Modelling inter-colour regions of Colour Naming Space

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1. Abstract

Although colour vision has common characteristics across humans, there is no universal agreement on how the colour space should be segmented to represent the names assigned by observers from different cultural backgrounds. To this respect, anthropologists and linguists have identified a limited set of eleven universal colour categories (names), that are present in most evolved languages, which could form the basis for a cross-cultural segmentation. In this work we present a mathematical formulation of fuzzy-sets to model this colour name assignment task, with a special focus on the inter-colour regions. In our model, the CIELab colour space is divided into eleven basic categories using a Triple Sigmoid as the fuzzy sets basis. To adjust the model's parameters, psychophysical stimuli was created (in the CIE Lab space) from pairs of isoluminant colours belonging to different neighbouring categories and the colours in between. These were presented on a calibrated CRT monitor (14-bit x 3 precision) and observers indicated whether the colours belong to a category or another in a Yes/No discrimination paradigm. Our results show that inter-colour boundary regions are much less defined than expected and colour samples other than those near the focal colours (colours most representative of a given name) are needed to define the position and shape of boundaries between categories.

2. Introduction

The segmentation of the colour space according to the names assigned to colours by humans is an important problem for many disciplines, including computer vision. So far there is a lack of understanding of the link between low level colour features and the high-level semantics that humans use to name these colours (the so-called semantic gap). In their large survey of languages, Berlin and Kay [1] found that there are 11 basic terms (categories) common to the most evolved languages. Since then, many workers have explored the relationships between perceived colours and language [2-7]. Most of these works have confirmed the existence of the 11 basic terms and have located the best representatives (also called *focal colours*, see **Figure 1**) and in some cases estimated the boundaries of each basic colour on different colour spaces.

In recent years, some computational models [8-12] have been proposed to automate the colour naming task. Although some of the results from previous psychophysical experiments were incorporated in these models, the available data is not enough for a precise modelling of the basic colour categories. The reason is (arguably) that most of the previous psychophysical experiments collected data by asking subjects to name a given set of colour samples without recording any other information. As a result, in most cases, the majority of the information is collected near the focal colours and there is a lack of information on how names are assigned in the colour boundaries.

3. A Fuzzy-Sets model

In 2007, Benavente *et al* [7, 10, 11] developed a computational model based on Berlin and Kay´s 11 basic colours, that uses Fuzzy membership functions (3-D regions which define the probability of a certain value (colour) to be named with its corresponding colour name) based on a combination of sigmoids with an elliptical centre.

This model also contains parameters which can be adjusted to modify the shape of its regions and does a reasonable job of fitting to previous psychophysical data [1, 2, 4]. Panel (a) of **Figure 2** (below) shows the characteristic sigmoids used as membership functions for this model. An example of how different membership functions combine to divide the CIELab colour space is shown in panel b.

The shape of the membership functions is determined by the following relationship:

$$TSE(\vec{p};\theta) = DS(\vec{p};\vec{t},\theta_{DS}) \cdot ES(\vec{p};\vec{t},\theta_{ES}) \qquad (1)$$
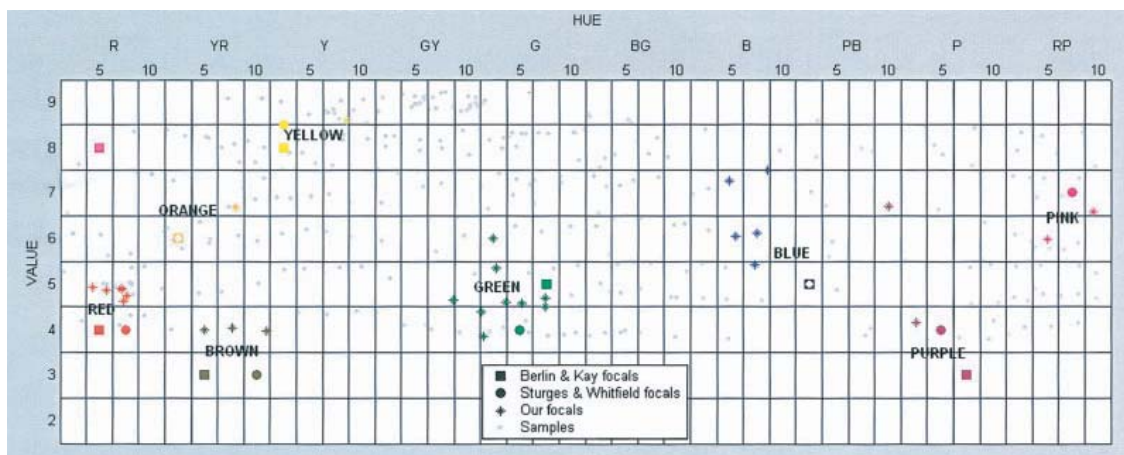

