TO DEVELOP A METHOD OF ESTIMATING SPECTRAL REFLECTANCE FROM CAMERA RGB VALUES

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ABSTRACT

Spectral reflectance represents physical information of an object surface. In a conventional colour management system the spectral reflectance will be converted to the common space which will describe object tristimulus value or how will that particular colour will look under some of the standard illuminants or real light sources. However, many applications will require the object reflection to be known and independent on the viewing illuminant.

This work will address this need and give an effort to reconstruct spectral reflectance of an imaging surface by using RGB camera signals as an input. The camera has been characterized by direct measurement of the camera sensitivity curves and three of the most used printing technologies are employed to obtain test samples.

By using decomposition and dimension reduction techniques like PCA and Wiener estimate and the domain of linear algebra, evaluation of a method performance by varying different parameters will be performed. Here, the accent will be on formation of the basis vectors and covariance matrix. Additional optimization will be introduced to try to model for used printed samples.

Observations show that if most of the parameters are carefully controlled that spectral reflectance is more or less satisfying and that is dependable on the sample used. Improvements in the analysis have given better approximations and after optimization have been employed, the reconstruction method could be used in many applications in graphic arts area.

Index Terms – Spectral Reconstruction, RGB to reflectance, PCA, Wiener estimate, Multispectral imaging

1. INTRODUCTION

The imaging sensor is essentially linear device in terms of opto-electronical conversion. If all noise sources would be eliminated, it should be possible to establish linear relation with the input signal. This would effectively provide a possibility to use a camera instead spectrophotometer. Possibility like this is usually reserved for the field of multispectral imaging [1,2,3] or trichromatic camera equipped with selected set of filters [4,5]. Usually this equipment is rather expensive and not ready available. This work has intention to develop a method of spectral reflectance reconstruction from RGB digital counts using just lower class SLR digital camera and available light source. If the accuracy of the reconstruction is good enough, then printer’s characterization and profiling could be made using the camera as an input instrument. Spectrophotometers are also expensive and slow, especially if the characterization targets containing over 900 colour patches.

1.1 SAMPLES

Offset machine Heidelberg Speedmaster was used to print on two different surfaces: regular offset paper and cardboard. Glossy paper was fed to Epson ProPhoto 4000 ink jet printer to give high reflective print sample, but in the contrast, same technology is used make a print on cotton with Myake Texjet printer. This surface has the least mean reflectance of all used in this project and this is due to its translucency. Finally, laser or electrophotography technology representative was Xerox Docucolor and it used regular paper as a surface. All the prints included IT87-3 CMYK target with 940 patches. The training set was primaries ramps, together containing 72 patches, while test set was containing 868 patches.

2. METHOD

Spectral characterization of the imaging system (Canon 300 D) was performing by direct measurement using the monochromatic light outputted from Bentham Dm150 double monochromator. The wavelength step was set to 10nm range where for each of these steps, five images were acquired. To discover spectral sensitivity curves the average values were extracted from multiple images. Obtaining an imaging sensor sensitivity curves requires on board non – linear processing to be turned off. For this purpose the dcraw [6] utility has served as it provided with possibility not only to switch off some of the post processing, it also
provided a possibility to change some of the internal post-processing. When image is formed on the sensor as black and white, light information, interpolation techniques are employed to recover colour information. For all images used in this work, the interpolation algorithm was adaptive one (AHD), which provides the highest quality of interpolation. Other processing like, white balance, gamma correction, colour space conversion have been switched off and the final outputted image was saved as 16bit TIFF. One of the conditions if camera system was to be used as a measuring instrument is that it should exhibits linear response on the input signal. When on board processing has been discarded, one of other distracting factors is noise. There are many sources of noise that can occur within digital camera systems. One of those and probably the most important is the dark current noise which is a function of the sensor integration and read-out time and exponential function of a sensor temperature. To measure dark current noise, series of images are obtained with lens cap on so that both random and noise produced by the sensor temperature could be obtained. If it is assumed that one pixel is formed from the input light, with certain exposure settings, noise can expressed as:

\[ P_i = e \int S \ast I \ast R + n \]  

(1)

where \( P_i \) is a value of one pixel, e is exposure length, S, I and R are spectral sensitivity function, illumination source SPD and input reflectance retrospectively and n is random noise. The linearity of the camera response on input signal is shown on Figure 1.

\[ \text{Figure 1. Evaluation of camera linearity for each channel} \]

