Influence of f-number on Colour Matrix Behaviour

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Abstract – The behaviour of the colour matrix is studied in relation to the f-number (f#) of the light incident on the sensor. From this study, we find that the colour matrix elements appear to depend linearly on the inverse of the square of f#. The impact of this is discussed in terms of a noise model and the potential cause from crosstalk. Additionally, a simple, first principles, model is presented in explanation of the effect.

I INTRODUCTION

Standard image sensors provide a fundamentally greyscale output with colour generation being the result of interpreting the sensor pixel response when colour filter layers are included in the light path of the pixel. Typically this is an RGB colour filter pattern arranged in the well know Bayer pattern. Colour output must therefore be mapped from the underlying colour filtered raw, greyscale, sensor response to a valid colour space which a human observer can understand. A typical colour space would be the defined in the sRGB standard[1]. A common technique for colour space conversion and colour correction uses the linear algebra approach of a colour matrix, usually coupled to the use of a white balance matrix to map the captured sensor data to the desired output colour space response, as in equation 1.

$$\begin{bmatrix} R_O \\ G_O \\ B_O \end{bmatrix} = \begin{bmatrix} C_{RR} & C_{GR} & C_{BR} \\ C_{RG} & C_{GG} & C_{BG} \\ C_{RB} & C_{GB} & C_{BB} \end{bmatrix} \times \begin{bmatrix} W_R & 0 & 0 \\ 0 & W_G & 0 \\ 0 & 0 & W_B \end{bmatrix} \times \left[\begin{bmatrix} R_S \\ G_S \\ B_S \end{bmatrix} - \begin{bmatrix} R_{off} \\ G_{off} \\ B_{off} \end{bmatrix} \right] \quad 1$$

In this equation, we see the sensor data first having any offsets removed, to ensure a correct black level. Next, a white balance correction applied in order to ensure that neutral tones are properly represented in the image. Finally, the colour space correction or colour matrix is applied. So, with knowledge of the target points in the output colour space, this equation transforms the sensor data into the output colour, assuming a linear relationship between the input and output colour spaces.

Derivation of the colour matrix depends on the illumination used and knowledge of the target point in the end colour space. This calibration process can be a source of variability and error in the output colour, unless care is taken to control the image environment during the calibration process. Questions then arise over which factors in the imaging system impact the derived colour matrix and what impact they can have on perceived image quality. Clearly the spectral behaviour of the sensor and colour filters have a major influence on the colour matrix. Also, such features as the use of micro-lenses infrared filters, image stack height can all influence the colour matrix required to produce good colour accuracy.

In terms of the impact that the colour matrix has on perceived image quality, we find that being a full 3x3 matrix, the colour matrix has the ability to mix noise present in other channels into the channel of interest. Therefore when considering image quality, we need to look at the magnitude of the colour matrix elements as well as the overall channel noise to determine the noise content in the final image, since each channel contains a portion of noise from the other colour channels.

In this paper, we describe an experiment in which we find a relationship between the value of the colour matrix elements and the f# used for image collection. We examine the impact that the colour matrix can have on the perceived noise level in an image and present a simple first order model to help explain the observed relationship between f# and colour matrix value.

II EXPERIMENTS

II.A COLOUR MATRIX DETERMINATION

Using a two million pixel sensor array fabricated on a 0.18µm CMOS process, giving pixels of 4.0µm pitch, a series of colour matrices were derived using a Comsicar/Pentax C1614A 16mm CS-mount CCTV lens, having f# variable from 1.4 to 16. The colour matrices were collected from the sensor at a range of f#, using the same sensor set-up, lighting and lens. The colour matrix is derived as follows: Using a Gretag Macbeth colour controlled light box, images of each of the 24 Macbeth Colour Checker™ patches are collected in 8bit Bayer image format. That is, no colour interpolation is performed. The image is an 8 bit "raw Bayer" format. From these images the Red, Green and Blue channel responses are extracted from the chart patch and averaged across the number of pixels in the image portion. Having the sensor RGB responses for each of the 24 Colour Checker patches, the results are then analyzed by forming a set of simultaneous equations to match the sensor RGB responses to the RGB coordinates of the Macbeth Colour Checker patches.

