Assessing Texture Difference for Metallic Coating on Different Media

S. Kitaguchi, M.R. Luo, *S. Westland, **E.J.J. Kirchner and **G.J. van den Kieboom
Department of Colour and Polymer Chemistry, University of Leeds (UK)
**** School of Design, University of Leeds (UK)***
*****Technology Center Colorimetry, Akzo Nobel Coatings, Car Refinishes (The Netherlands)***

Abstract

The use of a digital image for assessing texture appearance was investigated. Since there are still limitations to reproduce texture appearance of a physical object on display devices using a digital image such as resolution, physical size and viewing distance, the influences of the changes of the conditions were examined. In the present work, we focus on coarseness of a metallic paint coating. By comparing with the scaled perceptual coarseness difference of the metallic paint coating panels with that of their reproduced images assessed in several different conditions, the results showed that the perceptual coarseness difference could be assessed from displayed images. Although the absolute coarseness appearance was difficult to be reproduced, it was found that the coarseness difference did not influenced by the slight changes of the conditions. Also, performance of the computational coarseness model [1] developed for predicting the perceptual coarseness from an image was verified by comparing with the perceptual coarseness obtained by the visual assessments.

Introduction

While the digitisation of information or the use of digital images to represent physical objects for product control and communication is not new in many industries, it is not trivial to measure information or reproduce a digital image of their appearance. Many studies have been performed for estimating colour appearance under cross-media viewing conditions. However, these studies mostly are limited to uniform surfaces [2,3]. There are still many difficulties to accomplish cross-media reproductions especially for complex pictorial images or surface textures, because of limitations of the spatial resolution or optical system of devices technologies. As characterised by the modulation transfer function (MTF) of the optical system, imaging devices never achieve perfect reproductions. Also, even when a high resolution digital camera can capture fine details of texture, the resolutions of display devices are typically not high enough for displaying a digital image of an object with the same physical size. One common practice is to display a larger image and let it be viewed from further away. However, it was found that there is a change of appearance due to varying the physical image size and the viewing distance as reported by Johnson *et al.* [4]. Obviously, for objects larger than the physical size of the display device, it is impossible to reproduce a digital image with the same physical size as the object. However, it is a great advantage to be able to measure appearance from an image, and to visually assess the appearance of a representative image rather than a physical object.

The aim of this study is to investigate the use of digital images for visually assessing the texture difference relative to what we can see on the same pair of physical samples. Since it is impossible to reproduce the image having identical appearance to an object, because of reasons just mentioned, and since in practice it is not easy to control viewing conditions except when assessing in the laboratories, the influences of the changes in conditions (size and distance) to the texture difference were thus investigated. In this study, we focus on the coarseness appearance of metallic paint coating panels. Visual assessments were carried out to compare the perceptual coarseness difference on metallic panels (physical objects) with that of the images displayed on a monitor. We also investigated whether the perceptual coarseness difference is affected by the viewing distance or the size. In addition, the performance of the computational model [1] developed for predicting the perceptual coarseness from an image was evaluated using the visual results accumulated here.

Visual Assessment: Physical Sample

Sample Preparation: Physical Samples

Metallic paint coating panels (physical samples) with varying coarseness levels and colours were prepared. Coarseness variations of the metallic paints were caused by the spatial distributions of aluminum flakes of different sizes. Totally, there were 156 panels including 6 grey, 50 purple, 50 green and 50 blue panels.

