Further developing a colour mark similarity measurement framework – Part II: Defining a similarity score
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Introduction and formulation

My previous two discussions[1,2] of a possible framework for measuring the similarity between two colours (in the context of colour trademarks) involved the definition of each colour in terms of its RGB (red-green-blue) specification. For RGB definitions, each individual colour component is expressed as an integer value between 0 and 255, giving a spectrum of colours from [0,0,0] (black) and [255,255,255] (white), or a 3D colour 'space' containing 16.8 million (i.e. 256^3) different options.

In this context, the degree of difference between any two colours ([$\boldsymbol{R_1}$,$\boldsymbol{G_1}$,$\boldsymbol{B_1}$] and [$\boldsymbol{R_2}$,$\boldsymbol{G_2}$,$\boldsymbol{B_2}$]) is expressed as the geometric 'distance' ($\boldsymbol{d}$) between the two colour points in this 3D space, defined (according to Pythagoras' theorem) as:

$$\boldsymbol{d} = \sqrt{\ [\ (\boldsymbol{R_1} - \boldsymbol{R_2})^2 + (\boldsymbol{G_1} - \boldsymbol{G_2})^2 + (\boldsymbol{B_1} - \boldsymbol{B_2})^2\ ]}$$

However, in mark similarity assessments, it may be more convenient to express the degree of similarity as a *score* (expressed as, say, a percentage), which aligns well with the familiar terminology of stating marks to be similar to a 'low', 'medium' or 'high' degree (but is, in some ways, more preferable, as it allows an *exact value* to be quantified).

From the framework previously proposed, it is a relatively simple matter to derive such a *similarity score* for a pair of colours ($\boldsymbol{S_{col}}$), based on the distance ($\boldsymbol{d}$) between them in colour space. The first stage is to define a *difference* score ($\boldsymbol{D_{col}}$) expressing the distance ($\boldsymbol{d}$) as a *proportion* of the maximum *possible* distance between two colours in RGB space (i.e. the distance between [0,0,0] and [255,255,255], equal to $\sqrt{(3 \times 255^2)}$, or approximately 441.7, i.e.:

$$\boldsymbol{D_{col}} = \boldsymbol{d} \ /\ \sqrt{(3 \times 255^2)}$$

In this case, $\boldsymbol{D_{col}}$ will take a value between 0 and 1 (or can be multiplied by 100 to give a percentage). From this, the similarity is just:

$$\boldsymbol{S_{col}} = 1 - \boldsymbol{D_{col}}$$

or, in full:

$$\boldsymbol{S_{col}} = 1 - \{\ \sqrt{\ [\ (\boldsymbol{R_1} - \boldsymbol{R_2})^2 + (\boldsymbol{G_1} - \boldsymbol{G_2})^2 + (\boldsymbol{B_1} - \boldsymbol{B_2})^2\ ]}\ \} \ /\ \sqrt{(3 \times 255^2)}$$

or, equivalently:

$$\boldsymbol{S_{col}} = 1 - \sqrt{\ \{\ [\ (\boldsymbol{R_1} - \boldsymbol{R_2})^2 + (\boldsymbol{G_1} - \boldsymbol{G_2})^2 + (\boldsymbol{B_1} - \boldsymbol{B_2})^2\ ] \ /\ (3 \times 255^2)\ \}}$$

The relationship between the similarity score ($\boldsymbol{S_{col}}$) and the distance ($\boldsymbol{d}$) is therefore as shown in Figure 1 and Table 1.

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[1] https://circleid.com/posts/towards-a-quantitative-approach-for-objectively-measuring-the-similarity-of-marks
[2] https://circleid.com/posts/further-developing-a-colour-mark-similarity-measurement-framework-building-a-database

Figure 1: The relationship between colour similarity score ($\boldsymbol{S_{col}}$) and distance (***d***)

Sim. score ($\boldsymbol{S_{col}}$)	Diff. score ($\boldsymbol{D_{col}}$)	Distance (***d***)
0.00 (0%)	1.00 (100%)	441.7
0.01 (1%)	0.99 (99%)	437.3
0.05 (5%)	0.95 (95%)	419.6
0.10 (10%)	0.90 (90%)	397.5
0.25 (25%)	0.75 (75%)	331.3
0.50 (50%)	0.50 (50%)	220.8
0.75 (75%)	0.25 (25%)	110.4
0.90 (90%)	0.10 (10%)	44.2
0.95 (95%)	0.05 (5%)	22.1
0.99 (99%)	0.01 (1%)	4.4

Table 1: The relationship between colour similarity score ($\boldsymbol{S_{col}}$) and distance (***d***)

On this basis, the most similar pair of colours considered in the previous study ([250/99/4] (Home Depot) and [254/82/0] (Reese’s); both shades of orange) would be assigned a similarity score ($\boldsymbol{S_{col}}$) of 0.959 (or 95.9%) and the least similar ([51/0/114] (Cadbury’s purple), and [255/255/0] (Slip ‘N Slide yellow)) a score of 0.217 (or 21.7%).

