EVALUATION OF UNIFORM COLOUR SPACES FOR IMAGE PROCESSING

M. Mahy, L. Van Eycken, P. Wambacq, A. Oosterlinck*

Keywords : Color, Images, Processing, Vision.

Abstract : Since the adoption of CIELAB and CIELUV in 1976, several other uniform spaces have been developed. We evaluated most of them by making use of visual data and found that they could be divided into two different classes, i.e. spaces to predict small colour distances and spaces to calculate larger differences. We indicated the main difference between both classes and constructed a simple Colour Difference Formula (CDF) for small colour differences.

In contrast to grey image processing techniques, almost no attention has been paid to colour image processing. Therefore we determined some basic rules to adapt grey image processing procedures for colour images is such a way that the images are handled in agreement with the human visual system. This was mainly done by making use of tristimulus spaces and uniform colour models. However, as opposed to what was expected, it is almost impossible to detect differences between most uniform spaces even if they differed significantly according to visual data. We indicated that this was mainly due to non uniformities of the colour spaces, non modelled visual effects and quantization errors.

Based on this evaluation we recommend the use of different spaces for the determination of small and larger colour differences. The chosen spaces should be mathematical stable and simple. A good candidate for small resp. larger colour differences is CDF, resp. CIELAB.

Uniform colour spaces

Tristimulus spaces [Wyszecki,1982] are mainly used to specify colours. They indicate if two colours match, but they cannot predict visual differences if no match is obtained. To calculate psychometric differences uniform

*ESAT-MI2, Katholieke Universiteit Leuven, Belgium

spaces should be used. However, these scales are difficult to model. As a result, quite a lot of other uniform colour spaces have been constructed since the adoption of CIELAB and CIELUV by the CIE in 1976 [CIE,1986].

Most uniform colour spaces are zone models [Wyszecki,1982]. They consist of different zones, each representing a particular processing unit of the Human Visual System (HVS). All the evaluated models are built up of two zones. The first zone models the colour values generated by the three different kind of cones, i.e. the tristimulus values. In the second zone these values are transformed non linearly before they are combined into one achromatic channel and two chromatic channels, i.e. a red-green and yellow-blue signal. We studied most zone models developed after the standardization of CIELAB and CIELUV. These are Labhnu [Richter,1980], the space of Frei [Frei,1977], ATD [Guth,1980], the space of Seim and Valberg [Seim,1986], OSA 78 [MacAdam,1978], OSA 90 [MacAdam,1990], the model of Nayatani [Nayatani,1987] and the model of Hunt [Hunt,1991]. Also Hunter Lab [Wyszecki,1982], a space developed before 1976, is studied because it is still often used in industry [Kuehni,1990].

Apart from these zone models also some colour distance formulas have been constructed to predict colour differences of about a Just Noticeable Difference (JND). The studied colour distance formulas are FMC1, FMC2 [Chickering,1971], CMC(0.7:1.0) [CMC,1984] and BFD(0.7:0.9) [Luo,1987a, Luo,1987b]. These distance functions can only be used to determine small colour differences because most are not symmetric or do not comply with the triangle inequality. In the following paragraphs we will also refer to these distance measures as "uniform colour spaces". To evaluate these spaces, it was necessary to adapt some of them. All the modifications and parameters can be found in [Mahy,1994a, Mahy,1994b].

Uniformity of colour spaces

There are quite a lot of uniform colour spaces which are optimized to predict certain experimental data, but there is no guarantee that such a space is also able to approximate other experimental data. To know which uniform colour space should be used for a specific application, we evaluated them by comparing their uniformity for small and larger colour differences. Therefore we made use of two kinds of experimental data, i.e. colour discrimination data to investigate the uniformity for colour differences of about a JND and appearance systems for larger differences [Wyszecki,1982].

Based on this study we could divide uniform colour spaces into two different classes, a class to calculate small colour differences and another one for larger distances [Mahy,1994a]. The distance functions are typical examples of the first class whereas most other spaces such as CIELAB, CIELUV and Labhnu belong to the second class.

The main difference between both classes is reflected in a different scale factor between the distance unit along the lightness component and the unit in the chroma plane. These factors can be found in column 'Aver. W_l' of table III in [Mahy,1994a]. CIELAB for example is quite uniform for larger distances (about 10 JND), but to make it uniform for small distances the unit of the lightness axes should be enlarged with a factor 2.4.

Visual determination of JND's

To check if uniform colour spaces could be made more uniform for small colour differences by rescaling the lightness axis compared to the chroma unit, we determined the size of a JND along the three main axes of the uniform colour spaces. Therefore images consisting of consecutive rectangles, of which the colour only differed with a given step, were evaluated. The colour distance for which pseudo contours just become visible corresponds to the visual determined JND. This was done for colours along the lightness axis and the opponent colour axes. To avoid problems with quantization errors, the minimum lightness of all colours was 50 CIELAB units [Mahy,1994b].

The visually determined JND values along the different axes are given in table 1. Column 'lightness' corresponds to the JND's along the lightness axis, whereas the columns 'red-green' and 'yellow-blue' contain the values of the chroma components. For the ATD space, the values are 100 times enlarged. In case of the distance functions, the JND's are determined along the main axes of CIELAB.

For most spaces the lightness axis is quite uniform, but the JND's along the chroma axes are chroma dependent. The chroma axes for all the colour models except CMC(0.7:1.0) and BFD(0.7:0.9) are most sensitive at the origin (grey value). For the distance functions CMC(0.7:1.0) and BFD(0.7:0.9) however, the chroma axes are most sensitive for the most saturated colours. In table 1 only the minimum JND values are given.

