Application of HDR Colour Imaging to Modeling of Glints in Metallic Coatings

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ABSTRACT

The aim of this study was to develop a computational model to predict perception of glints of metallic coatings. A model utilised a high dynamic range (HDR) image of the metallic coatings as input. A feature corresponding to glint was extracted based on statistical analyses of the image. The model performance was verified comparing with the perceptual glint scaled by observers.

1. INTRODUCTION

Glint of metallic coatings is categorised as micro appearance which is small-scale non-uniformity when viewed at a distance of a meter or less (McCamy 1998). It is commonly caused by reflected light from aluminium flakes contained in coatings and appears differently depending on the illumination/viewing geometry. This is not specular reflection or gloss which are categorised as macro appearance, i.e., the appearance as metallic coatings are seen from a distance of a few meters (McCamy 1996). Here, glint is specifically defined as “Tiny spot that is strikingly brighter than its surrounding, in other words, bright spots. It is visible under directional illumination conditions only. The glint may be expected to switch on and off when the observation geometry is changed.” The majority of work on the appearance of coatings is at the macro appearance level (McCamy 1996). In recent years, micro appearance is considered for appearance modelling and simulations (Ďurikovič 2003, Ershov et al. 2001). But, such methods often need input parameters that correspond to physical property of coating samples (information related to structure and components of coatings) and therefore cannot be applied when the physical property is unknown, i.e., in the car paint refinishes, it is often necessary to evaluate appearance without any information of the physical property. Therefore, we aim to develop a model to predict glint using a digital colour image of metallic coatings and using no information of the physical property of coatings. The presence of glints means that it is impossible to capture the full dynamic range of such a scene in a single image due to the limitations in most image-capture devices. Therefore, it was attempted to capture a HDR image and the glint model was developed based on the HDR image as input. In this paper, we start with an investigation of perceptual glint using metallic coating panels. The procedure of creating the HDR image is then described. Finally, the model for the glint prediction is introduced and its performance is assessed.

2. VISUAL ASSESSMENT

Visual assessment was conducted to determine the best illumination/viewing geometry to observe glint and scale the glint of metallic coating panels (samples). The samples were placed on a tilting table under a spot light such that observers could see the glint effect by changing the angle of the tilting table, i.e., bright spots are appearing and disappearing depending upon the angle, as illustrated in Figure 1. For each assessment, observers were first asked to change the angle of the tilting table to find the angle that provides the maximum glint. By applying magnitude estimation techniques (Bartleson 1984), the observer was then asked to assign a number that best describes the glint of a test sample in comparison with a reference sample having a glint value of 50. There were no upper limit for the glint scale, but, in this experiment, a value of 1 was assigned as no glint and 50 for the glint of the reference sample. A gray colour panel having a moderate glint level was used as a reference sample. A total of 105 test samples were used (5 gray colour samples, 20 samples in each of blue, brown, green, red and yellow colour) covering a range of degrees of perceptual glint. The test samples were presented in random order in each session. The position of the test sample was randomly selected either on the right- or left-hand side of the reference sample during the assessment so as to prevent any bias. Ten observers with normal colour vision assessed each sample twice. During the assessment, the observers were asked to use a chin rest to fix their position.

A geometric mean of the scale values given by the observers was used to represent the mean observers' data for each sample. The rational for using the geometric mean is to make an estimate of the scale value that is not excessively influenced by large values. The traditional arithmetic mean would be biased by large values that occur because of the use of an open-ended scaling. Repeatability was investigated by calculating R-squared between the results of each observer's first and second session and was on average equal to 0.87. Observer accuracy (between each observer's data and the average of all observers' data) was an R-squared value of 0.89 on average. The angle of the tilting table adjusted by the observers for each sample was recorded in terms of θ as indicated in Figure 1. The average angle for all assessments was 58° with the maximum and minimum angles of 68 °and 45°, respectively. There was no difference in the angle selected between different panel colors.