Coarseness Scaling: Physical Sample

Visual assessments were carried out to scale the perceptual coarseness difference of physical samples. A total of 10 observers (4 female and 6 male) with normal colour vision participated in the experiment. In this study, a specially designed viewing cabinet as shown in Figure 1 was used to present the samples to an observer. It incorporates diffuse light from two bottom sides (a CIE illuminant D65 simulator) and a flat base to present samples [5]. The reason of using the diffuse light is to avoid any specular reflection or gloss of the metallic paints, which could disturb the coarseness appearance. Each observer looked down onto the samples from the viewing window in Figure 1. The distance from the observer's eye to the sample was about 54 cm. Categorical judgment method [6] was applied to scale the perceived coarseness difference. Two metallic paint panels were presented for each trial in the viewing cabinet as illustrated in Figure 1. One was a reference sample and the other was a test sample. A grey sample with a middle coarseness level was used as the reference sample. Each observer was asked to assign a category for a test sample comparing with the reference sample, whose category was 5, according to the observer's perception in terms of coarseness on a 1-9 scale as shown in Table 1. All samples were presented in a random order. Each observer carried out the assessment twice. A total of 3100 (10 observers × 2 sessions × 155 samples) categorical judgments were accumulated.

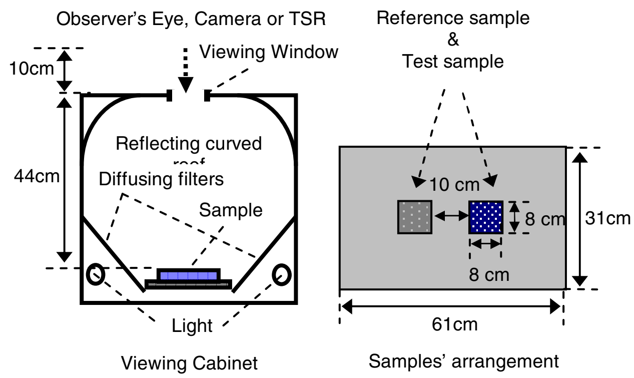

Figure 1. Schematic diagram of a Viewing Cabinet (left). Samples are placed on the base. Two light sources are positioned at the 2 bottom corners at each side and both emit light to the walls. The top corners have curved surfaces to reflect light uniformly onto the sample. An observer looked down the sample from the viewing window. An illustration of samples' arrangement and an observer's viewing field (right).

Table 1: 1-9 categories used for the visual assessment.

Category 1	Extremely Fine
Category 2	Very much Fine
Category 3	Moderately Fine
Category 4	Slightly Fine
Category 5	Reference Sample
Category 6	Slightly Coarse
Category 7	Moderately Coarse
Category 8	Very much Coarse
Category 9	Extremely Coarse

Visual Assessment: Image Sample

Sample Preparation: Image Samples

Digital images of the physical samples were captured via a digital camera, Nikon D1X, in the same viewing cabinet used for presenting the physical sample to observer as shown in Figure 1. The camera was located at the viewing window on the top of the cabinet in Figure 1. Then, the images were reproduced for a LCD monitor, Eizo ColorEdge CG220, whose chromaticity and the white point of the monitor were set to D65 and 100 cd/m^2 through the transformations from camera device-dependent values to device-independent values and finally to monitor device-dependent values. Because of limitation of imaging devices to reproduce the appearance of the physical sample with the same physical size, the appropriate size and resolution of the image samples were selected by the visual assessment. A flowchart given in Figure 2 illustrates the reproduction procedures. In the following subsections, a camera, a monitor characterisation and an image selection stage are introduced.

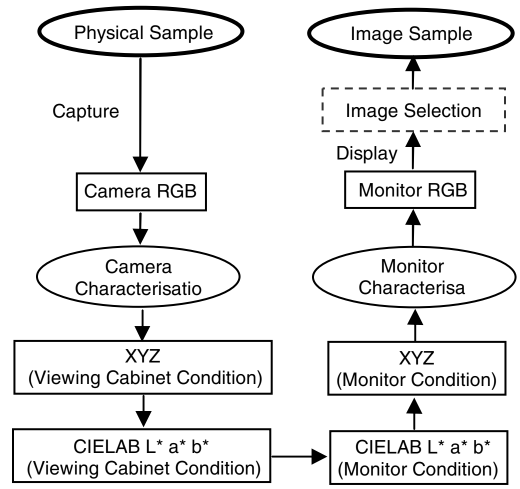

Figure 2. The work flow for reproducing an image sample from a physical sample.

