Grey Colour Sharpening

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1. Abstract

We propose a colour to greyscale algorithm providing colour separation as well as edge and texture enhancement. An image dependent grey-axis is computed based on the colour distribution in the image. An initial greyscale image is created by a point-wise operation where the grey value is the magnitude of the RGB coordinates re-mapped to the grey axis. The resulting greyscale image is enhanced by applying a novel correction mask. This mask, resembling an unsharp mask, is the sum of the difference between each of the colour components and a blurred version of the greyscale image. The resulting greyscale images are rich in detail without undesirable artifacts.

2. Introduction

The problem of converting a colour image to greyscale is a typical data reduction problem. Thus, as long as the colour information in the original image offers clues to separate objects, to define edges or texture; some information will be lost in the conversion. Based on this definition we can argue that the best colour to greyscale conversion is achieved by preserving the maximum amount of information available in the colour image. In this sense, the solution to any colour to greyscale algorithm has to start by defining the meaning of information.

The traditional, and most commonly employed, approach to colour to greyscale conversion, assumes that the grey value of each pixel in an RGB colour image can be calculated as a weighted sum of the red, green and blue coordinates of that pixel. Such a transformation can be expressed as:

$$Grey = \alpha Red + \beta Green + \gamma Blue \tag{1}$$

where α, β and γ are positive scalars with typical values of: $\alpha = 0.30$, $\beta = 0.59$ and $\gamma = 0.11$. Converting a colour image to greyscale using the weighted sum defined in Equation (1) would normally result in pleasing black and white images but suffers from the problem of adjacent iso-luminance colours, i.e. neighbouring colours with different hues but the same luminance value. Thus the worst case scenario is having a number of hues in an image with the same luminance value. In this case the result of converting the image to greyscale will be a uniform grey.

Prior to introducing our approach, we state that: there is no unique solution to the problem of converting a colour image to greyscale; and an optimised conversion depends on the application considered. As an example, an optimised conversion for a colour image with 10 distinct colours with the same luminance value could be assigning a distinct grey value to each colour. Such a choice would result in adequate separation; and might be acceptable for graphics art. However, the same approach would fail for natural scenes where a the green of a tree or the blue of the sea cannot reasonably be mapped to black or white just to achieve colour separation.

The main reason why the problem of colour to greyscale conversion is interesting is that we have access to the higher dimensional information, i.e. the colour. This information allows us to perform operations on the colour image prior to converting it to black and white [1]. Said differently, we are able to change and enhance the resultant greyscale image using operations which are not possible had we only had a greyscale image. As an example of that we could convert the pixel values of an image to greyscale using the weighted sum defined in Equation (1) and then add a percentage of the pixels' chroma to the result [2].

Due to the wide availably of digital colour images and the need for advanced imsge processing, in recent years, there has been an increase in the development of spatial colour imaging algorithms [3]. Relating to the problem of colour to greyscale, Bala *et al*[4] proposed a solution to the problem of iso-luminance which is based on calculating the edges of the colour image in the chromaticity space and then adding those edges which are due to colour change to the greyscale image.

In this paper, we present an algorithm to create a sharp a greyscale from a colour original. The basic idea is similar to that proposed by Bala *et la* [4] where we argue that the pixel wise conversion results in a loss of high frequency information. However, the intention of the algorithm is to produced sharp greyscale reproductions rather than enhance the separation between iso-luminance colours. Having said that, our results suggest that the new approach results in better separation than that achieved by Bala *et la*

[4].

The algorithm is developed in two steps: first we solve for an image dependent axis to which all the colour are projected. We chose this axis to be the most significant eigenvector of the global covariance matrix of the colour values in the RGB space. This choice, independent of the second step, results an enhanced separation between the different colour regions; especially when the number of colours in the image is small. In the second step of the algorithm, we solve for a high frequency image based on the three colour channels, red, green and blue. For all channels, the high frequency images are calculated using unsharp masking [5]. Different to the traditional approach of calculating an unsharp mask, where the original image, based on each colour channel, is subtracted from a blurred version; we subtract the red, green and blue images from a blurred version of the grey image. This choice was made to locate the high frequency elements which have been lost due to the conversion.

3. Grey Colour Sharpening

3.1. Calculating an Image Dependent Grey-Axis

We start with an $m \times 3$ data matrix, P, where each row, in P, contains the colour information of each pixel in an RGB image $I(x, y, z)$; where x and y are the horizontal and vertical coordinates of the pixel and $z = 1, 2$ or 3 is the red, green or blue channel. Based on the information contained in P we calculate the 3×3 correlation matrix P_c such that:

$$P_c = P^T P \tag{2}$$

Having calculated, P_c we solve for the eigen decomposition:

$$P_c = UDU^T \tag{3}$$

where the column in U are the eigenvectors of P_c and D is a diagonal matrix whose diagonal elements are the eigenvalues of P_c arranged in order of significance and T is the matrix transpose operator. Further, the eigenvectors in U are normalised by their length.