Figure 1: Exemplary focal colours represented in the Munsell colour space, from the work of Berlin and Kay (1969) (squares), Sturges and Whitefield (1995) (circles) and Benavente et al (2005) (crosses).

where TSE is the acronym for *Triple-Sigmoid* with *Elliptical* centre (the product of all functions), ES represents the *Elliptical-Sigmoid* function (which defines the central achromatic region):

$$ES(\vec{p};\vec{t},\theta_{ES}) = \frac{1}{1+e^{-\beta_e\left(\left(\frac{\vec{u}_1 R_\phi T_t \vec{p}}{e_x}\right)^2 + \left(\frac{\vec{u}_2 R_\phi T_t \vec{p}}{e_y}\right)^2 - 1\right)}} \qquad (2)$$

and DS (*Double Sigmoidal* function) is the product of the functions S1 and S2 (Sigmoidal functions oriented with respect to x and y respectively).

$$DS(\vec{p};\vec{t},\theta_{DS}) = S_1(\vec{p};\vec{t},\alpha_y,\beta_y)\cdot S_2(\vec{p};\vec{t},\alpha_x,\beta_x) \qquad (3)$$

$$S_i(\vec{p};\vec{t},\alpha,\beta) = \frac{1}{1+e^{-\beta \vec{u}_i R_\alpha T_t \vec{p}}};i=1,2 \qquad (4)$$
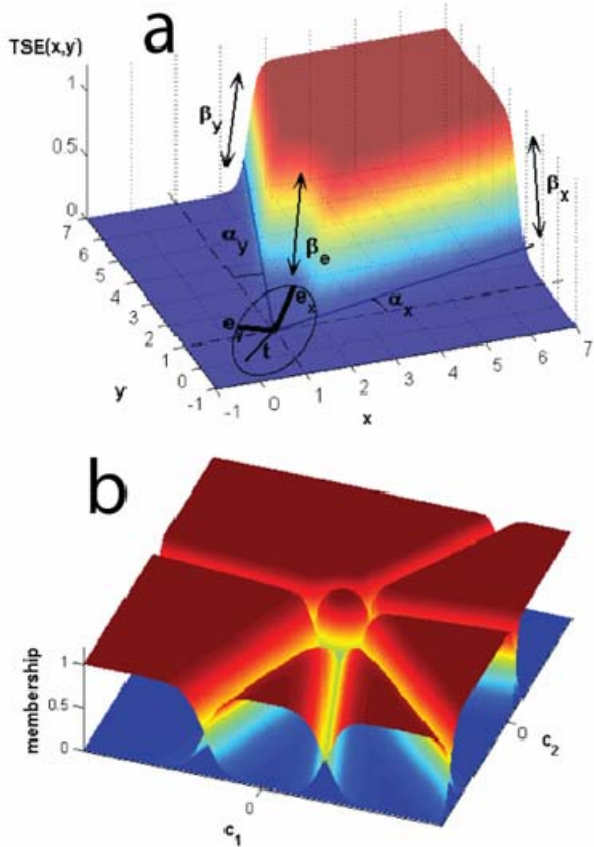