If the ratio of the JND in the chroma plane to the JND along the lightness axis is compared to the scale factors of table III in [Mahy,1994a] (column 'Aver. W_l'), we see that they are much too large. A profound investigation indicated that this was due to the crispening effect [Mahy,1994b], a visual effect by which small colour differences are increased [Wyszecki,1982]. This effect only occurs for the luminance channel which multiplies small differences with a factor of $\pm$ 3.5.

Both the visual evaluations of JND's and discrimination data indicated that most spaces can be made more uniform by making use of a chroma dependent scale factor. In this way, CIELAB becomes about as uniform as the best distance function. This adapted distance function, the Colour Dif-

Colour space	lightness	red-green	yellow-blue
Hunlab	0.4 ± 0.1	1.50 ± 0.25	1.50 ± 0.25
CIELAB	0.4 ± 0.1	1.75 ± 0.25	1.50 ± 0.25
CIELUV	0.4 ± 0.1	2.75 ± 0.25	2.75 ± 0.25
ATD (X 100)	1.4 ± 0.4	2.0 ± 0.5	2.5 ± 0.5
Labhnu	0.4 ± 0.1	2.5 ± 0.25	2.0 ± 0.25
Frei	0.3 ± 0.1	0.6 ± 0.1	0.5 ± 0.1
SVF	0.12 ± 0.04	0.40 ± 0.05	0.30 ± 0.05
Hunt	0.4 ± 0.1	1.25 ± 0.25	1.25 ± 0.25
Nayatani	0.4 ± 0.1	0.6 ± 0.1	0.5 ± 0.1
OSA 74	0.12 ± 0.02	0.30 ± 0.05	0.25 ± 0.05
OSA 90	0.12 ± 0.02	0.30 ± 0.05	0.25 ± 0.05
FMC1	1.4 ± 0.2	3.0 ± 0.5	2.5 ± 0.5
FMC2	1.0 ± 0.2	4.0 ± 0.5	3.5 ± 0.5
CMC(0.7:1.0)	0.4 ± 0.1	1.50 ± 0.25	1.25 ± 0.25
BFD(0.7:0.9)	0.4 ± 0.1	1.75 ± 0.25	1.75 ± 0.25

Table 1: Visually determined JND values for the lightness component and the chroma axes (red-green and yellow-blue) for the different colour spaces. The values are given in the units of the corresponding colour space.

ference Formula (CDF) [Mahy,1994a], between two colours with CIELAB coordinates (L_1^*, a_1^*, b_1^*) and $(L_2^*, a_2^*, b_2^*)$is given by

$$\Delta E = \sqrt{(L_1 - L_2)^2 + (a_1 - a_2)^2 + (b_1 - b_2)^2} \tag{1}$$

with

$$\begin{aligned} L_i &= \frac{L_i^*}{0,7 - 0,003 \times C} \\ a_i &= \frac{a_i^*}{1,0 + 0,004 \times C} \\ b_i &= \frac{b_i^*}{1,0 + 0,004 \times C} \end{aligned}$$

$i \in \{1,2\}$
C the average CIELAB chroma value of both colours

Quantization errors

Colours are normally represented in tristimulus spaces. If 8 bits are used per component, the error on tristimulus values is $\pm$ 1/2 on a scale of 255. However, due to the non linear transformation to uniform colour models or the colour distance function the quantization error can increase significantly. We determined these errors for the transformation from CIERGB with 8 bits per component to different uniform colour models [Mahy,1994b]. The results are given in table 2. In the column 'maxima' the maximum quantization errors are given for the components C_1, C_2 and C_3, and in column 'CIERGB' the CIERGB values are given for which the quantization error reaches the maximum. In column 'averages' the average quantization error over all the colours are given for the three components. The first component C_1 is the achromatic channel and the second C_2 and third C_3 component are the red-green and yellow-blue channel respectively. In case of the distance functions FMC1 and FMC2, resp. CMC(0.7:1.0) and BFD(0.7:0.9) these are the components of XYZ resp. CIELAB. The units are each time the units of the corresponding colour space. Only for the ATD space the values are 100 times enlarged.

If the quantization errors in table 2 are compared with table 1 (the visually determined JND's), the quantization errors are quite large for most spaces. For some spaces there are singularities. For example, ATD and the space of Frei are singular for black and the OSA spaces are singular for the OSA variable $Y_{10} = 0.287$. As a result the calculations for table 2 started from the CIERGB value (1,1,1) instead of (0,0,0) and no data is given for the OSA spaces. Other spaces such as Seim and Valberg, FMC1, FMC2 and the model of Nayatani are highly unstable. These effects will drastically influence the usability of these colour spaces to predict colour differences. As a result we will choose a space for which the quantization effects are less apparent such as CIELAB, CIELUV and the model of Hunt. Nevertheless 8 bits per component are not enough to quantize colours uniformly in a tristimulus space.

