Characterising a digital camera for stained glass

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ABSTRACT

Two stained glass test panels were constructed as characterisation targets, with 50 glass tiles each. Rear illumination from a flash lamp in a softbox diffuser enabled images to be captured directly with a digital camera. Image processing corrected for the non-uniformity of the illumination. Two third-order polynomial models were tested for their accuracy in transforming transmissive colour stimuli into camera signals. A model with 20 terms gave the best performance with a mean ΔE^*_{ab} error of 3.6. The largest errors occurred for dark colours close to the edge of the spectral locus, which are very saturated and easily fall outside the colour gamut of a digital camera.

1. INTRODUCTION

Stained glass windows present interesting challenges for imaging.[1] It is highly desirable when using digital photography to capture the true colours of the glass, meaning the colours that would be seen by a standard human observer in standard illumination and viewing conditions. To achieve colorimetric image capture, a characterisation model is needed to convert from the Red-Green-Blue (*RGB*) colour signals generated by the camera to a device-independent colour space such as CIE tristimulus values (*XYZ*). Generally speaking, the colour gamut for transmissive objects is larger than for reflective objects, because the glass colours may be more saturated and have higher densities than for reflective surfaces.

It is possible to measure the spectral sensitivity of the camera channels directly with the aid of a calibrated monochromatic light source, but this is a time-consuming procedure best performed in the laboratory.[2] Instead polynomial models based on the least squares error minimisation method are widely used for characterising digital cameras, because they can be applied without knowledge of the spectral sensitivity of the camera's sensors. According to previous studies[3], a third-order polynomial should give sufficient accuracy. Fourth or higher orders may actually worsen the model performance because the high-order terms tend to amplify the image noise and yield poor predictions for extrapolation outside the range of the training data set.

2. GLASS PANELS

Figure 1. Two stained glass panels custom-made for camera characterisation: (left) training panel with grey scale on left side and rows organised in hue order; (right) test panel with more random arrangement.

Two glass test panels, with 50 stained glass tiles each, were constructed as characterisation targets as shown in Figure 1. The glass tiles were 1.3 by 1.8 inches (3.4 by 4.6 cm) in size, arranged in 5 rows by 10 columns, to give overall panel dimensions of approx. 16 by 10 inches (40 by 25 cm). The glass tiles were chosen from over one thousand pieces of glass with the help of an experienced stained glass window restorer, Keith Barley of Barley Studios in York. The criteria for choosing these pieces were:

- The training set should contain some neutral or near-neutral colours, with a 'tone scale' from transparent (white) to near opaque (black).
- Choose colours typically found in real stained glass windows.
- Make the colour gamut as large as possible.
- The glass should be uniform (no bubbles inside, no texture, colour looks uniform)
- Choose different colours and layout for test set.

Before they were leaded together, the glass tiles were measured individually using a Macbeth *Color-Eye 7000A* spectrophotometer to determine their transmission spectra. The spectral transmittance data were converted to colorimetric values using the CIE D65 illuminant and 2-degree observer. Figure 2 shows how the colours of the selected glass pieces were distributed in the *x*-*y* chromaticity diagram.

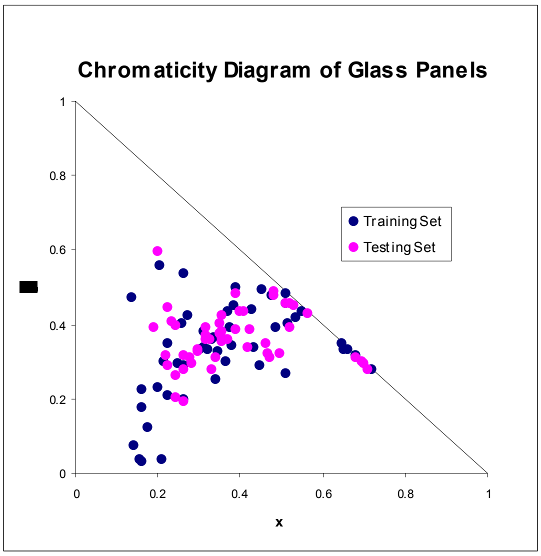

Figure 2. Chromaticity distribution of 100 stained glass tiles.