Figure 2: *Examples of the Fuzzy membership regions proposed by Benavente et al to segment the colour space, based on a combination of sigmoids and elliptical figures*
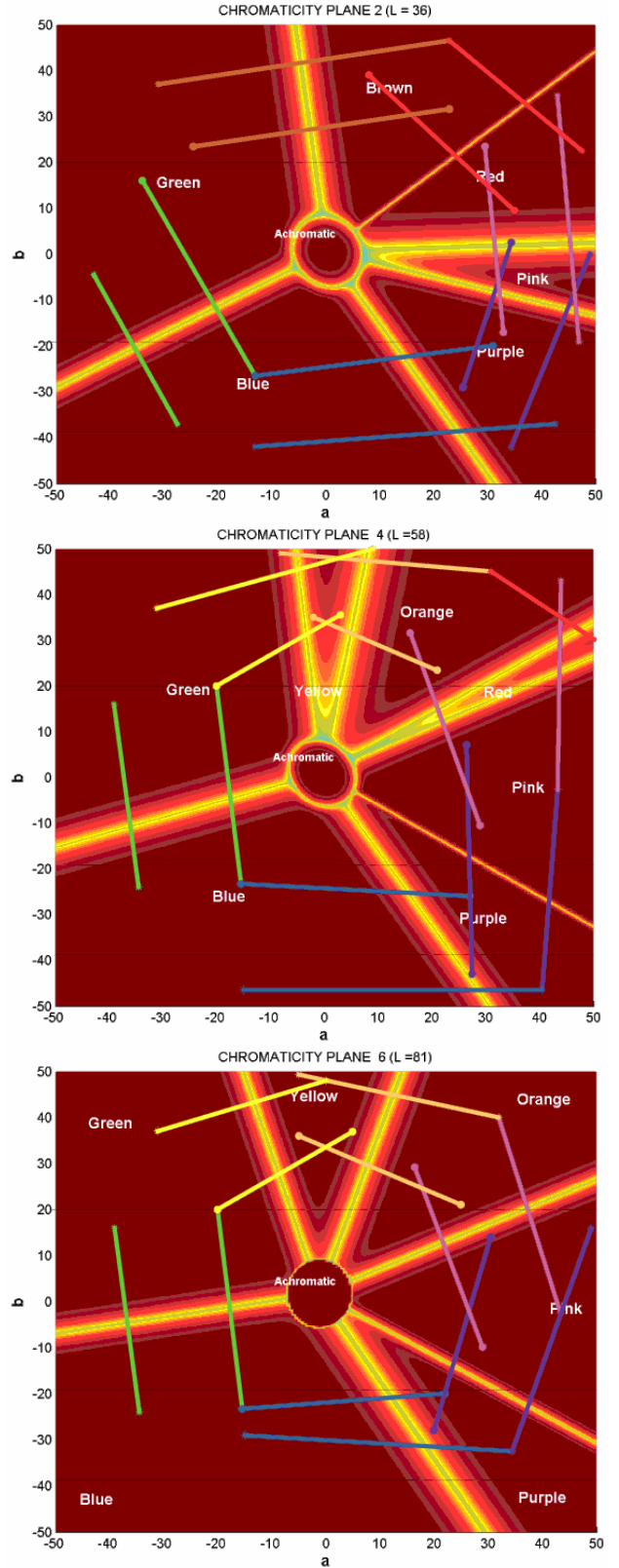

Figure 3: *Disposition of the initial colours in CIELab space. They were selected to lie across the boundaries of the colour name regions of Benavente et al al [5, 6].*

4. The problem

One arguable weakness of this approach is that it relies on subjective membership values given to colour samples by observers using an arbitrary rating scale [4, 7, 10, 11]. Moreover, these ratings are likely to be more accurate near the focal colours and less accurate near the colour boundaries, i.e. the positions of the boundary lines may not be accurately defined, and the same is true for the slopes of the membership functions.