If the average quantization errors are compared with the visually determined JND's, the quantization errors are always smaller. This indicates that the quantization errors are only too large in a small part of the colour spaces. Calculations indicated that the largest errors occur for dark colours, and decrease if the colours become lighter. As a result, the quantization errors can be reduced considerably if the colour values are quantized after a non linear transformation. An interesting class of non linear transformations is given by

$$s' = s_n \left(\frac{s}{s_n}\right)^{1/i} \tag{2}$$

	maxima				averages		
	C_1	C_2	C_3	CIERGB	C_1	C_2	C_3
Hunlab	1.6	19.6	40.5	(1,1,175)	0.2	0.6	0.6
CIELAB	1.8	7.7	6.0	(1,1, 1)	0.2	0.6	0.6
CIELUV	1.8	4.6	8.8	(1,1,118)	0.2	0.6	0.6
ATD (X100)	0.5	0.5	0.5	(1,1, 1)	0.5	0.4	0.6
Labhnu	1.8	18.8	12.2	(1,1, 1)	0.2	0.9	0.6
Frei	11.9	20.5	14.1	(1,1, 1)	0.1	0.2	0.2
SVF	9.9	99.6	43.8	(1,1, 10)	0.1	0.2	0.1
Hunt	0.9	3.9	2.8	(1,1, 1)	0.2	0.8	0.6
Nayatani	2.6	12.6	8.0	(1,1, 1)	0.2	0.5	0.4
FMC1	110.2	102.0	31.2	(1,1, 1)	1.0	1.1	0.3
FMC2	63.4	53.5	18.0	(1,1, 1)	1.5	1.4	0.5
CMC(0.7:1.0)	5.0	12.0	9.4	(1,1, 1)	0.2	0.3	0.3
BFD(0.7:0.9)	3.5	16.3	12.7	(1,1, 1)	0.2	0.4	0.4

Table 2: Maximum and average quantization errors for the different components of the colour spaces if the colours are given in CIERGB with 8 bits per component.

with s a tristimulus value and s_n the maximum value of s. Such a function is used

- in the transformation from XYZ to CIELAB, with i equal to 1 or 3, depending on the value of $\frac{s}{s_n}$
- if the colour values are transformed to be displayed. This transformation, that is called the gamma correction, gives the relation between the voltage sent to the display and the light output [Hunt,1988]. Typically γ is about 2.2.

The quantization errors for gamma corrected CIERGB values are given in table 3. We immediately see that the maximum quantization errors are reduced considerably for most spaces. For CIELAB, CIELUV and ATD for example the maximum errors are even lower than the visually determined JND's. As a result 8 bits per component for gamma corrected RGB values are sufficient to encode colours uniformly.

Correlation between colour differences

To compare colour spaces with each other, linear regression analysis was applied to colour differences. This relation is given by

	maxima				averages		
	C_1	C_2	C_3	CIERGB	C_1	C_2	C_3
Hunlab	0.2	2.9	5.9	(23, 26,255)	0.2	0.7	0.8
CIELAB	0.3	1.4	1.0	(27, 30, 47)	0.2	0.7	0.6
CIELUV	0.3	1.4	1.2	(194, 86, 96)	0.2	0.8	0.7
ATD	1.1	1.0	1.1	(1, 1, 1)	1.3	1.2	2.2
Labhnu	0.3	4.9	2.9	(1, 1, 2)	0.2	1.0	0.7
Frei	3.6	6.2	4.0	(8, 7, 9)	0.2	0.3	0.3
SVF	4.0	43.1	31.3	(31, 4,132)	0.4	0.2	0.1
Hunt	0.3	1.4	1.1	(204,209,213)	0.2	0.8	0.6
Nayatani	0.3	1.7	1.2	(33, 33, 31)	0.2	0.5	0.4
FMC1	261.2	225.8	122.1	(1, 1, 2)	1.7	1.5	0.6
FMC2	145.2	114.3	67.9	(1, 1, 2)	1.9	1.6	0.6
CMC(0.7:1.0)	0.8	2.1	1.6	(30, 30, 30)	0.3	0.3	0.3
BFD(0.7:0.9)	0.5	2.7	2.1	(30, 30, 30)	0.3	0.4	0.4

Table 3: Maximum and average quantization errors for the different components of the colour spaces if the colours are gamma corrected CIERGB values with 8 bits per component.

$$\Delta E_1 = a\Delta E_2 \tag{3}$$

with ΔE_1 the distance according to the first space,
ΔE_2 the distance according to the second space,
a the inclination of the linear regression line.

The inclination a is obtained by minimizing the MSE which is given by

$$\mathrm{MSE} = \sum_{i=1}^{n} \frac{\Delta E_{1i} - a\Delta E_{2i}}{1+a^2} \tag{4}$$

with i the summation over all colour pairs and n the number of colours.

As indicated in section 'Uniformity of colour spaces', different colour spaces should be used to determine small and larger colour differences. Therefore we determined the linear regression line for small and larger colour distances. For larger distances differences between surface colours, corresponding to illuminant E, were calculated which lie on a grid in CIELAB with a sample distance of 6 CIELAB units. To avoid effects due to quantization errors, the lightness of all colours is larger than 10. For small colour differences all colour differences between colours on a grid of 5 X 5 X 5