Different matrix eigen-system algorithms have different conventions on the arrangement of the eigenvectors; where for some the first column in U is the most significant, while others place the most significant vector as the last. In this paper, we take the first column, u_1 in U as the most significant dimension.

To calculate our image dependent greyscale we start by defining a 3×3 projection matrix, P_u onto u_1:

$$P_u = u_1 u_1^T \tag{4}$$

Having defined the projection operator, P_u onto the most significant eigenvector, u_1, we calculated the grey value of each colour pixel as the norm of the projection element of the three dimensional colour vector p onto u_i, i.e.:

$$g = \|PP_u\|^2 \tag{5}$$

where g is an $m \times 1$ vector whose elements are the image dependent grey-values of I. When the elements of g are rearranged according the their spacial coordinates, x and y we get the greyscale image $G(x, y)$.

3.2. Calculating the High Frequency Masks

Having calculated the greyscale image $G(x, y)$, we proceed to the next step of our proposed algorithm where we calculate a high frequency mask for each colour channel. In our implementation this mask is calculated based on unsharp masking where we start by blurring $G(x, y)$ using a Gaussian filter of the form:

$$Gu(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{6}$$

where r is the blur radius $\left(r^2 = x^2 + y^2\right)$, and σ is the standard deviation of the Gaussian distribution. This formula produces a surface whose contours are concentric circles with a Gaussian distribution from the centre point. An example of such a filter where: $x = y = 50$ and $\sigma = 5$ is shown in Figure (1). The blurred image is then calculated

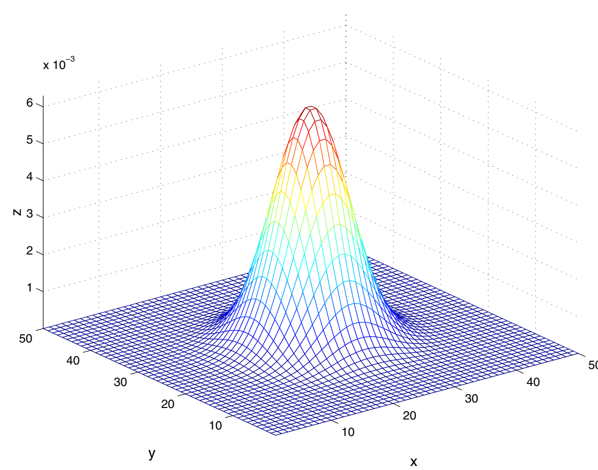

Figure 1: A two dimensional Gaussian filter with: $x = y = 50$ and $\sigma = 5$

by convolving $G(x, y)$ with $Gu(u, v)$, i.e.:

$$Gb(x, y) = Gu(x, y) \otimes G(x, y) \tag{7}$$

where $\otimes$ is the convolution operator. The kernel size of the Gaussian filter defined by u and v as well as the standard deviation σ controls the level of blurring, where the larger the kernel and standard deviation the more blurred the image is.

Based on the blurred greyscale image $Gb(x,y)$ we calculate the high frequency masks for the red, green and blue channels as the difference between those and $Gb(x,y)$:

$$H_r(x,y) = I(x,y,1) - Gb(x,y) \quad (8)$$
$$H_g(x,y) = I(x,y,2) - Gb(x,y) \quad (9)$$
$$H_b(x,y) = I(x,y,3) - Gb(x,y) \quad (10)$$

where $H_r(x,y)$, $H_g(x,y)$ and $H_b(x,y)$ are the high frequency masks of the red, green and blue channels respectively.

To sharpen our black and white reproduction we add an averaged sum of the high frequency masks to the greyscale image, i.e.:

$$G_s(x,y) = G(x,y) + \omega\left(H_r(x,y) + H_g(x,y) + H_b(x,y)\right) \quad (11)$$

where ω is a positive scalar. Finally, we clip values of the sharpened image to be between zero and one.

$$G_s(x,y) = \left\{ \begin{array}{lll} 1 & if & G_s(x,y) \geq 1 \quad and \\ 0 & if & G_s(x,y) \leq 0 \end{array} \right\} \quad (12)$$

4. Experiments and Results

To test our algorithm we made use of a synthetic image consisting of a number of colour patches which had different hues but similar luminance values. It is understood that converting such an image to greyscale using a weighted sum of the RGB values would result in a uniform grey surface. However, when the most significant eigenvector was used as the greyscale axis, a noticeable separation between the patches was achieved. This is true because the eigenvector is aligned in a direction which is optimised to maximise the variance between the points in the *rgb* space. The result of the conversion is shown in Figure (2). Further, to test the performance on pictorial images and examine the influence of adding the high frequency components from the red, green and blue channels, we used two digital images one of different coloured caps and the other of a garden scene. As described in the previous sections, we first converted the images to greyscale using the colour distribution dependent axis and the subtracted each colour channel from a blurred version of the grey image. For the results shown in this section we blurred the greyscale image using a Gaussian filter with $x = y = 15$ pixels and a standard deviation $\sigma = 1$.