Camera Characterisation

A camera characterisation model, *i.e.* a polynomial model using the least squares method [7] as given in Equation (1) was used to obtain XYZ values (device-independent values) of each pixel of each sample image form the camera RGB values.

$$t = Ac \tag{1}$$

where A is the transform matrix, c contains the camera RGB values and t contains the XYZ values. For a linear transform, A is a 3×3 matrix, c and t are both 3×1 matrices. In this study a variety of linear and nonlinear transforms (up to fourth order) were evaluated. Usually, a standard chart such as the GretagMacbeth Color Checker Digital Chart or a set of Munsell colours is used as training data to determine the coefficients in the transform matrix. Since surface material differences could affect the performance of the camera characterisation model, a transform matrix derived from a chart which has a matt surface may not be applicable for other samples having a glossy surface such as metallic paints coatings. Therefore, the average RGB values of the sample images and the corresponding XYZ values of the physical samples measured by a tele-spectroradiometer (TSR) were used as training data to derive the transform matrix. The viewing cabinet in Figure 1 was also used to measure samples by the TSR. Therefore, the image capturing and measuring conditions were consistent with the visual assessment using the physical samples, because any viewing geometry differences could seriously affect the appearance of the metallic paint coatings. The model was tested using the leave-one-out method (use one sample as a test and the others for deriving the model as training data), acceptable model performance was obtained. We found an average colour difference, ΔE^*_{ab}, of 0.55 with a maximum of 1.73.

Monitor Characterisation

After the transform from camera RGB values to XYZ values, they were encoded into monitor RGB values using a monitor characterisation model. The monitor characterisation model developed by Day *et al.* [8] was applied. This model consists of three one-dimensional look-up tables (LUTs) for the transformation from digital counts to scalars: *sR sG* and *sB*, and a transformation from the scalars to XYZ values using a primary matrix as given in Equation (2).

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix}_{predicted} = \begin{pmatrix} X_{r,max}-X_k & X_{g,max}-X_k & X_{b,max}-X_k \\ Y_{r,max}-Y_k & Y_{g,max}-Y_k & Y_{b,max}-Y_k \\ Z_{r,max}-Z_k & Z_{g,max}-Z_k & Z_{b,max}-Z_k \end{pmatrix} \times \begin{pmatrix} sR \\ sG \\ sB \end{pmatrix} + \begin{pmatrix} X_k \\ Y_k \\ Z_k \end{pmatrix} \quad (2)$$

where *X,Y,Z* are the tristimulus values, the subscripts "*r,g,b*", "*max*" and "*k*" define each channel, its maximum output and the black-level output respectively. Since the channel independency of this monitor was not very satisfactory, the 1D-LUTs were obtained from a 36-steps grey scale, equally spaced in digital counts from 0-255. The 3×3 primary matrix in Equation 2 was optimised by minimising the average ΔE^*_{ab} for a set of training colours including 1017 colours. The test errors between predicted and measured XYZ values for a set of 155 test colours were ΔE^*_{ab} of 0.75 (average) and 2.09 (maximum). This model showed a better performance than polynomial [9] and GOG [10] models.

Image Selection

Although the resolution of the camera is high enough to capture the fine detail, the resolution of the display devices was much lower. In order to display the image sample with the same size as the physical sample (8 × 8 cm^2), the image had to be captured with a lower resolution. This resulted in much smaller perceptual coarseness differences between the image samples comparing with those of the physical samples due to the loss of the texture detail. Therefore, the images were captured with higher resolution to obtain details as much as possible. This resulted in an image size of 21 × 21 cm^2 on the monitor and a viewing distance of 140 cm, in order to keep the same angular display size of 8.5° for both physical samples' and image samples' experimental conditions (specification of this viewing geometry is given in Table 2 as Condition 1). It was found that the coarseness appearance in Condition 1 did not perfectly agree with that of the physical sample. This is caused by the loss of detail in the imaging-forming system (both camera and monitor) as characterised by the MTF. But also because the study by Johnson *et al.* [4] showed a disagreement in perceptual appearance of images having the same retinal size if the viewing distances are different. But how does this affect if an observer can assess the coarseness difference of the images comparing with the coarseness difference between the physical samples? To investigate this, the coarseness difference was visually assessed using Condition 1.