Colour spaces	cor.	a	Colour spaces	cor.	a
Hunlab-CIELAB	0.60	0.88	ATD-Frei	0.50	45.42
Hunlab-CIELUV	0.70	1.36	ATD-SVF	0.60	15.94
Hunlab-ATD	0.47	0.01	ATD-Hunt	0.47	95.00
Hunlab-Labhnu	0.68	1.18	ATD-Nayat.	0.47	77.61
Hunlab-Frei	0.19	0.44	ATD-OSA74	0.53	15.02
Hunlab-SVF	0.87	0.20	ATD-OSA90	0.50	16.34
Hunlab-Hunt	0.86	1.22	ATD-FMC1	0.67	193.03
Hunlab-Nayat.	0.80	0.92	ATD-FMC2	0.52	162.18
Hunlab-OSA74	0.87	0.18	ATD-CMC	0.77	39.10
Hunlab-OSA90	0.83	0.19	ATD-BFD	0.67	47.12
Hunlab-FMC1	0.70	2.76	Labhnu-Frei	0.42	0.41
Hunlab-FMC2	0.77	2.15	Labhnu-SVF	0.74	0.17
Hunlab-CMC	0.44	0.49	Labhnu-Hunt	0.83	1.04
Hunlab-BFD	0.35	0.58	Labhnu-Nayat.	0.52	0.76
CIELAB-CIELUV	0.86	1.49	Labhnu-OSA74	0.71	0.15
CIELAB-ATD	0.65	0.02	Labhnu-OSA90	0.67	0.16
CIELAB-Labhnu	0.96	1.29	Labhnu-FMC1	0.55	2.46
CIELAB-Frei	0.46	0.55	Labhnu-FMC2	0.68	1.86
CIELAB-SVF	0.69	0.22	Labhnu-CMC	0.80	0.46
CIELAB-Hunt	0.77	1.37	Labhnu-BFD	0.74	0.53
CIELAB-Nayat.	0.45	1.04	Frei-SVF	0.37	0.31
CIELAB-OSA74	0.63	0.19	Frei-Hunt	0.14	2.83
CIELAB-OSA90	0.59	0.20	Frei-Nayat.	0.32	2.03
CIELAB-FMC1	0.46	3.34	Frei-OSA74	0.27	0.27
CIELAB-FMC2	0.58	2.49	Frei-OSA90	0.28	0.29
CIELAB-CMC	0.79	0.60	Frei-FMC1	0.43	5.95
CIELAB-BFD	0.72	0.70	Frei-FMC2	0.25	5.04
CIELUV-ATD	0.64	0.01	Frei-CMC	0.54	0.99
CIELUV-Labhnu	0.92	0.87	Frei-BFD	0.40	1.21
CIELUV-Frei	0.28	0.34	SVF-Hunt	0.80	6.02
CIELUV-SVF	0.69	0.15	SVF-Nayat.	0.83	4.70
CIELUV-Hunt	0.85	0.91	SVF-OSA74	0.85	0.91
CIELUV-Nayat.	0.43	0.64	SVF-OSA90	0.84	0.97
CIELUV-OSA74	0.74	0.13	SVF-FMC1	0.81	12.98
CIELUV-OSA90	0.70	0.14	SVF-FMC2	0.82	10.27
CIELUV-FMC1	0.43	2.18	SVF-CMC	0.58	2.81
CIELUV-FMC2	0.61	1.62	SVF-BFD	0.47	3.40
CIELUV-CMC	0.69	0.39	Hunt-Nayat.	0.63	0.73
CIELUV-BFD	0.64	0.46	Hunt-OSA74	0.83	0.15
ATD-Labhnu	0.71	84.51	Hunt-OSA90	0.79	0.16

Colour spaces	cor.	a	Colour spaces	cor.	a
Hunt-FMC2	0.72	1.77	OSA74-CMC	0.50	3.18
Hunt-FMC1	0.51	2.37	OSA74-BFD	0.39	3.88
Hunt-CMC	0.52	0.42	OSA90-FMC1	0.67	14.14
Hunt-BFD	0.48	0.49	OSA90-FMC2	0.66	11.23
Nayat.-OSA74	0.82	0.19	OSA90-CMC	0.48	3.01
Nayat.-OSA90	0.77	0.20	OSA90-BFD	0.35	3.71
Nayat.-FMC1	0.88	2.81	FMC1-FMC2	0.85	0.81
Nayat.-FMC2	0.81	2.34	FMC1-CMC	0.58	0.18
Nayat.-CMC	0.43	0.52	FMC1-BFD	0.47	0.21
Nayat.-BFD	0.32	0.62	FMC2-CMC	0.55	0.24
OSA74-OSA90	0.98	1.07	FMC2-BFD	0.54	0.28
OSA74-FMC1	0.70	14.83	CMC-BFD	0.89	1.26
OSA74-FMC2	0.73	11.66			

Table 4: Correlations between colour spaces for small colour differences.

points were taken into account with a sample distance of 0.5 CIELAB units along the L^*-axis and 1 CIELAB unit in the chroma plane. The central colour of the grid was shifted in CIELAB in the gamut of surface colours corresponding to illuminant E with 5 CIELAB units along the lightness axis and 16 units in the chroma plane. To determine small colour differences, the unit of the lightness axis was corrected properly compared to the unit in the chroma plane. For the calculations 4.731.477 colour pairs were calculated for larger differences and 4.072.234 pairs for small differences.

The correlation (see column 'cor.') and inclination (see column 'a') for small colour differences are given in table 4. Results for larger colour differences (for the results see [Mahy,1994b]) are quite similar. Distances determined in the first resp. second space of column 'Colour spaces' correspond to the x resp. y axis.

Based on the correlation, it is possible to check which colour spaces give rise to similar colour differences apart from a global scale factor. Image processing techniques which are based on similar spaces will result in identical results. From tables 4 we can conclude that

- CIELAB, CIELUV and Labhnu are quite similar,
- OSA 74 and OSA 90 are highly correlated
- the space of Frei and ATD do not correlate with other spaces,
- FMC1 and FMC2 give rise to similar differences,

- CMC(0.7:1.0) and BFD(0.7:0.9) do not differ significantly

The inclination a on the other hand gives the relation between the units of the spaces. For example, one CIELAB unit corresponds to about 1.5 CIELUV units.

Colour image processing

In this section grey image processing operations will be adapted to manipulate colour images in agreement with the HVS. In general this adaptation is not difficult, however it doesn't often happen in practise.

Overview of colour image processing operations

In literature, different colour spaces are used to manipulate colour images. For some applications such as edge detection, segmentation and enhancement these are tristimulus or gamma corrected tristimulus values. As a result a visual evaluation of the processed images has no sense.