II.B Noise impact analysis

In looking at the noise impact on image quality, we have determined a relationship between the noise in the colour channels and the end noise in the image. The gain factors in the colour matrix allow signals to be added and subtracted among the colour channels, to produce accurate colour reproduction. These gain factors are arranged to ensure that the colour matrix is neutral preserving; therefore the primary colour channel element depends on the crosstalk elements for that channel. However, as the three colour channels are independent and uncorrelated, we find that the noise present in each channel adds as in a sum of squares manner. Therefore, the overall noise in any single channel contains noise from each of the two other channels[2]. This random, uncorrelated noise is also multiplied through the presence of the colour matrix elements as given in equation 2 (for the red channel),

$$\sigma_{Ro}^{2} = C_{RR}^{2}.\sigma_{Ri}^{2} + C_{GR}^{2}.\sigma_{Gi}^{2} + C_{BR}^{2}.\sigma_{Bi}^{2} \qquad 2$$

If we assume equal noise in each of the channels,

$$\sigma_{Ri} = \sigma_{Gi} = \sigma_{Bi} = \sigma_{ncc} \qquad 3$$

Then each channel equation only needs to consider the colour matrix elements,

$$\sigma_{Ro}^{2} = \left(C_{RR}^{2} + C_{GR}^{2} + C_{BR}^{2}\right)\sigma_{ncc}^{2} \qquad 4$$

In the case of an ideal colour transformation, the noise present after transformation would be the same as that present before. Therefore, we can take a ratio of the noise present in any individual channel and compare it to the noise after the transformation to provide a noise degradation factor (NDF) for the channel, equation 5.

$$NDF = 20.Log_{10}\left(\sqrt{C_{RR}^{2} + C_{GR}^{2} + C_{BR}^{2}}\right) \qquad 5$$

This factor is expressed in dB's in order to readily compare it with the noise performance of the raw sensor. In this case, the NDF is for the red channel but the expression is the same for each individual channel, replacing the colour matrix elements with the elements for the channel row in question.

To assess the impact of this we have used synthetic colour matrices of known NDF values to generate colour processed images of the noisy flat grey fields. The synthetic matrices were generated by modelling the relationships between colour matrix elements and deriving components which would provide a specific noise degradation factor of the correct level. A flat mid grey image was generated and a known amount of Gaussian noise was added, in order to simulate the presence of noise in a real image. This flat grey field was then processed through matrices which represented each colour channel individually and finally the full matrix. The results are presented in the following section.

III Results

III.A Colour Matrix Derivation

For the sensor system in question, the result of the colour matrix derivations at f# ranging from 1.4 to 5.6, we have observed and the results presented in the graphs of figure 1. These graphs show the colour matrix value plotted against the inverse of f# squared. An apparently straight line relationship is observed. In this case we observe that the colour matrix element values approach a minimum at high f#. Similarly we also find that the colour matrix elements which represent nearest neighbour pixels show the highest dependency on f#, with the diagonally related elements, mixing between blue and red and vice-versa, showing a very weak dependency on f#.

III.B Noise Impact Analysis

Figure 3 presents the result of applying an 11dB NDF to a flat mid-grey 24bit RGB image field with 12.8LSBs of Gaussian noise applied equally to all three channels (central image). In terms of LSB noise content after applying the colour matrix, each channel contains 47LSBs of noise. The images showing the noise related to a colour channel are obtained by applying a colour matrix with the other two channels set to unity. The all channels image uses the full colour matrix to mix in 11dB of noise degradation into all colour channels. In this figure, we can see that the noise content of the image does not manifest itself equally across the three channels. The green channel displays a much more noticeable noise content, with the blue channel noise being the least noticeable, following from the CIE photopic response[3].

IV Simple Model

In looking at the geometric arrangement of the illumination and the sensor structure with microlens, (figure 4), we can define the effective focal length of the microlens, equation 6, where n_{sub} is the refractive index of the sensor optical stack.