There is a problem for Condition 1 that the coarseness appearance and the coarseness difference were much smaller than the physical samples. In common practice, we usually come close to an object to see the details. Therefore, to achieve image samples having an equivalent perceptual coarseness difference to the physical samples, observers were asked to assess the images at varying viewing distances as shown in Table 2. In other words, the images looked magnified to the observers when the viewing distance decreased, although the image itself did not change. Since the angular size of the displayed image was kept constant under all the conditions, the actual image size was made smaller by showing only part of the full image as illustrated in Figure 3. The observer was asked to scale the coarseness difference between the two image samples (a fine and a coarse grey colour image sample) comparing with that of the corresponding physical samples presented in the viewing cabinet as shown in Figure 3 (different viewing cabinet from the one used for coarseness scaling for the physical samples). The coarseness difference of the two image samples was estimated under the nine viewing conditions (Table 2) comparing with the coarseness different of the physical samples (assigned as grade 5) using the magnitude estimation method [6]. The viewing condition for the physical samples presented in a viewing cabinet had a sample size of 8 × 8 cm^2 and the viewing distance of 54 cm, and the luminance level was adjusted to be same as that of the monitor's white point (100cd/m^2). Geometric mean of each observer's data was used as a measure for each condition. The result is given in Figure 4. It can be seen that the closest match was obtained under Condition 6, although the differences obtained for different conditions are hardly significant.

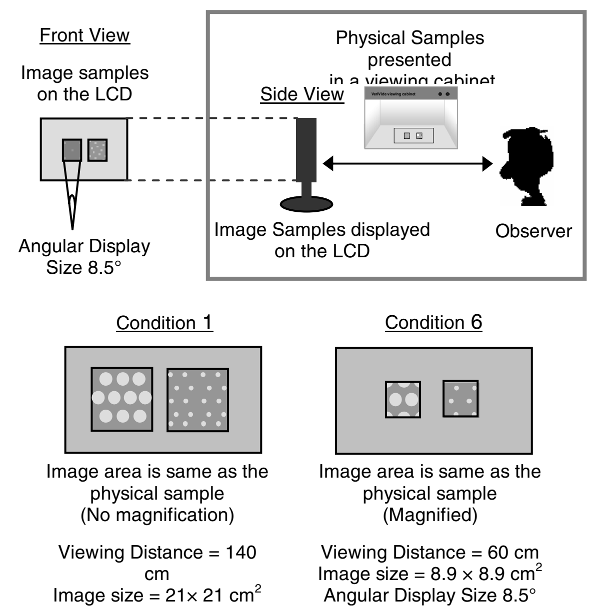

Figure 3. Arrangement of two physical samples in the viewing cabinet and two image samples displayed on the monitor (top). Example of the image samples for Condition 1 and Condition 6 (bottom) respectively.

Table 2: The conditions for the visual assessments.

Condition	Magnifying Ratio (%)	Image size (pixel)	Image size (cm)	Viewing Distance (cm)	Angle display size (degree)
1	100	832 x 832	20.7	140	8.5
2	117	714 x 714	17.8	120	8.5
3	140	595 x 595	14.8	100	8.5
4	175	476 x 476	11.9	80	8.5
5	200	417 x 417	10.4	70	8.5
6	233	357 x 357	8.9	60	8.5
7	280	298 x 298	7.4	50	8.5
8	350	238 x 238	5.9	40	8.5
9	466	179 x 179	4.4	30	8.5