To sharpen edges, Faugeras proposes to process only the luminance component [Faugeras,1979]. Because the Contrast Sensitivity Function (CSF) of the achromatic channel is significantly more sensitive than the CSF of the chromatic channels, pure colour edges are less important than luminance edges. Also for edge detection several researchers indicate that luminance edges are more important than colour edges. As a result colour spaces are used with a luminance-like component and two chromatic components. These chromatic components are not always well chosen. Nevatia for example took rg-chromaticity coordinates [Nevatia,1977], but chromaticity coordinates are singular at black [Kender,1976] and they do not correspond to visual colour differences. Robinson has evaluated several colour spaces for visual edge detection [Robinson,1977]. A colour edge was defined as the maximum of the gradient of the three components. He found that good results are obtained with colour spaces with a luminance-like component.

Otha studied colour spaces for image segmentation [Otha,1980]. Based on a histogram the images were divided in two regions by choosing a proper threshold. On each image part this technique was repeated until no further segmentation was possible. Otha did not detect significant differences by making use of several colour spaces, so he proposed to use the simplest one. Tominaga on the other hand segmented the image based on its principal components [Tominaga,1992]. CIELAB was used, but he reported that similar results are obtained with other colour spaces.

The use of colour spaces

In most cases, image processing techniques can be split up into local averaging operations and colour differences. According to the characteristics of the HVS these operations should be performed in different spaces [Mahy,1990].

- A local averaging has to be performed in a tristimulus space. The choice of the tristimulus space is not important because they are all related to each other by a linear transformation.
- Colour differences on the other hand should be determined in a uniform space. The choice depends on the size of the colour differences that are to be predicted. For differences of about a JND, a colour difference formula could be used (e.g. CDF), whereas for larger distances CIELAB should be a good choice.

Quantization errors

By using uniform colour spaces, often artifacts are introduced due to quantization errors. These errors are a result of a bad colour quantization, mainly for dark colours. To avoid this effect, colours can be transformed out of the dark region as follows [Mahy,1991]

$$\begin{pmatrix} R' - R_{ill} \\ G' - G_{ill} \\ B' - B_{ill} \end{pmatrix} = \begin{pmatrix} 1-k & 0 & 0 \\ 0 & 1-k & 0 \\ 0 & 0 & 1-k \end{pmatrix} \begin{pmatrix} R - R_{ill} \\ G - G_{ill} \\ B - B_{ill} \end{pmatrix} \tag{5}$$

with (R, G, B) the original RGB values
(R', G', B') the rescaled RGB values
$(R_{ill}, G_{ill}, B_{ill})$ the RGB values of the illuminant
k a scale factor with $0 \leq k \leq 1$

In this way grey values are transformed to grey values, the black point is shifted to $(kR_{ill}, kG_{ill}, kB_{ill})$ and the white point remains the same. This transformation preserves the hue, but decreases chroma and increases luminance. This is no problem because we are mainly interested in colour differences and not in colour appearance. On the other hand darker colours exhibit the largest errors, but the accuracy of these colours is the worst.

In contrast to grey images, colour images consist of three components. How to process these components correctly depends on the operation.

In the HVS there are two main zones of colour coding, i.e. a RGB and an opponent colour coding. These colour channels have several features. If we want to process a particular visual characteristic that is different for the three channels/components, the images should be processed component per component in a proper colour space. If however the processed characteristic is the same for the three channels, the components should be processed together.

Convolutions : An example of an operation for which the processed features are the same for the three components are convolutions. Because convolutions can be seen as an additive mixture of colours, they should be performed in an additive space. The convolution mask per pixel should be the same for the three components, so the operation can be performed component per component. If the masks were different for the three components, the processing would not be invariant for the choice of the tristimulus space. Therefore we make a distinction between the following types of convolution masks.

- If the mask is independent of the image content, the convolution can be performed component per component in any tristimulus space. Typical examples are noise reduction operations by means of averaging, rotations and image resizings [Mastin,1985, Pratt,1991].
- If the convolution mask is image dependent such as the gradient inverse filter [Wang,1981], the sigma filter [Mastin,1985] and the edge preserving filter [Nagao,1979], the three components should be taken together to determine the mask values. If these operations were performed component per component, mainly pixels along edges will have strong deviating colours. In the edge preserving filter this is the result of averaging the colours at one side of the edge for one component whereas the new value for another component is the average of the colours at the other edge side. If the colours at both sides of the edge are quite different the new colour will in general deviate significantly.

Edge detection : Colour edge detection is one of the operations which often poses problems [Delcroix,1988, Nevatia,1977, Pratt,1991, Robinson,1977, Shiozaki,1986, Tominaga,1987, Trahanias,1993]. If we assume that edges should be characterized by their size and direction, the gradient is a good candidate. The only problem we have is to generalize the concept of the gradient for grey images.

Mathematically, colour images can be written as

$$\begin{aligned}\mathcal{F}:\mathbb{R}^2\to\mathbb{R}^5:(x_1,x_2) &\mapsto (x_1,x_2,C_1(x_1,x_2),C_2(x_1,x_2),C_3(x_1,x_2))\\ &\mapsto (x_1,x_2,\overline{p}(x_1,x_2)) \qquad (6)\end{aligned}$$

with (x_1,x_2) the coordinates of the pixels in the image
$\overline{p}(x_1,x_2)=(C_1(x_1,x_2),C_2(x_1,x_2),C_3(x_1,x_2))$
$(C_1(x_1,x_2),C_2(x_1,x_2),C_3(x_1,x_2))$ three colour components