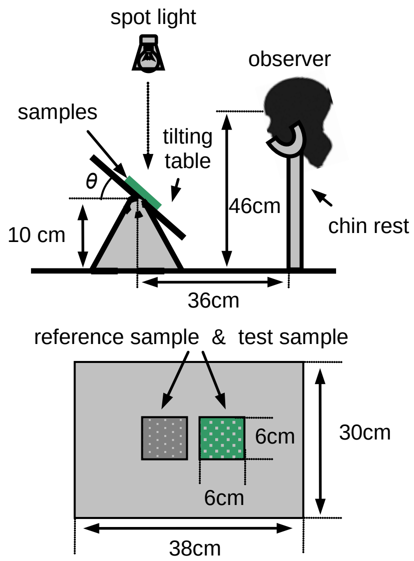

Figure 1. Schematic diagram of the viewing conditions and sample arrangement.

3. COMPUTATIONAL MODEL FOR GLINT PREDICTION

3.1 HDR image capturing by multiple exposures

A HDR image was generated from images captured at two exposure levels (exposure 1 and 2) using a digital camera. In this study, the HDR camera function as illustrated in Figure 2 (d) was derived based on the camera responses of 12 grey-scale uniform patches and their scene intensities which were the sum of the SPD measured using a tele-spectroradiometer (TSR). As described in Figure 2 (a-c), there are three regions; A = images captured with exposure 1 was used to recover scene properties, C = images captured with exposure 2 was used; B = the average of responses from both exposures was used. The result of combining the data from exposures 1 and 2 was seen in Figure 2(d) where a camera response was possible that exceeded the dynamic range of either of the individual exposures. It should be noted that linearisation and

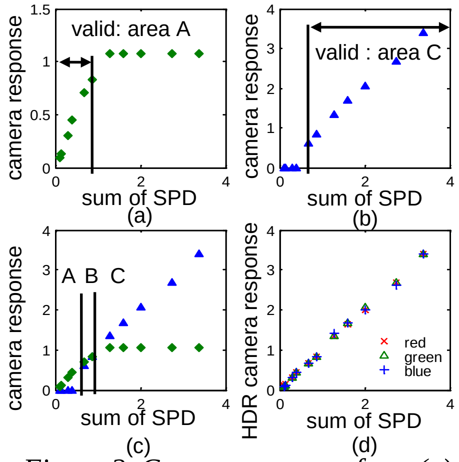

Figure 2. Camera response from (a) exposure1 and (b) exposure 2; (c) Illustration of regions A,B and C; (d) Combined HDR camera response.

spatial uniformity correction were performed to the raw images before combining the two images captured at the different exposure levels.

3.2 Colour space transformation

In order to analyse the HDR image in terms of a device-independent value, a linear regression characterisation model (Cheung 2006) was utilised to transform the HDR values of each pixel in the sample images to CIE XYZ values. The characterisation model was derived from a set of data which consisted of the average HDR values of 164 selected patches from a GretagMacbeth ColorChecker DC and 106 metallic coating samples and the corresponding CIE XYZ values based on the measurement using a TSR. The model performance was tested using the leave-one-out method (use one metallic coating sample as a test and the others for deriving the model as training data) and a median colour difference, ΔE^*_{ab}, of the test samples was 4.76.
The properties of human perception have better spatial resolution for the achromatic channel than for the chromatic channels (Wandell 1995). Additionally, even in coloured samples, a close visual inspection reveals that the bright spots appeared to be achromatic. Therefore, only the luminance channel (Y value) was used for extracting the glint information.