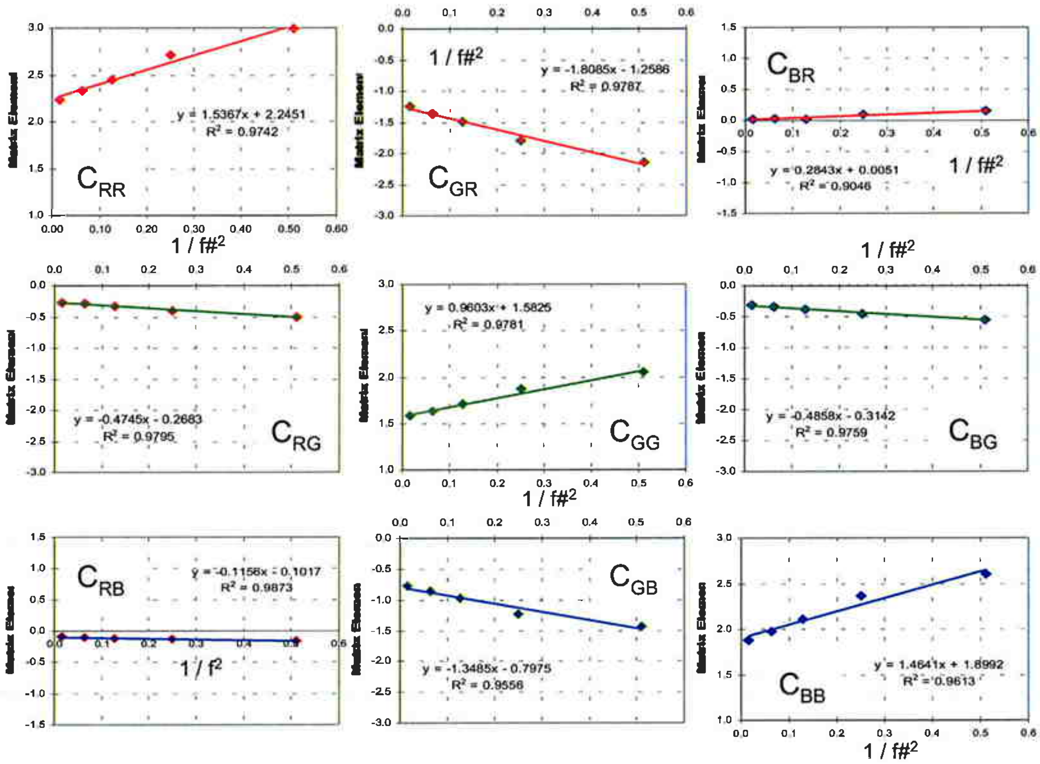
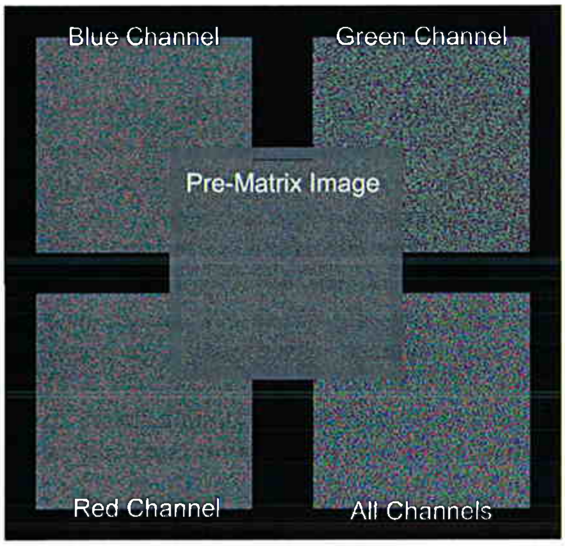


Figure 1 Colour Matrix Element Dependency on Inverse of Square of f#.



Effect of +11dB Noise Degradation from Colour Matrix Applied to Each Individual Channel & All Channels

Figure 3 Impact of Colour Matrix on Noise Perception

Therefore, we find that the radius of the spot of the exit pupil of the lens, D, imaged by the microlens onto the photodiode is given by equation 7.

Increasing the f# of the incoming light for a given lens results in the image area of the exit pupil on the photodiode increasing as a squared function of the f#, since the f# describes only linear dimensions in the optical system.

In the graph of figure 5, we compare the spot size to the pixel pitch and look at how this depends on f#. In this case we find that we do not have a linear relationship in the inverse of f# squared, but we have a clear relationship which is due to the increasing area of illumination of the photodiode.

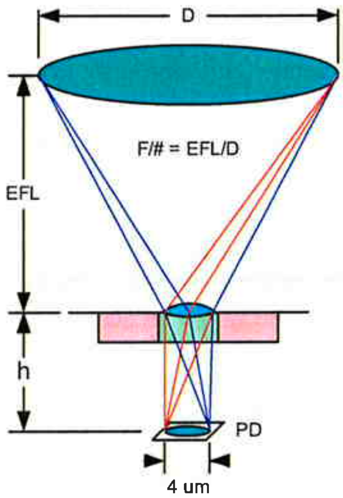


Figure 4 Geometric Model of Senor Optics

$$F_{\mu lens} = \frac{h}{n_{sub}} \qquad 6$$

$$R_{spot}(f\#) = \frac{F_{\mu lens}}{2.f\#} \qquad 7$$

The photodiode, being smaller than the pixel pitch, needs to be illuminated such that the carriers generated are captured by the diode. Illumination outside the diode will result in carriers being generated which can find their way to other diodes in addition to the normal diffusion crosstalk[4]. The degree of illumination outside the diode area depends on the spot area and as this depends on the f#, then there will be a crosstalk element which depends on the square of the f#, which should be broadly consistent with the relationship in figure 5.