An infinitesimal change of $\mathcal{F}$ is given by

$$d\mathcal{F} = \frac{\partial\mathcal{F}}{\partial x_1}\partial x_1+\frac{\partial\mathcal{F}}{\partial x_2}\partial x_2 \qquad (7)$$

with

$$\frac{\partial\mathcal{F}}{\partial x_1} = (1,0,\frac{\partial C_1(x_1,x_2)}{\partial x_1},\frac{\partial C_2(x_1,x_2)}{\partial x_1},\frac{\partial C_3(x_1,x_2)}{\partial x_1}) \qquad (8)$$

$$\frac{\partial\mathcal{F}}{\partial x_2} = (0,1,\frac{\partial C_1(x_1,x_2)}{\partial x_2},\frac{\partial C_2(x_1,x_2)}{\partial x_2},\frac{\partial C_3(x_1,x_2)}{\partial x_2}) \qquad (9)$$

If $\mathbb{R}^5$ is Euclidean, the length of vector $d\mathcal{F}$ can be written as

$$d\mathcal{F}.d\mathcal{F} = \begin{pmatrix} dx_1 & dx_2\end{pmatrix}\begin{pmatrix} f_{11} & f_{12}\\ f_{21} & f_{22}\end{pmatrix}\begin{pmatrix} dx_1\\ dx_2\end{pmatrix} \qquad (10)$$

with

$$f_{ij} = \frac{\partial\mathcal{F}}{\partial x_i}.\frac{\partial\mathcal{F}}{\partial x_j} \qquad (11)$$

If $(dx_1,dx_2)=dr(\cos\theta,\sin\theta)$, then the direction of the gradient corresponds to the angle θ for which L^2 is maximum with

$$L^2 = \begin{pmatrix}\cos\theta & \sin\theta\end{pmatrix}\begin{pmatrix} g_{11} & g_{12}\\ g_{21} & g_{22}\end{pmatrix}\begin{pmatrix}\cos\theta\\ \sin\theta\end{pmatrix} \qquad (12)$$

and

$$g_{ij} = \frac{\partial\overline{p}}{\partial x_i}.\frac{\partial\overline{p}}{\partial x_j} \qquad (13)$$

L^2 is extreme if

$$\theta = \frac{1}{2}\arctan\left(\frac{2g_{12}}{g_{11}-g_{22}}\right) \tag{14}$$

If θ is a solution for this equation, then this also true for $\theta \pm \pi$. One solution corresponds to the minimum for L^2, the other with the maximum.

The gradient is well defined because by means of a rotation in $\mathbb{R}^2$ L can be made maximal for a change along a new x_1'-axis. So

$$L = \sqrt{g_{11}'} = \sqrt{\left(\frac{\partial C_1(x_1,x_2)}{\partial x_1'}\right)^2 + \left(\frac{\partial C_2(x_1,x_2)}{\partial x_1'}\right)^2 + \left(\frac{\partial C_3(x_1,x_2)}{\partial x_1'}\right)^2}$$

If $(C_1(x_1,x_2), C_2(x_1,x_2), C_3(x_1,x_2))$ are the components of a Euclidean uniform space, L corresponds to the colour difference between the colours at both sides of the edge. So the three components should be processed together for edge detection. It is also easy to show that this definition is in agreement with the classical gradient for grey images.

Unsharp masking : For some operations it is possible to process only one component. If the characteristic to be adapted is only present in one component, only this component has to be manipulated.

Because the CSF of the luminance channel is significantly more sensitive than the opponent colour channels and most edges are at least partially due to luminance differences [De Valois,1988], unsharp masking on the luminance component (or any related magnitude) gives good visual results.

In natural images there are quite a lot of intensity changes due to shadows. Also the Karhunen-Loève transformation [Rosenfield,1976] indicates that a luminance-like component is the most important one [Otha,1980]. This does not mean that every space that contains a luminance component is an adequate space. If XYZ is used, the X and Z components will remain the same, but the Y-value along edges will increase or decrease. If the colours are transformed back to RGB, mainly the green component will be changed. If the luminance value at one side of the edge decreases, the green component will also diminish, so the colours will look redder and/or bluer. As a result, a neutral edge will become red/blue at one side and greener at the other side (this can be shown analogously). If the CSF of the chromatic channels are really negligible, the operation should be performed in a space that models a luminance-like channel and two opponent colour channels. In this way the hue and chroma of the colours are kept the same, that is not the case if X and Z remain unchanged. In some cases unsharp masking is only applied on the green component of RGB. This gives only good results if the rg-chromaticity coordinates are kept the same.

Weighting factors

In colour image processing, the contribution of the opponent channels to the distance function has to be suppressed related to the lightness difference [Lang,1988, Mahy,1994a]. To determine these weighting factors, we have quantized several colour images in uniform colour spaces. This has been done separately for the three components of the uniform spaces. The quantization step for which just no pseudo contours or local colour clusters are apparent corresponds to the Visual Permissible Quantization step (VPQ). Mainly smooth colour shadings influenced the determination of VPQ's.

Based on these values, 1 CIELAB unit along the lightness axis corresponds to 3 CIELAB units in the chroma plane. This indicates that the chroma components could be reduced with a factor three compared to the lightness axis. This explains the choice of the weighting factors in the distance function of CIELAB and CIELUV in [Mahy,1991].

If the VPQ's are compared with the scale factors W_l in table III of [Mahy,1994a] to make spaces more uniform, we see that these values are in agreement with each other. Because mainly colour clusters and pseudo contours have been evaluated, the VPQ's are valid for small colour differences. So the comparison of these values with table III in [Mahy,1994a] is justified.