A possible solution to this problem is to redefine the boundary regions by means of a new psychophysical experiment designed so that subjects have a very limited choice of responses (to reduce the influence of colour memory in their decision). With the aim of validating the Benavente *et al* model, and to provide a better adjustment of the sigmoidal functions, we designed a new colour naming experiment that specifically collects psychophysical data in the regions of the colour space where it is more needed (borders between focal colours).

5. Methods

Subjects were presented with calibrated square colour patches at the centre of a CRT monitor (Viewsonic pf227f) using Cambridge Research Systems Bits++ video processor capable of displaying colours with 14-bit precision. The patches subtended 5.2 deg to the observers, the viewing distance was 166 cm, and the presentation time was 500 ms. The background to the colour sample was black, but to give observers a white reference, there was a white frame 23 mm wide at the borders of the screen (Lum = 124.83 cd/m2).

Consecutive presentations were separated at least by 1 second. The short presentation times were chosen to avoid possible colour afterimages (caused by fatigued cells in the retina) or any other adaptation effects.

There were 10 naïve observers (all native English

speakers) and 2 experienced observers (native Spanish speakers with a good level of spoken English). The experimental colours were chosen to lie along a line (in CIELab space) crossing the border between two colour names according to the Benavente *et al* [7, 10, 11] model. The two initial colours (or reference colours) had the same "L" value and were chosen to be sufficiently apart so that their names were not confused. There were 37 colour pairs in three L planes in total (L=36, L=58 and L=81). **Figure 3** (all three panels) show the arrangements of these initial colours in CIELab space.

After each presentation, observers were asked to select the name that best described the colour that they had just seen among two words appearing onscreen after the presentation (yes/no paradigm). The algorithm selected the (intermediate) colours to be presented next following a QUEST [13] protocol (num. of trials =40). Each colour pair was repeated 3 times and 50% thresholds were determined using the QUEST's mean threshold estimate [14, 15].
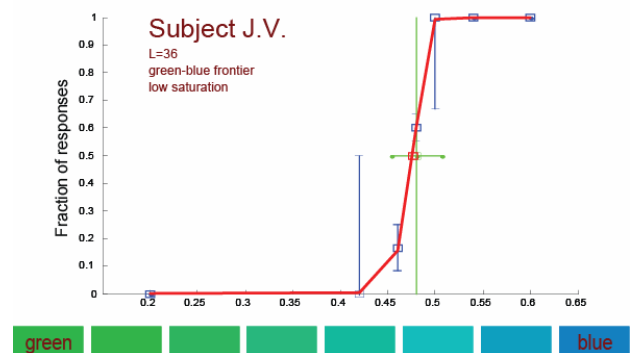

