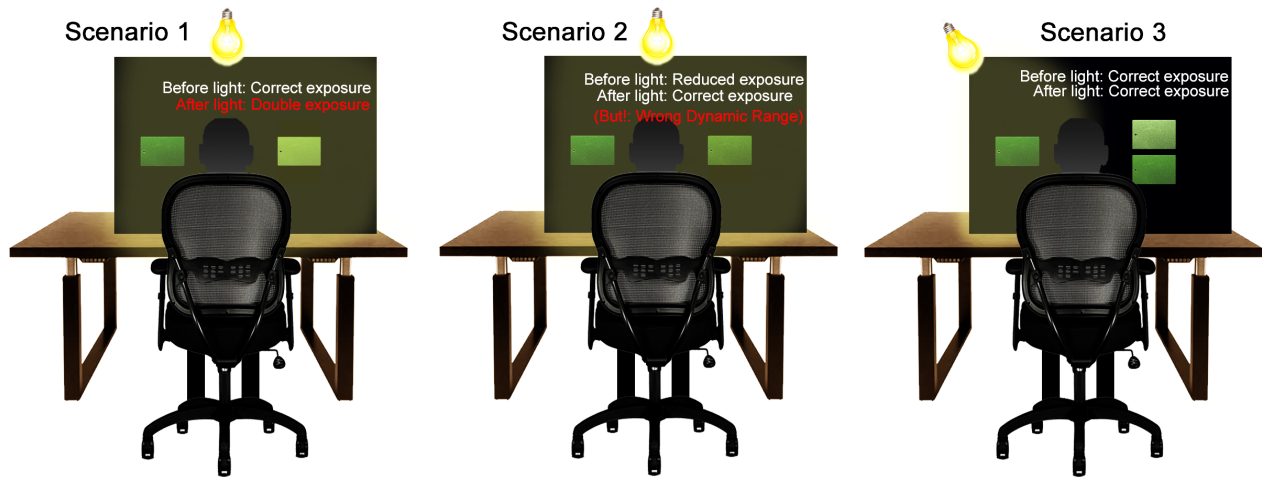


Fig. 5. [a,b,c] Diagram of the setup in the three scenarios suggested. The test photographs are to the right and the real sample reference to the left. In the first two scenarios the illumination is common to both sides of the comparison, whereas in the third case it only affects the physical sample. Notice the important luminance difference between both sides of the comparison in the first scenario, due to the additional light emitted by the display. The use of paired comparisons in the third scenario simplifies the assessment of the images.

lower exposure to compensate for the additional luminance introduced by the display (Figure 5.b); this solution would indeed produce images with a similar luminance as the physical samples when viewed under the same illumination. However, as explained in our previous article [11], image exposure plays an important role in our perception when observing photographs of materials, so by reducing image exposure when we capture the photographs we might inadvertently be favoring certain aspects of the material and, therefore, biasing our perception.

As a solution to the problems mentioned above we propose to visualize the photographs and the reference side by side, but using a different luminance—but the same illuminant spectrum—on each side (Figure 5.c). This scenario is more versatile because it allows for independent tuning of the illumination and reproduces more closely the observation conditions in the reality given that the user will never be looking at the simulated results next to the physical object. Since we seek to produce a perceptually realistic simulation it is acceptable for observers take a short time while switching their focus from the reference to the photographs and vice versa. In this work, we perform an experiment using this new methodology, showing that it produces better results than those obtained with the previous comparison scenarios.

III. RESULTS

We took photographs of a sample paint plate at several exposure times, and chose three different values, short (1/15 seconds), medium (1/8 seconds), and long (1 second), trying to minimize the amount of undersaturation and oversaturation present in the images in the RGB color space after color correcting for the display’s gamut (see Table I) and maximize contrast. Indeed oversaturated and undersaturated pixels will all be clipped upon display to the maximum and minimum values, respectively, so some of the information above a certain threshold is lost and cannot be recovered. Controlling the amount of saturation is then crucial to keep as much information from the RAW photographs as possible. In general, the longer the exposure time the less contrast the images have,

because they use a narrower part of their potential dynamic range.

We color corrected the images so that the radiometric signal emitted by the display matches that of the physical sample when the photographs were taken. Using the medium exposure image as reference, we created a modified version of the short and long exposure images by scaling the XYZ color tristimulus values by a factor such that the maximum luminance (maximum Y) is as close as possible to that of the medium-exposure image (see Figure 7), avoiding oversaturating more than a 0.3% of the RGB image pixels—this percentage was chosen experimentally to obtain a reasonably low amount of perceivable oversaturated pixels. By scaling the XYZ tristimulus values of images taken at different exposure times, using the luminance of the reference image as target, we obtain a new set of images where they all have a similar dynamic range but different contrast (see Figure 7), which allows us to analyze the role of dynamic range and contrast in perception as well.