3. PHOTOGRAPHY

For photography of the complete panels, a flash lamp with a photographic softbox was used as the light source. The glass panel was placed directly in front of the diffuser of the softbox, with the camera approximately one meter distant. A Rollei medium-format studio camera with a Schneider 80mm AF lens was mounted on a tripod. The aperture was set to *f*16 to ensure that there were no over-exposed regions within the image. The exposure speed was set to 1/1000 second so that the ambient light was effectively eliminated. The intention was to simulate the actual conditions to be used *in situ* for photography of stained glass windows in heritage buildings.[4]

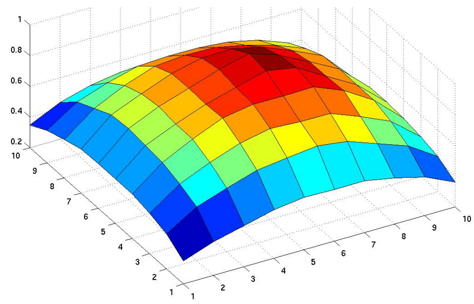

Figure 3. Non-uniformity of the light surface.

Although in the softbox there are two layers of woven diffuser material to smooth the distribution of the flash light, the illuminating surface is still not uniform. Figure 3 shows the characteristics of the illuminated area, based on analysis of a 'white image' without the glass panel. It is very obvious that the luminance is higher in the centre and lower around the edges. Deriving the colour transform matrix without correcting such non-uniformity would give a fault result. Therefore an illumination profile was generated before further testing.

The average pixel values for an area within each glass tile were corrected by dividing by the corresponding relative luminance value. The illumination profile can be applied in two ways: to either CIE *XYZ* or *RGB* values. For the former, we adjust the *XYZ* values of the glass tiles so that the modified values reflect what would be seen in the actual scene. For the latter, we normalise the output image as if it were uniformly illuminated. The performance of each method indicates its accuracy for image correction, and both may be needed in real practice.

4. POLYNOMIAL REGRESSION

Polynomial models based on the least-squares method are widely used for characterising digital cameras because they can be applied without knowledge of the camera's sensors. Polynomials of different degrees give different accuracy of characterisation. It is desirable to match the degree of the polynomial to the inherent trends within the data, and not to choose a degree higher than necessary. Fifth order or higher may worsen the model performance because the high-order terms tend to amplify noise significantly and to diverge rapidly when extrapolating outside the range of the training data set. The characterisation model can be represented in a simple form as follows:

$$\mathbf{H} = \mathbf{M}\,\mathbf{R} \tag{1}$$

where:
$\mathbf{H}$ is a vector of colour stimuli $[X_i\ Y_i\ Z_i]^{\mathrm{T}}$, $i = 1, 2, \ldots n$, where n is the number of samples;
$\mathbf{M}$ is a 3 x m matrix of coefficients where m is the number of terms in a polynomial of degree d;
$\mathbf{R}$ is a vector of camera output signals $[R^j_i\ G^k_i\ B^l_i]^{\mathrm{T}}$, where $0 \le j+k+l \le d$, $i = 1, 2, \ldots n$.

By the well-known method for solving a least-squares problem, the solution $\mathbf{M}$ of (1) is:

$$\mathbf{M} = \mathbf{H}\,\mathbf{R}^{\mathrm{T}}\,(\mathbf{R}\mathbf{R}^{\mathrm{T}})^{-1} \tag{2}$$

which can be easily performed in the Matlab image processing toolkit using the Pseudo-inverse function. In this study, two different third-order polynomial equations were tested, one with 14 terms (Model I, omitting the six cubic cross-products) and the other (Model II) with the full 20 terms:

Model I $\mathbf{R} = [R\ G\ B\ R^2\ G^2\ B^2\ RG\ RB\ GB\ R^3\ G^3\ B^3\ RGB\ 1]^{\mathrm{T}}$
Model II $\mathbf{R} = [R\ G\ B\ R^2\ G^2\ B^2\ RG\ RB\ GB\ R^3\ G^3\ B^3\ GR^2\ RG^2\ RB^2\ BR^2\ BG^2\ GB^2\ RGB\ 1]^{\mathrm{T}}$

5. MODIFICATION OF MODEL

The key idea of the polynomial method is to determine a transformation matrix that fits the training data with the best overall performance. Because it is just a regression fitting, according to some cost function, it may produce negative values for extreme cases, e.g. for some input values close to zero the output value may be less than zero. A simple and commonly used method to deal with such values is to clip them to zero. But we know that a colour with one or more zero CIE *XYZ* values rarely exists, especially for zero *X* and *Z* values. Therefore clipping to zero is not a good way to handle these negative values.