The weighting factors have also been determined for edge detection. For CIELAB, we found that the chroma scales should be suppressed with a factor 5 compared with the lightness scale. To determine these values, we tried to find as many visual edges as possible with a minimum of noise edges. This value is larger than these based on the VPQ's because

- the quantization errors of the chroma components are considerably larger than those of the lightness component. To reduce noise edges, the weighting factors of the chroma components have to be large enough. Because these values are influenced by quantization errors, the weighting factors will differ from image to image. Images with small RGB values will be have significantly larger reduction factors for the chroma components because the quantization errors for these colours are the largest.

- due to the difference in the CSF of the opponent colour channels and the luminance channel, the contribution of the chroma axes will be reduced. This is logical because small but relatively clear edges in the chroma components will be less visible than the same edge (equal colour difference of the colours at both sides of the edge) in the lightness component. If chroma edges are detected in the same way as lightness edges, sometimes edges will be detected that are not visible. As a result the chroma components will be reduced due to the CSF.

The weighting factors are determined by non uniformities of the colour space, unmodelled visual effects and quantization errors. To choose the weighting factors optimally, they should be influenced by as few effects as possible. These factors will be less dependent for a certain image set and as a result will be more generally valid. This can be obtained by a good quantization of the RGB values (e.g. gamma corrected RGB values) and by picking up non modelled visual effects in the processing. As a result the weighting factors will only be needed to correct non uniformities of the colour space.

Conclusions

In this paper we evaluated uniform colour spaces developed after the adoption of CIELAB and CIELUV. Based on visual data they could be divided into two classes, one to predict small colour differences and another one to calculate larger differences. The main difference between spaces out of each class is that the lightness unit has to be resized compared to the chroma unit. Visual evaluations of the size of a JND along different axis indicated that this correction factor is chroma dependent. Based on these evaluations and discrimination data we were able to correct CIELAB, a quite uniform space for larger differences, such that it is as uniform as the best space for small colour differences.

Most spaces of the same class are not significantly different. Correlations between colour differences obtained in different spaces indicated that some are quite similar. Spaces between which almost no differences are found are OSA 78 and OSA 90, and CMC(0.7:1.0) and BFD(0.7:0.9). Also CIELAB, CIELUV and Labhnu have quite high correlation factors. This means that if these spaces are used in image processing, it will be quite difficult to see significant differences between them.

For image processing purposes it is also important that the models are mathematically stable. Calculation of quantization errors indicated that some spaces, such as ATD and the space of Frei are singular for some colours. The OSA spaces on the other hand are singular for colours with $Y_{10} = 0.287$. Other spaces such as the space of Seim and Valberg, FMC1, FMC2 and the model of Nayatani are unstable.

As a result we will use different spaces to predict small and larger colour differences. A preferred space has no singularities, is stable and is mathematically as simple as possible. Good candidates are CDF, our correction of CIELAB, for smaller differences and CIELAB for larger colour distances.

To adapt image processing techniques for colour images, the correct kind of colour space has to be used for the different subtasks. If this is a smoothing operation, a tristimulus space should be chosen. To determine colour differences, uniform spaces should be taken.

The choice of the tristimulus spaces is not important because they are all related to each other by a linear transformation. To determine colour differences, different spaces have to be used for small and larger differences. However, almost no difference is seen in the processed images if spaces out of both classes are used.

This is normal for the determination of *local parameters* because in most cases colours in a small neighbourhood do not differ that much, so colour differences according different colour spaces are equal except for a rescaling factor. If however the colours are quite different, we are in most cases only interested in segmenting the neighbourhood into two regions. Also in this case most spaces will end up with the same result, because colours which are quite different in one space will also be different in other spaces.

The influence of the colour space on the determination of *global parameters*, such as the threshold for edge detection, is quite significant. This is due to the fact that the parameters are the same for the entire colour space. The threshold for edge detection for example has to correspond to the colour difference that just can be seen. If in this case tristimulus spaces are used, the result will be significantly worse than if a good uniform space is employed.

Nevertheless even for the determination of global parameters almost no difference is seen in processed images if several uniform spaces are used. This is due to the fact that the differences are masked by

- non uniformities of uniform colour spaces
- unmodelled visual effects such as induction effects, CSF, crispening effect, Helmholtz-Kolraus effect, ...
- quantization errors

Nevertheless if tristimulus and uniform spaces are used correctly, and different uniform spaces are used to calculate small and larger colour differences, the determination of processing parameters, and as a consequence the processing itself will be valid for a larger set of images. The choice of the tristimulus space is not important, but as uniform space we opt for a space

- without singularities

- with small quantization errors
- that is mathematically simple
- that is as uniform as possible

For larger colour differences CIELAB is a good choice, whereas CDF is an adequate space to determine small colour differences.

Acknowledgments

This research has been sponsored by the Flemish Institute for the promotion of scientific and technological research in industry and the Belgian government – "Diensten voor programmatie van het Wetenschapsbeleid" – in the framework of COST.

Literature Cited

CIE
1986 CIE publication 15.2, 2nd ed.
Chickering, K. D.
1971 "FMC Color-Difference Formulas: Clarification Concerning Usage", J. Opt. Soc. Am., vol. 61, no. 1, pp. 118-122.
CMC
1984 "CMC Colour-Difference Formula", Color Res. Appl., vol. 9, pp. 250.
Delcroix, C. J., and Abidi, M. A.
1988 "Fusion of Edge Maps in Color Images", SPIE, vol. 1001, Visual Communications and Image Processing, pp. 545-554.
De Valois, R. L., and De Valois, K. K.
1988 "Spatial Vision", Oxford Psychology series no. 14, (Oxford University Press), 1st ed..
Faugeras, O. D.
1979 "Digital Color Image Processing Within the Framework of a Human Visual Model", IEEE Transactions on Accoustics, Speech and Signal Processing, vol. ASSP-27, no. 4, pp. 380-393.
Frei, W., and Baxter, B.
1977 "Rate-Distortion Coding Simulation for Color Images", IEEE Transactions on Communications, vol. 25, no. 11, pp. 1385-1392.
Guth, S. L., Massof, R. W., and Benzschawel, T.
1980 "Vector Model for Normal and Dichromatic Color Vision", J. Opt. Soc. Am., vol. 70., no. 2, pp. 197-212.