To make sure that input is coming in form of some stable signal, the outside illumination conditions also should be controlled. With inclusion of flare and illumination uniformity measurement it is believed that all the conditions are controlled. To obtain magnitude of these, the Gretag Macbeth DC test chart with outside in central patches have been measured Minolta CS-1000 telespectroradiometer and imaged with the camera. For light source, two tungsten lamps were positioned 45° to the imaging surface (Figure 2). Once an image was created, it needs to be corrected for non-uniformity, noise and flare. If the image is denoted as \( I(x,y) \) then normalized image would be:

\[ \text{In}(x,y) = k \ast (I(x,y) - \text{noise - flare}) / (L(x,y) - \text{noise - flare}) \]  

(2)

where \( k \) is normalizing constant chosen that maximum pixel value of the normalized image is not higher than maximum measured value for white of the surface, and \( L \) is luminance profile (Figure 3).

\[ \text{Figure 2. Imaging setup} \]

\[ \text{Figure 3. Luminance profile of the imaging surface} \]

3. RESULTS

Spectral reflectance reconstruction is based on the prior knowledge about reflectance properties of imaged object. Whole spectrum could be represented with just three basis vectors. Prints were measured using Gretag Macbeth Spectrolino and the reflectance have been put through principal component analysis to obtain characteristic vectors for all used samples. Special care will be taken for media dependence, number of colour patches involved in analysis and ability of PCA to include enough variability needed for accurate reconstruction.
To form an input for PCA, four primaries (CMYK) tone scale from the IT87-3 test chart are chosen to represent whole variability within the spectrum. These are referred as training set. For the test samples, any of the secondary on the test chart could be used where chart could be divided regard to lightness on to dark and light regions. The first three principal components of the test samples are shown on Figure 4.

The most of difference between principal components formed for different prints could be seen in the first vector. The percentage of variability explained within principal components will depend on the combination of the surface and the pigments (Table 1).

Reconstruction error could be improved with increasing the percentage of variability explained within principal components. Due to trichromatic nature of the camera system the disagreement in matrix computation occurs when number of basis vectors is more or less than three and the only way to increase percentage of variance explained is to use more basis vectors. By using imaging sensor, as an inherently linear device, it could be said that RGB digital values are formed in a much same manner like CIE XYZ coordinates and then the output RGB digital values can be represented in the form of linear algebra as:

$$T = S * I * R$$

where $T$ is the $3 \times m$ matrix of RGB values, $S$ is $3 \times n$ spectral sensitivity matrix, $I$ is an $I \times n$ illumination source vector and $R$ is $n \times m$ matrix of reflectance. Index $m$ stands for number of colour patches or samples, and $n$ stands for number of sampling points within the visible spectrum.

Matrix $R$ of spectral reflectance could be represented with just three principal components used where dimension reduction from $n$ to 3 is performed using PCA. The newly formed matrix $B$ has a size of $3 \times n$. Reconstruction of the input spectrum can be presented then as the product of the principal component matrix and the matrix of coefficients $C$:

$$R_{rec} = k * B * C$$

where $k$ is normalizing constant used to normalize reconstructed spectrum on the given maximum reflectance value of the media. Matrix $C$ is formed from the system response on the given reflectance and is obtained through matrix inversion process:

$$C = \text{inv} (SI^T * B) * T^T$$

The mean error $\Delta r$ gained in a spectrum reconstruction is calculated as:

$$\Delta r = \frac{\Sigma (R_{rec} - R)}{n}$$

Where $n$ is the number of sampling points. Standard deviation is computed as

$$\Delta r_{std} = \left[ \frac{\Sigma (R_{rec} - R)^2}{n} \right]^{1/2}$$

The error derived from spectrum reconstruction can also be expressed as the colour difference $\Delta E^*$ in CIELab space. The initial results are calculated from training input set and have been evaluated with the test colour set within each of the used samples. The error metric is reported as mean and standard deviation of $\Delta R$ reconstruction difference in reflectance space and as mean, max and min CIE2000 $\Delta E$ colour difference formula (Table 2). This formula agrees better with visual colour differences for small to medium colour differences than the other formulae. Colour difference has been computed for CIE 1931 observer and A illuminant. Transformation form reflectance to XYZ coordinates has included D65 as a viewing illuminant.
Table 2. Spectral reflectance reconstruction error (Initial results)

<table>
<thead>
<tr>
<th>PCA</th>
<th>Medium DC</th>
<th>Textiles</th>
<th>Offset 1</th>
<th>Offset 2</th>
<th>Inkjet prints</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st</td>
<td>0.962</td>
<td>0.038</td>
<td>0.018</td>
<td>0.034</td>
<td>0.980</td>
<td>0.018</td>
</tr>
<tr>
<td>Mean</td>
<td>0.915</td>
<td>0.018</td>
<td>0.035</td>
<td>0.041</td>
<td>0.971</td>
<td>0.005</td>
</tr>
<tr>
<td>Min</td>
<td>0.33</td>
<td>0.31</td>
<td>0.10</td>
<td>0.14</td>
<td>0.27</td>
<td>0.05</td>
</tr>
<tr>
<td>Max</td>
<td>1.68</td>
<td>0.68</td>
<td>0.8</td>
<td>1.2</td>
<td>0.9</td>
<td>1.25</td>
</tr>
</tbody>
</table>