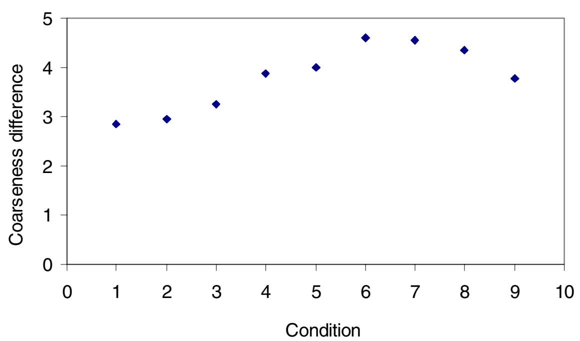

Figure 4. *Mean visual coarseness difference between under the nine condition comparing studied. Coarseness difference 5 indicates that a pair o the image samples displayed on the monitor has a equivalent coarseness difference to the physical sample pair presented in the viewing cabinet.*

Coarseness Scaling: Image Sample

According to the result from the image selection, the perceptual coarseness was scaled using Condition 6 which showed the closest perceptual coarseness difference between image samples to the physical samples. And also, the visual assessment was conducted using Condition 1 (no magnified image and the equivalent viewing condition with the assessment using the physical samples), in order to reveal the influence of the changes in the viewing conditions. For both conditions, a 1-9 scale categorical judgment was applied just as for the physical samples. For the assessment using Condition 6, all 156 image samples were assessed by 14 observers (6 female and 8 male). For the assessment using Condition 1, only a subset including 66 image samples was assessed by 10 observers (6 female and 4 male). Each observer repeated the assessment twice for further investigation of observers' repeatability.

Comparison of Visual Results

The arithmetic mean of the data from all observers was used as a measure of the perceptual coarseness for each sample. The repeatability (intra-observer agreement) was investigated by calculating the coefficient of determination (R-squared value) between the results of each observer's first session and second session. Observer accuracy (inter-observer agreement) was also reported between each observer's data and the average of all observers' data in terms of the R-squared value. The repeatability and accuracy results are summarised in Table 3. The result of the assessment in the viewing cabinet for the physical samples, using the monitor at Condition 6 and Condition 1 are labelled as "Physical sample", "Condition 6" and "Condition 1", respectively. It can be seen that the repeatability and accuracy results for all the samples are fairly similar in the conditions studied. This indicates that observers assess the coarseness difference equally accurate under these three conditions, although the absolute appearances of the coarseness under these conditions are different, *i.e.* there is much smaller perceived coarseness difference under Condition 1 than that under Condition 6 or using the viewing cabinet according to the experimental results presented in Figure 4.

The coarseness values for each sample obtained for the three conditions are compared in Figure 5. The correlation between the result for the physical sample and Condition 6 had an R-squared value of 0.92. The R-squared values were 0.89 and 0.95 between the physical sample and Condition 1, and between Condition 6 and Condition 1, respectively. The results indicate a good agreement between these conditions, although a slightly poorer agreement can be seen between the image samples and physical samples for the samples with smaller coarseness values. It might be caused by the noise which came into the processes of imaging the physical samples. It is concluded that coarseness difference can be accurately assessed using images reproduced on the monitor.

The result also suggests that for assessing the equally distributed fine detail over a sample like a metallic panel used in the experiment, the area presented to the observer is not so important. Observers tend to focus on only a part of the sample and not on the whole sample. Under Condition 6, only a part of the sample was presented to the observer comparing with the physical sample and the image sample under Condition 1. Condition 6 had less than half of area comparing with the others (see Table 2 and Figure 4), however the results showed no particular differences from Condition 1.

Table 3: Repeatability and Accuracy for the three conditions.

	Condition 6	Condition 1	Physical Sample
Repeatability	0.69	0.68	0.69
Accuracy	0.81	0.79	0.82

Model Predictions

The computational model for predicting the perceptual coarseness from digital images developed by the authors [1] was applied for the samples. This model assumes that the amplitude in the Fourier transform of the luminance channel of an image is a measure for the amount of contrast in the image and that the amount of contrast is correlated closely with perceptual coarseness. The model also assumes that the contrast-sensitivity function (CSF) [11] can be used to appropriately weigh the importance of contrast at the each spatial frequency. The model is expressed by Equation (3).

$$\mathrm{CM} = \log\left(\sum_{0}^{u_{max}} \frac{E(u) \times CSF(u)}{I \times S}\right) \tag{3}$$

where u is the spatial frequency in cycle/degree, u_{max} is the maximum spatial frequency contained in an image, $CSF(u)$ is the CSF [11], $E(u)$ is the Fourier energy, I is the mean value of the luminance channel and S is the size of an image in pixel units. Input parameters needed for the model are the sample size (in cm), the viewing distance (in cm) and the luminance of the reference white tile in a viewing cabinet or a white point of a monitor (in cd/m^2).