Hunt, R. W. G.
1988 "The Reproduction of COLOUR in Photography, Printing & Television" (Fountain Press, England).
1991 "Revised Colour-Appearance Model for Related and Unrelated Colours", Color Res. Appl., vol. 16, no. 3, pp. 146-165.
Kender, J. R.
1976 "Saturation, Hue and Normalized Color: Calculation, Digitization Effects and Use", Technical Report, Department of Computer Science, Carnegie-Mellon University.
Kuehni, R. G.
1990 "Industrial Colour Difference Progress and Problems", Color Res. Appl., vol. 15, no. 5, pp. 261-265.
Lang, H.
1988 "Weighting Factors for Luminance and Chrominance Noise and Their Signification for HDTV Color Signal Specifications", 2nd International Workshop on Signal Processing of HDTV, 29 February–2 March 1988, L'Aquila Italy.
Luo, M. R., and Rigg, B.
1987a "BFD(l:c) Colour-Difference formula Part 1 – Development of the formula", J. Soc. Dyers Colourists, vol. 103, pp. 86-94.
1987b "BFD(l:c) Colour-Difference formula Part 2 – Performance of the formula", J. Soc. Dyers Colourists, vol. 103, pp. 126-132.
MacAdam, D. L.
1978 "Colorimetric Data for Samples of OSA Uniform Color Scales", J. Opt. Soc. Am., vol. 68, no. 1, pp. 121-130.
1990 "Redetermination of Colors for Uniform Scales", J. Opt. Soc. Am., vol. 7, no. 1, pp. 113-115.
Mahy, M., Van Eycken, L., and Oosterlinck, A.
1990 "Color Control based on Uniform Color Spaces", presented at 'The Fifth International Congress on Advances in Non-Impacty Printing Technologies', November 12-17, San Diego USA.
1994 "Evaluation of uniform colour spaces developed after the adoption of CIELAB and CIELUV", Color Res. Appl., vol. 19, no. 2.
Mahy, M., Van Mellaert, B., Van Eycken, L., and Oosterlinck, A.
1991 "The influence of uniform color spaces on color image processing: A comparative Study of CIELAB, CIELUV, and ATD", IS&T, vol. 17, no. 5, pp. 232-243 (1991).
Mahy, M.
1994 "Studie van "kleur" voor visuele en fysische beeldverwerking", Ph.D. thesis at the Katholieke Universiteit Leuven (in Dutch).
Mastin, G. A.
1985 "Adaptive Filters for Digital Image Noise Smoothing: An Evaluation", Computer Vision, Graphics, and Image Process., vol. 31, pp. 103-121.
Nagao, M., and Matsuyama, T.

1979 "Edge Preserving Smoothing", Computer Graphics and Image Processing, vol. 9, pp. 394-407.

Nayatani, Y., Hashimoto, K., Takahama, K., and Sobagaki, H.
1987 "A Nonlinear Color-Appearance Model using Estévez-Hunt-Pointer Primaries", Color Res. Appl., vol. 12, no. 5, pp. 231-242.

Nevatia, R.
1977 "A Color Edge Detector and Its Use in Scene Segmentation", IEEE Transactions on Systems, Man and Cybernetics, vol. SMC-7, no. 11 November, pp. 820-826.

Otha, Y., Kanade, T., and Sakai, T.
1980 "Color Information for Region segmentation", Computer Graphics and Image Processing, vol. 13, pp. 222-241.

Pratt, K. P.
1991 "Digital Image Processing", (John Wiley & sons, Inc.), 2nd ed.

Richter, K.
1980 "Cube-root Spaces and Chromatic Adaptation", Color Res. Appl., vol. 5, no. 1, pp. 25-43.

Robinson, G. S.
1977 "Color Edge Detection", Optical Engineering, September/October.

Rosenfield, A., and Kak, A. C.
1976 "Digital Picture Processing", (Academic Press).

Shiozaki, A.
1986 "Edge Extraction Using Entropy Operator", Computer Vision, Graphics, and Image Processing, vol. 36, pp. 1-9.

Seim, T., and Valberg, A.
1986 "Towards a Uniform Color Space: A Better Formula to Describe the Munsell and OSA Color Scales", Color Res. Appl., vol. 11, no. 1, pp. 11-24.

Tominaga, S.
1987 "Expansion of color images using three perceptual attributes", Pattern Recognotion Letters, vol . 6, pp. 77-85.

Tominaga, S.
1992 "Color Classification of Natural Color Images", Color Res. Appl., vol. 17, no. 4, pp. 230-239.

Trahanias, P. E., and Venetsanopoulos, A. N.
1993 "Color Edge Detection Using Vector Order Statistics", IEEE Transactions on image processing, vol. 2, no. 2, pp. 259-264.

Wang, D. C. C., Vagnucci, A. H., and Li, C. C.
1981 "Gradient Inverse Weighted Smoothing Scheme and the Evaluation of Its Performance", Computer Graphics and Image Processing, vol. 15, pp. 167-181.

Wyszecki, G., and Stiles, W. S.
1982 "Color Science: Concepts and Methods, Quantitative Data and Formulae" (John Wiley & Sons, New York), 2nd ed.