Figure 5: Exemplary result from a single experiment (for subject J.V.) involving the green-blue colour-boundary (L=36, low saturation colour pair). The red line shows the psychometric function and the green line represents QUEST's mean threshold estimate.
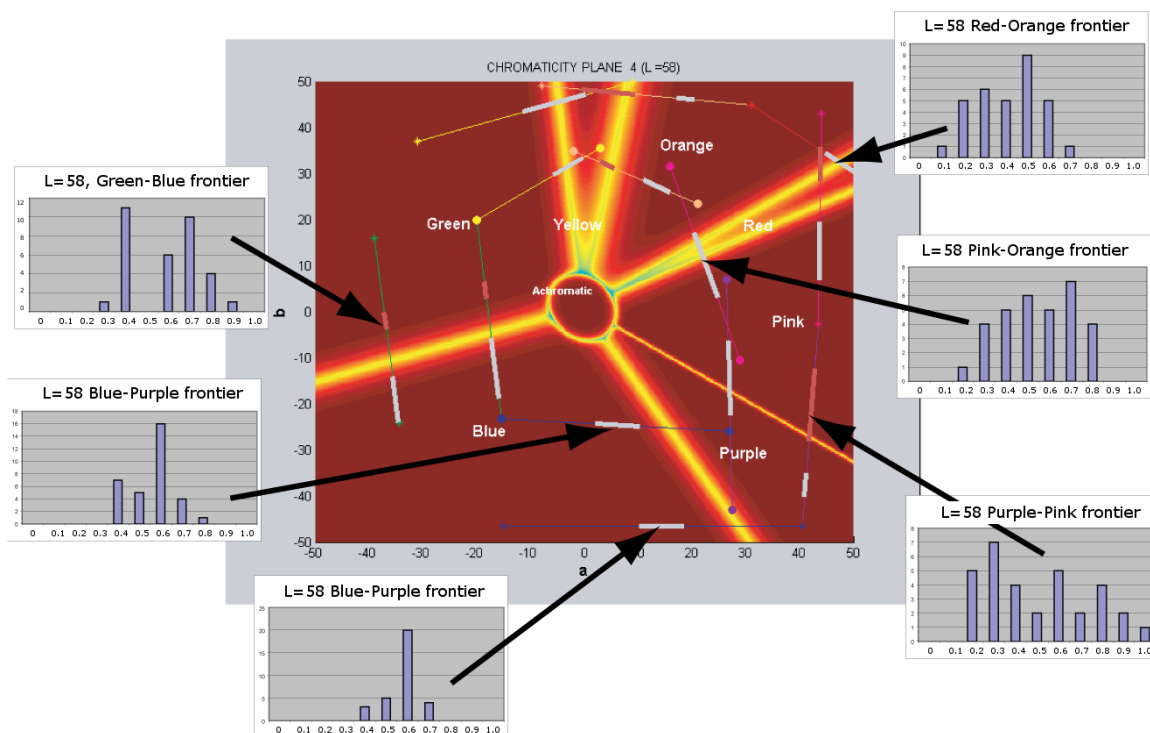

Figure 4: Experimental results for plane L= 58. Thresholds were measured for all observers on along the lines shown on the colour space (central plot). The grey and red bars show the regions where the majority of the thresholds were occurred. Some histograms showing the distribution of thresholds along these lines are shown as side-figures. The length of the bar is equal to the Standard Deviation of the calculated thresholds.

6. Results and conclusions

An exemplary set of results is shown in **Figure 5**. The x-axis represents the colour transition along the line crossing the low saturation blue-green colour name boundary. Each empty blue box represents the average of several presentations of colours in a given section of the continuous line (an x value of 0 equals "green" and 1 equals "blue" in this example). A higher value of y-axis means that colours were labelled as "blue" in most presentations and a low value means that the colour was labelled as "green" in most presentations. The threshold lies where colours were equally labelled "green" or "blue" by subjects (50% of responses).

Figure 4 shows a summary of the results for all 12 subjects corresponding to the intermediate (L=58) plane. Thresholds across colour boundaries were measured (3 times for each subject) and the regions where these thresholds fall are highlighted as bars. Grey bars represent the regions where the majority of the thresholds occurred for all subjects (the length of the bar is equal to the StDev of the distribution of thresholds). Red bars represent the position of secondary peaks in bi-modal distributions, signalling the presence of another possible threshold. Figure 5 also shows the histogram distribution of six exemplary boundary zones. In these histograms, the distance between each pair of colours was divided in ten "bins". The appearance of secondary peaks seems to indicate that in some cases there is a large uncertainty region where perhaps extra colour names (apart from the initial 11) may be needed to account for the large variability of the data. For example, in all cases the boundary between green and blue presents a secondary peak which may indicate the presence of an intermediate "turquoise" colour area. Other frontiers seem to be more or less unchanged.

Achromatic boundaries (those around the "achromatic centre") were not explored. We did not find any significant difference between the majority of speakers of English as a first language and the two speakers of English as a second language.

Figure 6 shows a possible new set of colour name boundaries, accounting for the new data (inter-colour regions have been redrawn). The enlarged "uncertainty regions" around the colour boundaries account for the fact that there were large variations in the position of the threshold across subjects and in some cases for the same subject.