It can be seen here that the reconstruction error is a function of mean reflectance values within samples where those with highest mean reflectance value have the largest reconstruction error. This implies that high gamut/dynamic range media carries a large variation in reflectance within colours and that PCA have no ability to adapt. Only solution for such media would be to use more principal components and this is where multispectral imaging takes over. Original and measured spectrum for test colours and primaries are represented on the following Figures (5 to 7).

Figure 5 and 6. Measured (top) and reconstructed (bottom) spectrum

Figure 7. Spectral reconstruction (dashed line) and the original spectrum (full line) for primaries and secondaries

The highest disagreement between reconstructed and original is occurring in blue spectrum and red spectrum, for which the cause might be illumination source used for imaging. Namely tungsten light source emits much less energy in blue region than in red which after matrix inversion high values in blue and low in red are reconstructed. Number of colours that have been put through PCA could extract basis vectors that are more capable for accurate reconstruction. With increasing number of input colours, the number of samples within one variable is increasing as well, which effectively gives more inputs to analyze and therefore, a better outcome. Such a variation will yield better reconstruction accuracy (Table 3) but it will require additional measurement effort.

Table 3. Reconstruction error for different regions of the test chart regard to number of colours involved in PCA

As it was proven that basis vectors formed from high reflective primaries give much higher accuracy within the dark colours tested region within same test sample, it would be reasonable to think that any PC formed from high reflective surfaces would give good reconstruction of low reflective surfaces. This assumption will be evaluated by using basis vectors formed from the measured samples of
Gretag Macbeth DC and Inkjet print (Table 4). These media show much higher luminance and mean reflectance compared to the other samples used, primarily because high reflective glossy surfaces. This might have real practical use, as just one measurement could provide with the input for many other surface spectrum reconstructions.

### Table 4. Reconstruction of the spectrum using single inputs PC formed from high reflective surfaces (Macbeth DC and Ink jet glossy)

<table>
<thead>
<tr>
<th></th>
<th>Gretag Macbeth DC</th>
<th>Textiles</th>
<th>Offset 1</th>
<th>Offset 2</th>
<th>Inkjet glossy</th>
<th>Linear</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\delta R)</td>
<td>0.029</td>
<td>0.033</td>
<td>0.035</td>
<td>0.037</td>
<td>0.039</td>
<td>0.028</td>
</tr>
<tr>
<td>(\delta R \text{ std})</td>
<td>0.044</td>
<td>0.031</td>
<td>0.047</td>
<td>0.068</td>
<td>0.033</td>
<td>0.024</td>
</tr>
<tr>
<td>(\text{mean } \delta R )*</td>
<td>2.5</td>
<td>9.5</td>
<td>5.7</td>
<td>6.2</td>
<td>4.2</td>
<td></td>
</tr>
<tr>
<td>(\text{max } \delta R )*</td>
<td>10.3</td>
<td>9.6</td>
<td>12.3</td>
<td>9.7</td>
<td>10.2</td>
<td></td>
</tr>
<tr>
<td>(\text{min } \delta R )*</td>
<td>1.1</td>
<td>1.4</td>
<td>1.8</td>
<td>1.1</td>
<td>0.8</td>
<td></td>
</tr>
</tbody>
</table>

Note here that sensitivity functions are actually system functions and they are product of imaging illumination source spectral power distribution and spectral sensitivity curves of camera imaging sensor (Figure 8).

### 3.1 Optimization of the System

Reflectance is smooth functions and to obtain a linear relationship between the sensor sensitivities and spectral reflectance, it is reasonable to make the sensitivity curves as smooth as possible. Current sensitivity curves are spiky and it is likely then, if multiple spikes are solved, the curves will exhibit more smooth nature. This should establish more linear relation with reflectance and therefore higher accuracy of the reconstruction. (8)

\[ S_i(\lambda_{k+1}) = S_i(\lambda_k) \quad k = 1, 2 \ldots m \]

(8)

\[ S_i(\lambda_{k+1}) \leq S_i(\lambda_k) \quad k = m, \ldots 34 \]

(9)

where \(S_i\) is sensitivity of the sensor for \(i\) sampling point, and \(m\) is the peak point. This constraint has been used in the work of Finlayson et al [7], and they have suggested that the peak for each channel will occur on some of the assumed points. However, the nature of mentioned authors work was to estimate spectral sensitivity curves where in this project they have been measured so the exact peak point \((m)\) for each channel is known. To obtain the real function that needs to be optimized for given constraint, the analysis of the curves shape will be according to the difference in reconstruction they produce. Most of the error is occurring due to the nature of the imaging light source so the optimization could be seen in this case as a white or channel balancing. Custom white balance has been tried to correct for illumination source but this approach has not yield significant improvement.