In the previous work [1], the model performance was verified by comparing with the perceptual coarseness of the physical samples. The model predicted the coarseness from the captured image of the physical samples with the high resolution and the experimental viewing condition. Hence, the model considers the high resolution image (832 × 832 pixel) as a physical sample size of 8 × 8 cm^2 which could not be simulated on the monitor because of the limited monitor resolution. Therefore, here, the model performance was evaluated for the images and the conditions under which the observers really assessed the displayed images (Condition 6 and Condition 1). The present visual results are used to test the model's performance for Condition 6, Condition 1 and also for the physical samples.

The model predictions which is the subtraction of the predicted coarseness value of the reference sample from that of each image, are plotted against the visual results in Figure 6. It shows that the visual results agree well with the model predictions for all conditions. The correlation between the model predictions and visual results had R-squared values of 0.91, 0.93 and 0.91 for Condition 6, Condition 1 and the physical samples respectively. The results prove an excellent performance of the model.

Discussion and Conclusion

The perceptual coarseness differences of metallic paint coating samples were assessed using two different media using image and physical samples. The visual results indicate that coarseness differences can be assessed from displayed images as accurate as from the original physical samples. The comparison between the two set of the visual results on the monitor suggested that the area or the magnification of the images do not affect the perceptual coarseness difference for metallic paint panels with fine details. This may be explained by assuming that observers seem to assess only part of a sample, but it may not true for pictorial images which observers needs to see whole images. Apart from this, a good agreement between visual results under the two monitor conditions was well predicted by the coarseness model. It was also found that although the spatial frequency information of an images is changed when changing the viewing condition (especially area and magnification), the model predictions for the magnified images (Condition 6) still agreed well with that for the non-magnified images (Condition 1).

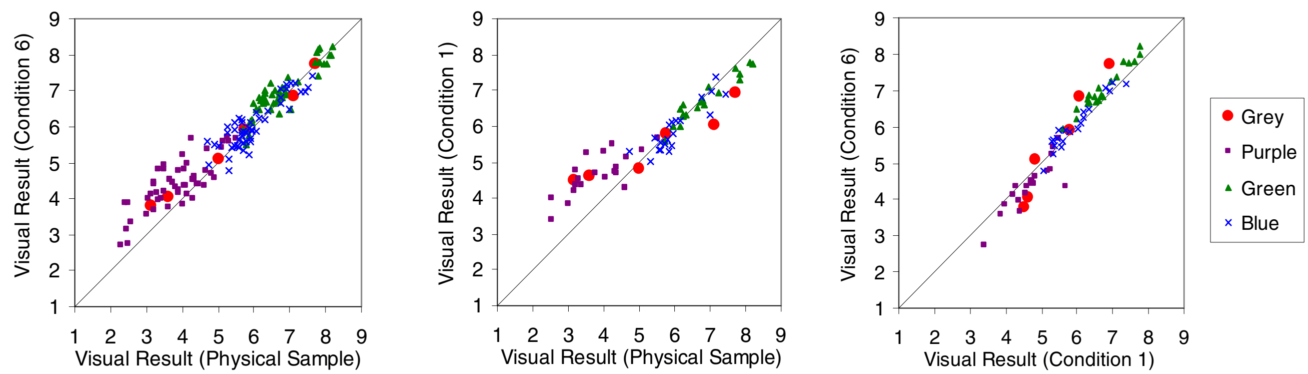

Figure 5. *Comparisons of the perceptual coarseness for the three conditions studied.*