Our results show that to adjust the model we need both samples near the focal colours together with psychophysical measures on the boundary regions. The later not only can help define further the position of the inter-colour regions, but also provide a measure of the uncertainty between colours.

It has been suggested that our choice of colour space (CIELab) is obsolete and that a more perceptually equidistant space (such as CIECAM02) should have been selected. We believe that the variability of results (some subjects produced large threshold variations even when presented with the same initial colour pair for the second time a few minutes later) is bound to mask any further refinements coming from the selection of colour space.
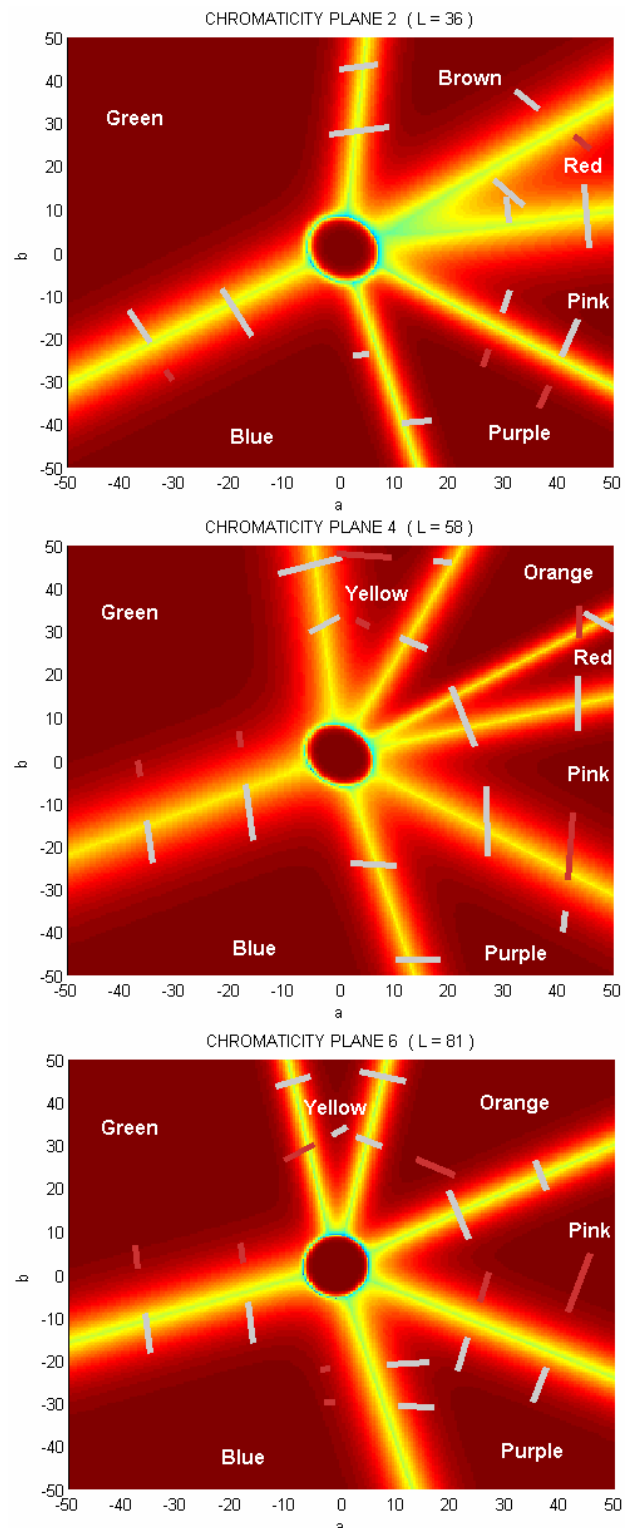
7. Acknowledgements

Figure 6: a new set of colour name boundaries, adapted to fit our experimental results

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9. Author Biography

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