For each of the five images listed in Table I we created two versions, monoscopic and stereoscopic, to also test whether or not the use of stereoscopy has any effect on the preference for a given sample. Altogether, this resulted in a set of 10 different images (see Table II). We created series of 45 pairs of images from the list—i.e. all possible combinations of the 10 images, excluding comparisons with themselves—combined randomly, and asked a group of 30 observers to compare the two images in each pair (test images) and say which one they perceived as “closer” to the reference paint plate—i.e. the physical plate that we took the original photographs from. The test images were arranged vertically on the right-hand side, whereas the reference was positioned to their left, 42 centimeters away (see Figure 5.c and 6); both the test images and the reference were observed through an aperture on a black surface to isolate them from their surroundings. The reference was illuminated independently from the test images during the experiment by a similar illumination to that used when the photographs were taken, to minimize the differences between the images and the physical reference; at the same time this

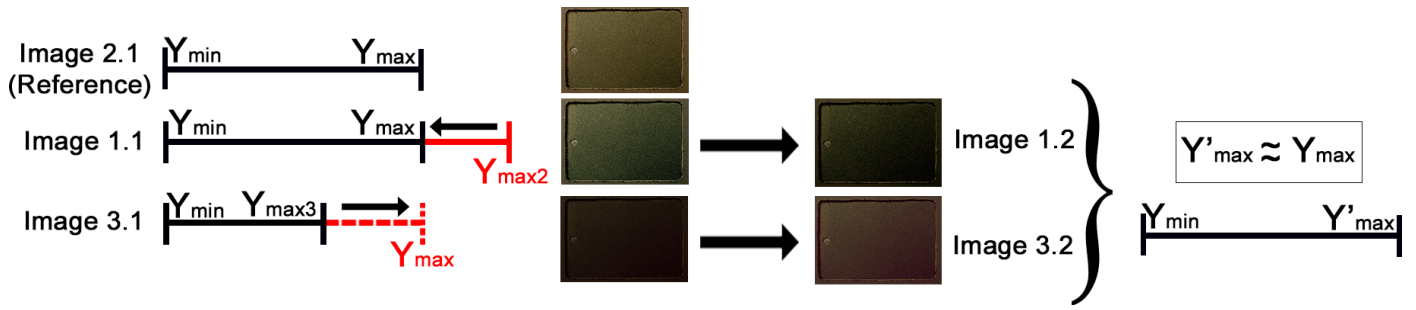


Fig. 7. Luminance scaling process. When the maximum luminance is greater than the reference ($Y_{max2} > Y_{max}$) the dynamic range is compressed, resulting in a darker background color but higher contrast between the background and the sparkle of the metallic flakes. Similarly, when the maximum luminance is lower than the reference ($Y_{max3} < Y_{max}$) the dynamic range is expanded, resulting in a brighter background, which reduces the contrast between the background and the sparkles.

Image	Exposure time (sec)	Luminance scaling factor	Max. luminance	Pixel saturation (%)
1.1	Short (1/15)	1	205.3	R = 0.158 G = 0.034 B = 0.032
1.2	Short (1/15)	0.51	104.7	R = 0.039 G = 0.006 B = 0.007
2.1	Medium (1/15)	1	104.7	R = 0.145 G = 0.028 B = 0.030
3.1	Long (1)	1	15.65	R = 0.009 G = 0.000 B = 0.000
3.2	Long (1)	1.78	27.85	R = 0.300 G = 0.000 B = 0.000

TABLE I. LIST OF IMAGES USED IN THE EXPERIMENT. THERE IS A BASE VERSION OF EACH IMAGE AND A SCALED VERSION OF IMAGES 1 AND 3. THERE IS NO SCALED VERSION OF IMAGE 2 BECAUSE IT IS THE REFERENCE IMAGE FOR LUMINANCE LEVELS. IMAGE 3.2 HAS A MAXIMUM LUMINANCE LOWER THAN THE REFERENCE (104.7) BECAUSE SCALING IT BY A HIGHER FACTOR WOULD RESULT IN A HIGH AMOUNT OF OVERSATURATED PIXELS.

helps to control the amount of light incident on the plate, which has an effect on the saturation of the cones in the eyes of an observer looking at it, resulting in a better reproduction of the photograph's environment. The observers were seated in a position between the test images and the reference, wearing a pair of stereoscopic shutter glasses (NVidia 3D Vision), at a distance of approximately 57 centimeters.

From the responses obtained in the experiment — responding to the question "which image from the test pair is closer to the reference?" — we computed the scores for each sample, according to the Bradley-Terry model [12]. These scores indicate the probability of each sample being chosen by an observer as closer to the reference over any other. Representing these scores in a logarithm scale — which represents better the relative nature of visual perception — we can group our ten samples into different similarity classes. Figure 8 shows five classes designated by colors green (1), blue (2), yellow (3), brown (4), and red (5).