In the colour image, the caps shown in Figure (3) are, from left to right: yellow, orange, green, pink and blue. Figure (3), shows the weighted sum approach to converting

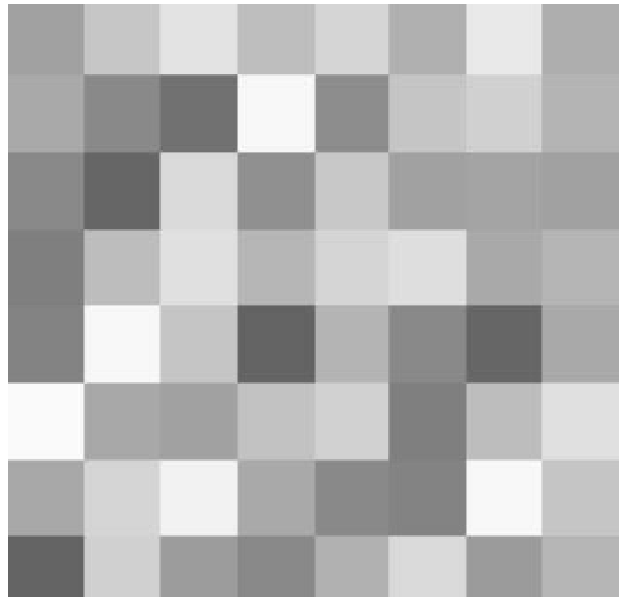

Figure 2: *A grey scale image which is the result of converting a number of colour patches with the same luminance and different hues. The greyscale axis was the most significant eigenvector of the data's correlation matrix.*

the image into greyscale. As we notice, the separation between the caps is greatly hampered in the greyscale representation. In Figure (4), the greyscale conversion is shown with the added high frequency masks calculated based on the algorithm presented in this paper. Further, the combined high frequency mask is shown in Figure (**??**). As seen in Figure (4), an enhanced separation between the caps is achieved as well as a noticeably sharpened image. To examine the difference between sharpening an image using our approach and that achieved by applying an unsharp mask to the resultant greyscale image, we sharpened the resultant greyscale image using the same Gaussian filter as the one used in the experiment. Our results show that sharpening the image using the information form the colour channels is guaranteed to result in a visually sharper image unless the colours of the original have little saturation in which case no noticeable difference is achieved. Finally, we tested the effect of sharpening the colour image prior to converting it to greyscale and again similar trends where the proposed algorithm resulted in sharper greyscale reproduction where observed.

In Figures (6), (7) and (8) we show the results for converting the garden image with the weighted sum, the most significant eigenvector and the high frequency map respectively. Again, we note that the proposed approach results in richer details and better separation between the colour regions.

Figure 3: *The weighted sum approach to converting the image into greyscale.*

Figure 4: *The most significant eigenvector approach to converting the image into greyscale with the added high frequency mask.*

5. Discussion and Conclusions

In this paper, we presented a method to convert a colour image to greyscale. The method incorporates two steps: in the first we solved for a grey-axis which is dependent on the image colour distribution and in the second we added the high frequency components. The resultant images were rich in details, sharp and provided good separation between iso-luminance colour regions.

6. biography

Ali Alsam is Associate Professor at the Norwegian Colour Laboratory in Gjøvik University College, Norway. He received a PhD degree in computational colour science from the University of East Anglia. His research interest include: colour science, computational colour, image processing, metamerism, vision, inverse problems, optimisation and convex analysis.

Øyvind Kolås is a lecturer at Gjøvik University College (GUC). He received a BSc in digital media technology from GUC in 2005, where he started working as a teaching assistant in 2002. For more than 10 years he has been contributing to open source, and is an active contributor to GIMP. Research interests include: New media art, image processing, computer graphics and human computer interaction.

Figure 5: *The high frequency mask for the caps image.*

Figure 6: *The weighted sum approach to converting the image into greyscale.*

References

[1] K. Rasche, R. Geist, and J. Westall. Re-coloring images for gamuts of lower dimension. *Computer Graphics Forum 24 Proc. EUROGRAPHICS*, page 423432, 2005.

Figure 7: *The most significant eigenvector approach to converting the image into greyscale with the added high frequency mask.*

Figure 8: *The high frequency mask for the garden image.*

[2] M. D. Fairchild and E. Pirrotta. Predicting the lightness of chromatic object colors using cielab. *Color Research and Appl. 16*, pages 385–393, 1991.

[3] Raja Bala. Challenges in color reproduction: Towards higher dimensions. *In Color Imaging X: Processing, Hardcopy, and Applications, San Jose, CA*, page 162169, 2005.

[4] Raja Bala and Reiner Eschbach. Spatial color-to-grayscale transform preserving chrominance edge information. *Color Imaging Conference*, pages 82–86, 2004.

[5] R. Gonzalez and R. Woods. *Digital Image Processing*. Prentice Hall, 2002.