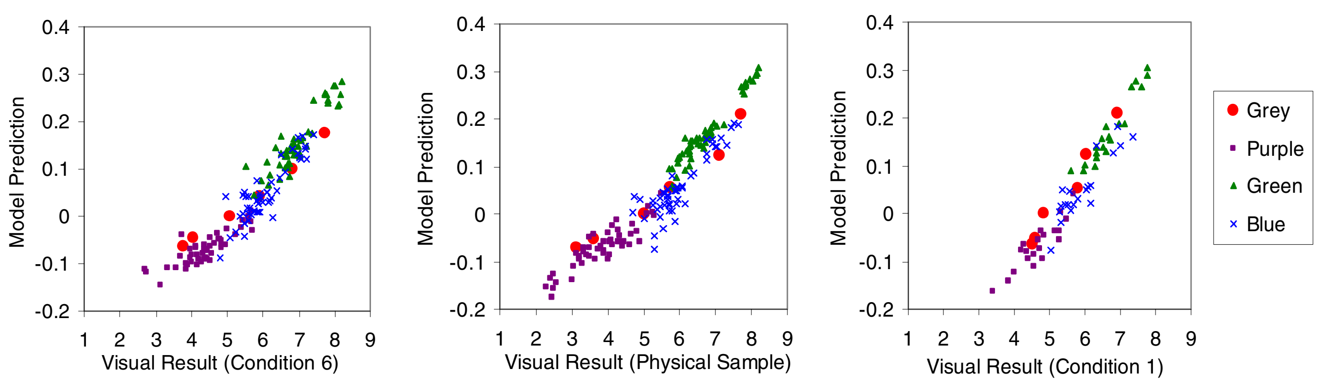

Figure 6. *Comparisons of model prediction for the three conditions studied.*

References

[1] Kitaguchi S., Luo M.R., Kirchner E.J.J. and Kieboom van den G.J., "Computation model for perceptual coarseness prediction", CGIV Conference, Jun 2006.

[2] CIE Technical Report, "A Colour Appearance Model for Colour Management Systems: CIECAM02", CIE 159: 2004

[3] CIE, Publication 131, "The CIE 1997 Interim Colour Appearance Model (SimpleVersion) CIECAM97s", CIE Central Bureau, Vienna, Austria (1998).

[4] Johnson G.M and Montag E.D, "Size Matters: The Influence of Viewing Distance on Perceived Spatial Frequency and Contrast", 13th Colour Imaging Conference, USA, pp.399-343, 2005

[5] Luo M.R., Cui G.H. and Li C., "British Patent: Apparatus and method for measuring colour (DigiEye system)", Derby University Enterprise Limited, October 2001.

[6] Engeldrum P. G., "Psychophysical Scaling: a toolkit for imaging systems", Optics & Photonics News, Imcotek Press; USA, 2000.

[7] Cheung V., Westland S., Connah D. and Ripamonti C., "A comparative study of the characterisation of colour cameras by means of neural networks and polynomial transforms". Color.Technol, 120, pp.19-25, 2004.

[8] Day A.D, Tapline L and Berns R.S, "Colorimetric Characterisation of a Computer- Controlled Liquid Crystal Display", Colour and Research Application, Volume 29, Number 5, pp.365-373, October 2005.

[9] Kang H.R., "Color Technology for Electronic Imaging Devices", SPIE Optical Engineering Press, 1997.

[10] Berns R.S, "Methods of Characterising CRT Display", Displays 16, 173, 1996.

[11] Westland S., "Models of the visual system and their application to image-quality assessment", Proceedings of the 10th Congress of the International Color Association, pp.309-312, Granada, Spain, 2005.

Acknowledgements

The authors would like to thank Akzo Nobel for supporting this project.

Author Biography

Saori Kitaguchi is a PhD student in Colour and Polymer Chemistry Department, University of Leeds, UK. She has a BSc degree in Chemistry and Materials Technology from Kyoto Institute of Technology in Japan and an MSc degree in Colour & Imaging Science from Colour & Imaging Institute, University of Derby, UK.