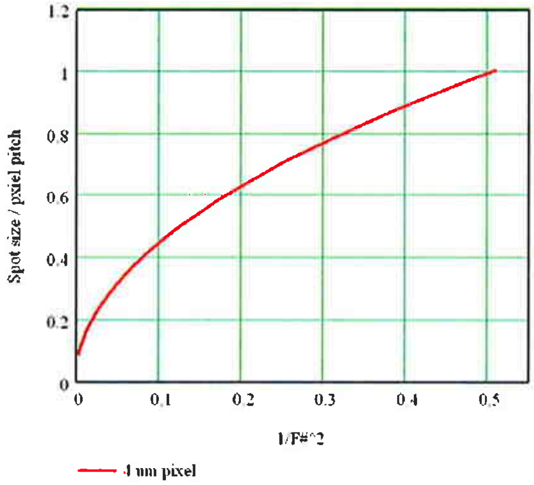


Figure 5. Influence of f# on ratio of Geometric Spot Size to Pixel Pitch.

V CONCLUSIONS

The data presented in figure 1 shows a clear dependency on f# for the colour matrix elements. In light of the simple model presented above, we should see in this data some curvature in the line describing the behaviour of the colour matrix elements with f#. While figure 1 shows a straight line fit to the data, we can see a systematic offset in all the nearest neighbour mixing components which is consistent with the behaviour presented in the graph of figure 5. We conclude therefore that the slope of the lines in figure 1 describe the degree of matching between the photodiode area and the area of the illumination spot imaged onto the photodiode from the primary lens, through the microlens. Where the image spot lies outside the photodiode, extra carriers are generated which can take part in crosstalk between neighbouring pixels. At higher f#'s the natural crosstalk in the system will dominate and the sensor system will deviate from the behaviour of figure 5 due to this interaction. So the high f# behaviour indicates the level of the sensor's natural diffusion crosstalk.

The low dependency of non-nearest neighbour crosstalk is probably due to the increased distance between the pixels, as can be seen by examining figure 6 for the distances between red and blue channels.

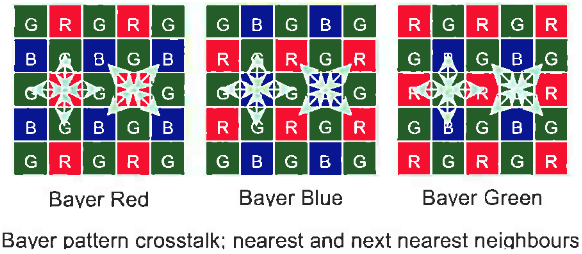


Figure 6 Crosstalk Neighbours in the Bayer Pattern

High colour matrix elements are undesirable due the ability of the colour matrix to mix noise between the three colour channels. This is shown in figure 3 by applying fixed NDFs to a synthetic noise image. Here we see that the perception of the noise in the green channel is higher than in the red and blue channels, despite the output noise level being the same. Therefore we see that higher matrix elements can be accommodated in the red and blue channels, than in green.

Maintaining low colour matrix elements is an important aspect of sensor and optical system design in order to produce good colour accuracy and noise performance. This work has shown that the colour matrix depends on the f# of the lens used to image the scene and, to first order, follows a simple geometric model. The detail of the behavioural fit is very specific to the individual sensor design.

This result is important in camera applications where f# is both fixed and variable. In fixed applications it can allow management of the imaging system design to provide a trade-off between light level at the sensor and noise in the end images. It could allow the camera system designer to select higher f# in preference to low light performance, providing better noise performance. Similarly in variable f# applications care must be taken to ensure that the signal processing systems can accommodate changes to the colour matrix, to maintain colour accuracy and avoid systems which produce de-saturated poor colour accuracy images at low f# or, noisy over saturated images at high f#.

References

[1] IEC FDIS 61966-2-1, Multimedia systems and equipment – Colour measurement and management Part2.1: Colour management (Default RGB Colour Space – sRGB)

[2] C. Poynton, (2003), Digital Video and HDTV Algorithms and Interfaces, p252, Morgan Kaufmann Publishers, Elsevier Science USA, ISBN 1-55860-792-7

[3] As [2], p205.

[4] Agranov, G, V. Berezin, R.H. Tsai, 2003, "Crosstalk and microlens study in a color CMOS image sensor", IEEE Trans. Electron. Dev. 50(1),4