By analysing the test results, we found that all of the negative outputs corresponded to very small input values. For some of them the absolute values of the measurement and prediction were close, and for others they were not. We therefore modified the model as follows, to deal with the negative prediction:

When deriving the model:
- Use polynomial fitting the get the transform matrix by using the training data.
- Apply matrix to training *RGB* data to obtain predicted *XYZ* values corresponding to each.
- Find all the negative values in the prediction and calculate average value for *X, Y, Z* respectively.
- These mean values are saved in *mX, mY, mZ*. If there is no negative, the *m?* value is set to zero, e.g. if all the *X* values are greater than 0, set *mX* to 0.

When using the model:
- Apply matrix to training *RGB* data to obtain predicted *XYZ* values corresponding to each.
- Look for any negative values in the prediction, replace this negative value with the *m?* value.
- If the *m?* value is zero, replace the negative with its absolute value.

6. RESULTS

Table 1 shows the results of fitting the measurement data. Model I performed better when the illumination profile was applied to the *XYZ* image data, whereas Model II performed better when the illumination profile was applied to the *RGB* data, with a mean error of 3.6 and maximum error of 12.9 for the test set. The largest errors occurred for dark colours close to the edge of the spectral locus, which are very saturated and easily fall outside the colour gamut of a digital camera. This error performance was worse than typically obtained for reflective colours[2], where a third-order polynomial may be expected to achieve a mean error of less than 2 and maximum error of approximately 10.

Table 1: Performance (in ΔE^*_{ab}) of two polynomial models for transmissive objects.

	Model I (14 terms)				Model II (20 terms)			
	Train		Test		Train		Test	
	Mean	Max	Mean	Max	Mean	Max	Mean	Max
Whole Profile XYZ	4	23.2	4.7	19.8	2.8	17.7	3.9	17
Whole Profile RGB	4.6	26.7	5.8	22.7	3.3	17.2	3.6	12.9

Overall Model II (with 20 terms) outperformed Model I (14 terms) for both average and maximum ΔE^*_{ab} error values. Figure 4 plots the errors in the CIELAB colour space between measurement and Model II prediction against lightness, chroma and hue angle of the measurement respectively. The largest errors (greater than 9) occurred for dark (L^* less than 25) and colourful (C^* more than 40) glass tiles. There is no obvious trend between hue angle and the error. Such a finding confirms that large errors may arise because of the large colour gamut of stained glass.

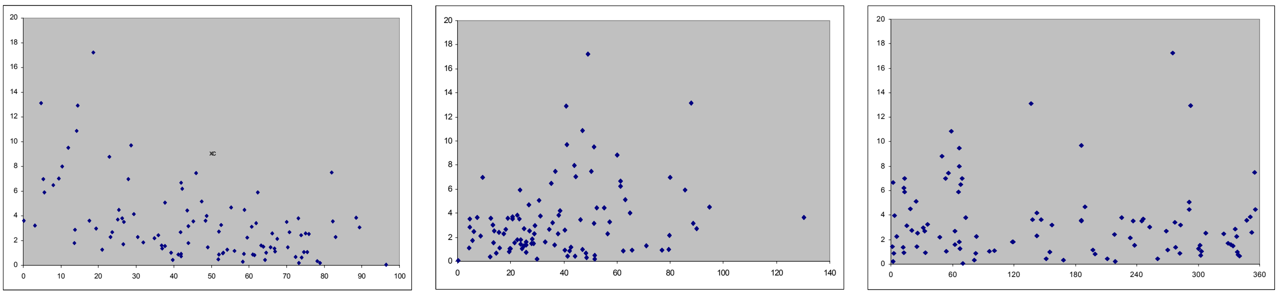

Figure 4. Distribution of errors (in ΔE^*_{ab}) between predicted and measured values of colours of glass tiles plotted against lightness L^* (left), chroma C^* (centre) and hue angle h_{ab} (right).

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