3.3 Glint feature extraction

In order to extract a feature corresponding to perceptual glint, the pixels in the image were classified into two groups: spots and background. The spots on the metallic coating sample are the bright regions which are caused by the characteristics of the aluminium flakes contained in the coating. The background is defined as the region where there are no spots. A single threshold which partitions an image histogram was determined based on the assumption that the distribution of the pixels that belong to the background in the image should be a bell-shaped histogram with most of the frequency counts bunched in the middle and with the counts dying off out in the tails. Histograms of solid colour coating panels were measured and can be seen to demonstrate this property; a example is given in Figure 3 (a). It is reasonable to assume that the histograms of the solid colour coating panels should be similar to that of the metallic coating samples used in this experiment if there were not for the aluminium flakes. Therefore, a threshold *t* can be determined by estimating an upper limit of the distribution of the background. As is illustrated in Figure 3 (b), when *m* represents the mode (the value most frequently occurs in an image) and *l* is the minimum value (lower limit) in an image, *t* is estimated to be $t = (2m - l)$. Any pixels with values greater than *t* were deemed to be the spots. Then, the intensity of the spots were measured by subtracting the mode from the pixel values which belonged to the spots and the sum of those intensity values was computed as output of the model. This can be summarised in Equation 1.

$$Glint\ Model = \sum[(I(i,j) \geq t) - m] \qquad \text{Equation 1}$$

where, $I(i, j)$ is a pixel value (Y value) of an image *I* at the pixel position of (i, j), *m* is the mode in an image and *t* is the threshold.

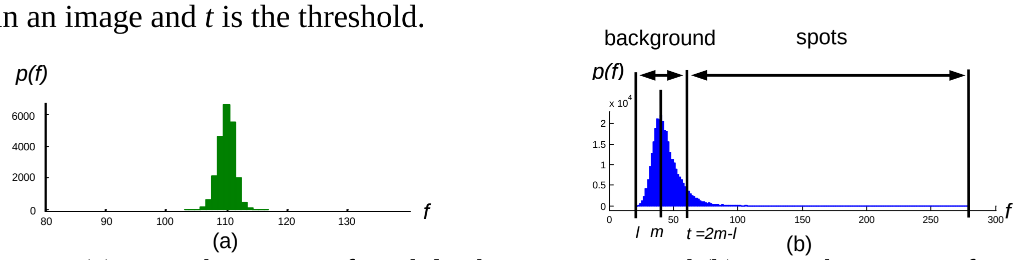

Figure 3. (a) Image histogram of a solid colour coating panel (b) Image histogram of a sample and an indication of the threshold t.

4. RESULTS AND CONCLUSIONS

An HDR imaging method was used to obtain useful images of the metallic coating samples contained aluminium flakes. The HDR images created had a capacity to measure reflected light upto five times greater than that from a similarly captured white patch in the grey-scale. The HDR of the captured images was sufficient to cover the full range of the glints in the samples; the maximum pixel value, when all of the measured samples were considered, was about 70% of the full HDR range available. This indicates that some of the pixels in the HDR image of the metallic coating samples had values several times greater than the white patch and therefore justifies the use of the HDR approach in this study. The HDR algorithm used was relatively simple compared to some others that have been reported in the literature (Reinhard et al. 2006). The relatively simple HDR approach was possible because of the extra information that was available by imaging grey-scale uniform patches under consistent lighting conditions. In this study, only two exposure levels were used but it would be possible to extend the method to combine three or more exposures using the method we applied.

The performance of the model developed for glint prediction is given in Figure 4 where the model predictions have been plotted against the results of the visual assessment (visual result). R-squared values between the model predictions and the visual results were 0.87 for all 105 samples, 0.97, 0.98, 0.89, 0.90, 0.97 and 0.86 for gray, blue, brown, green, red, and yellow samples respectively. The slight nonlinear relationship between the model predictions and the visual results was found in Figure 4. Although this can be corrected adding parameters to the model in order to fit the predictions linearly to the visual results, even without any correction, the model, that was developed based on the image statistics which were completely independent from the visual results, provided the encouraging results.

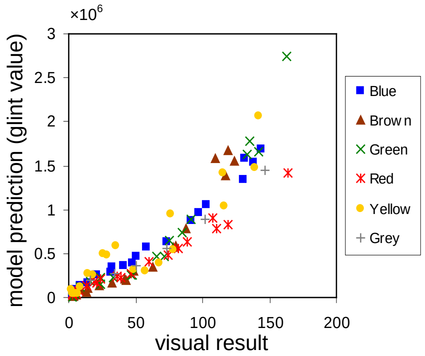

Figure 4. Model Performance.

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