In this experiment we are analyzing the effect of three

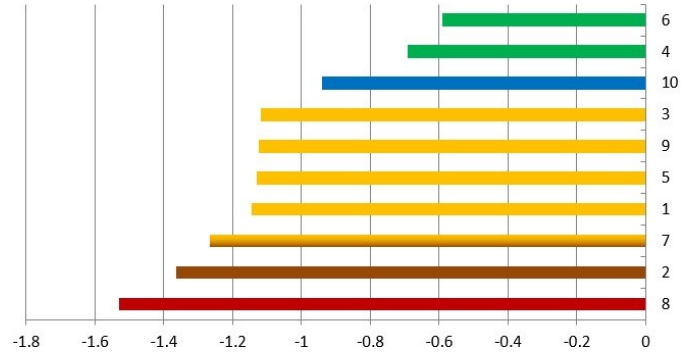


Fig. 8. Experiment results. The ordinates indicate the sample number (see Table II) and the abscissas indicate the Bradley-Terry scores in logarithmic scale.

Sample	Image	Type	Score	LOG score	Perceptual class
8	3.2	M	0.0296	-1.5287	5
2	1.2	M	0.0432	-1.3645	4
7	3.1	M	0.0543	-1.2652	3+4
1	1.1	M	0.0718	-1.1439	3
5	2.1	M	0.0740	-1.1307	3
9	3.2	S	0.0751	-1.1244	3
3	1.2	S	0.0762	-1.1180	3
10	3.1	S	0.1149	-0.9397	2
4	1.1	S	0.2036	-0.6912	1
6	2.1	S	0.2574	-0.5894	1

TABLE II. BRADLEY SCORES AND LOG SCORES FOR EACH OF THE SAMPLES USED IN THE EXPERIMENT IN ASCENDING ORDER. THESE SCORES REPRESENT THE PROBABILITY OF EACH SAMPLE BEING JUDGED CLOSER TO THE REFERENCE OVER ANY OTHER. TYPES M AND S STAND FOR MONOSCOPIC AND STEREOSCOPIC RESPECTIVELY.

different factors on the perception of images from our paint samples: the use of stereoscopy, exposure time, and dynamic range and contrast. From the information in Table II we can see a tendency from observers to choose samples giving these factors a clear order of preference. Indeed we can see that stereoscopic samples are clearly preferred over monoscopic ones; when both samples are of the same type, contrast comes into play. Base images — i.e. those whose XYZ tristimulus values have not been tampered with — are preferred over the adjusted ones, with observers preferring medium-exposure images over short-exposure (excessive contrast) and long-exposure ones (low contrast). Based on these results we can

sort these three factors according to their relevance for the average observer to choose the resemblance of an sample image to the reference in the following order:

- 1) Stereoscopy over Monoscopy
- 2) Exposure time
 - a) Medium exposure
 - b) Short exposure (high contrast)
 - c) Long exposure (low contrast)
- 3) Dynamic range

This is consistent with the fact, explained earlier, that contrast is reduced for longer exposures times, and supports our previous claims [11] that image luminance and contrast — strongly linked to the exposure time— can alter the perception of sparkling due to its effect on flake size.

IV. CONCLUSIONS

The goal of perceptual validations is twofold: on the one hand it identifies and resolves anomalies in the rendering process, and on the other hand it studies the properties of the available physical samples and analyzes the response of the HVS to different aspects of the materials when observing the samples. We can then use the results obtained during validation to assign weights to certain aspects of the materials and optimize the rendering process by prioritizing the computations.

The comparison of virtual and physical samples provides us with important information regarding how human observers perceive each aspect of our complex paint samples. To be able to perform such comparisons we must be able to control at every moment the transformations performed over the data. The calibration of all the devices participating in the process is essential since it provides us with the tools to move between radiometric and colorimetric data and, in turn, between the physical and the colorimetric domain. The colorimetric transformations introduced by the devices must be taken into account to find the right observation conditions for the experiment and estimate the resulting signal.

Based on our experience from several tests, we believe that the best way to compare physical and virtual samples side by side is to introduce some sort of separation between both samples so that the illumination intensity can be controlled independently for each sample, to compensate for any possible irregularities inherent to the experimentation conditions. Furthermore, the proposed comparison scenario, closer to the paradigm of perceptual comparison, represents in a much closer way the observation conditions in the actual environment of the final product.

The results from this experiment show that these new experimentation conditions do indeed resolve all of the issues found in our previous experiment, which helps provide much more robust and meaningful results.

V. FUTURE WORK

We have shown that for a large enough population of observers and a given series of known criteria we can use paired comparisons to find the order in which those criteria are considered by human observers when assessing the quality of images of sparkling metallic materials. This is an important

finding in our work in image validation for it sets a solid starting point towards the allocation of weights to image features within potential future validation metrics to be used as part of the material rendering model.

Our rendering model currently uses a generic perceptual tone mapping operator [13], [14] to map the luminance of pixels in multi-spectral high-dynamic range images to a low-dynamic range display. Future works should benefit from the results of these perceptual experiments to help find a relationship between exposure time in the photographs and total luminance in the images generated by the rendering engine. In this regard, we propose to perform a new paired comparison where photographs will be replaced by CG images of the simulated materials in the comparisons with a physical reference; the goal is to integrate these results into the current rendering model to try to improve the performance of the tone mapping process by adapting it to the specific characteristics of the visualization of sparkling paint materials.

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