This is rather piece wise or local optimization rather than global and it is a task of minimizing the function for specific domain:

\[ \min \|R_{\text{rec}}(n-m) - R_{\text{ref}}(n-m)\| \]

(10)

where \(R_{\text{rec}}\) is a reconstructed spectrum and \(R_{\text{ref}}\) is measured, \(n\) and \(m\) are start and end point. The reconstruction spectrum \(R_{\text{rec}}\), could be expressed as a product of product of:

\[ R_{\text{rec}} = C \times S \]

(11)

where \(C = pc \times rgb\) or product of principal components and camera digital outputs and \(S\) is the system response or product of camera spectral sensitivities and imaging illumination source spectral power distribution. The equation now can be expressed as:

\[ \min \|C \times S - R_{\text{ref}}\| \]

(12)

and is subject to defined constrains. This yields optimized system curves shown on Figure 9.
By analysis of the system curves and reconstruction error it can be seen that reconstructed spectrum have more intensity in blue and less in red channel then measured spectrum, and with applying the last equation on different sections of the curves where the error is occurring, the new system response curves have been obtained. Also, wavelength interval ranging from 380 - 400 nm and from 680 - 710 have very low light intensity where the evaluated camera produce great amount of noise so it has been assumed that the error produced in this regions is due to low sensor sensitivity and therefore the 0 response is assigned. This correction will have an impact to the overall reconstruction accuracy in reflectance space but will not produce very small if any change in colour difference due to low CMFs values in these regions. Final results after optimization of the system curves are shown in Table 5.

![Figure 9. Optimized system functions](image)

Table 5. Reconstruction results after all evaluated parameters involved and after optimization

<table>
<thead>
<tr>
<th>Optimization</th>
<th>Textiles</th>
<th>Offset 1</th>
<th>Offset 2</th>
<th>Ink jet glass</th>
<th>Laser</th>
</tr>
</thead>
<tbody>
<tr>
<td>AD 101</td>
<td>0.001</td>
<td>0.002</td>
<td>0.007</td>
<td>0.012</td>
<td>0.003</td>
</tr>
<tr>
<td>mean ΔE*</td>
<td>1.1</td>
<td>1.4</td>
<td>1.4</td>
<td>1.6</td>
<td>1.1</td>
</tr>
<tr>
<td>mean ΔE CIELAB</td>
<td>0.78</td>
<td>0.17</td>
<td>1.2</td>
<td>1.6</td>
<td>0.85</td>
</tr>
</tbody>
</table>

4. DISCUSSION

There are a lot of factors to be analyzed in formation of principal components. Previous work have shown that most important consideration is the percentage of variability explained and that it needs to be over 99 % to achieve satisfying reconstruction accuracy. Some of the used test samples manage to go over this number, but others have failed. This is the reason why several authors have used up to eight principal components to be able to accurately reconstruct reflectance out of surfaces of different structure. It has been suggested that as many colours as possible should be available for PCA. This might not be the excellent choice, because as the number of elements within one variable increases, the ability of PCA to convey enough variability will decrease. This was a case with textile prints where the input colours number have increased up to 940, but the variance explained within first three components have fallen for 2%. Still, there were some improvements with the raised number of colours within this sample but they were insignificant, where in the case of inkjet glossy print it was quite opposite. Here, the accuracy has been doubled with more colours involved in analysis. The conclusion has been the same, it is media dependent. It is found that overall precision of the reconstruction is depending on the average luminance or mean reflectance values of the surfaces, where those with higher luminance values will yield less precise reconstruction results. One of the reasons for this could be that principal components cannot carry enough variability to describe high reflective surface – pigments combinations. This also applies and confirms the assumption made before that low reflective surfaces could be accurately reconstructed from the input basis vectors formed from high reflective surfaces. This could reduce the number of measurements radically and if the reconstruction gives satisfying accuracy, the possibility of obtaining the hundreds of reflectance functions out of one shot of the camera. If the high level of reconstruction accuracy want to be achieved, some sort of optimization is necessary if using trichromatic camera.

6. REFERENCES