It is also worth noting that the assertion in the original study, that it might be appropriate for colour-mark protection to apply up to a distance (***d***) threshold of 10 units, is equivalent to saying that the protection ‘bubble’ would cover colours which are at least 97.7% similar to each other.

Visualising the colour landscape

As mentioned above, there are 16.8 million distinct colours definable in RGB space, where each colour component is expressed as an integer value between 0 and 255. This means that there are 281 trillion ($(256^3)^2$) possible *pairs*, or two-colour *combinations*, each of which will have a calculable similarity score.

In order to gain an overview of the high-level characteristics of the overall colour landscape (and the meaning of the similarity score formulation within it), it is convenient to sub-divide the colour space into cubes ('sub-blocks') of size 16 × 16 × 16, and consider the (as near as possible) central colour in each of these sub-blocks. This gives a subset of 4,096 distinct colours, from [8,8,8] to [248,248,248].

For convenience, we can 'order' these as: 'colour 1' = [8,8,8], 'colour 2' = [8,8,24], 'colour 3' = [8,8,40], … , 'colour 17' = [8,24,8], 'colour 18' = [8,24,24], 'colour 19' = [8,24,40], … , 'colour 257' = [24,8,8], etc., in each case firstly incrementing the blue component through the possible range of values, then the green component, and then the red (with the ordering thereby as shown in Figure 2).

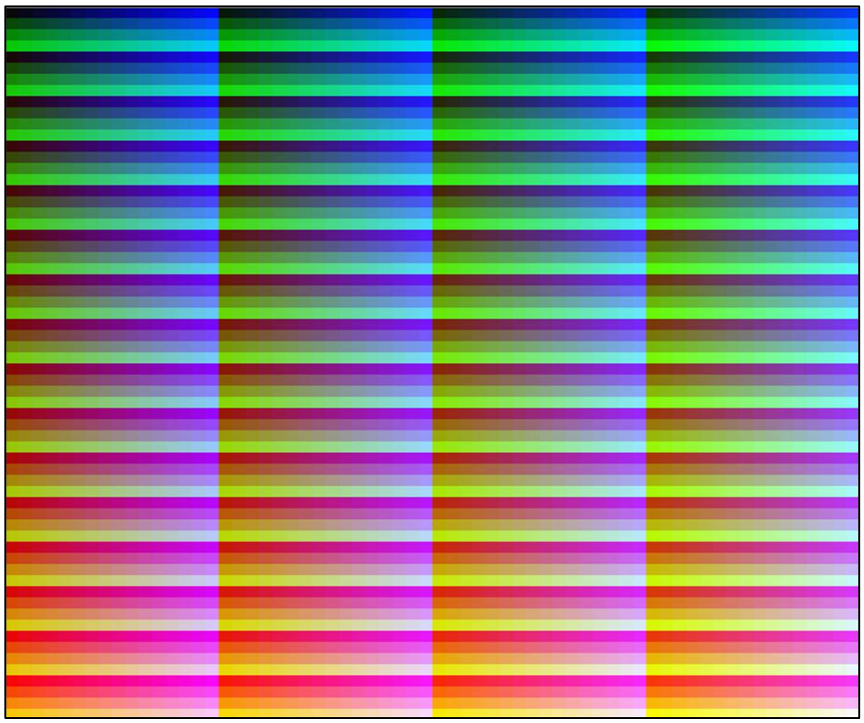

Figure 2: The central colours in each of the 4,096 16 × 16 × 16 sub-blocks of RGB space (colours ordered from left to right, then top to bottom – i.e. 'colour 1' top-left; 'colour 64' top-right; 'colour 4033' bottom-left; 'colour 4096' bottom-right)

From this subset of 4,096 colours, there are a total of 16,777,216 (i.e. $4{,}096^2$) distinct colour pairs. The distribution of similarity scores across these 16.8 million permutations is shown in Figures 3 and 4.

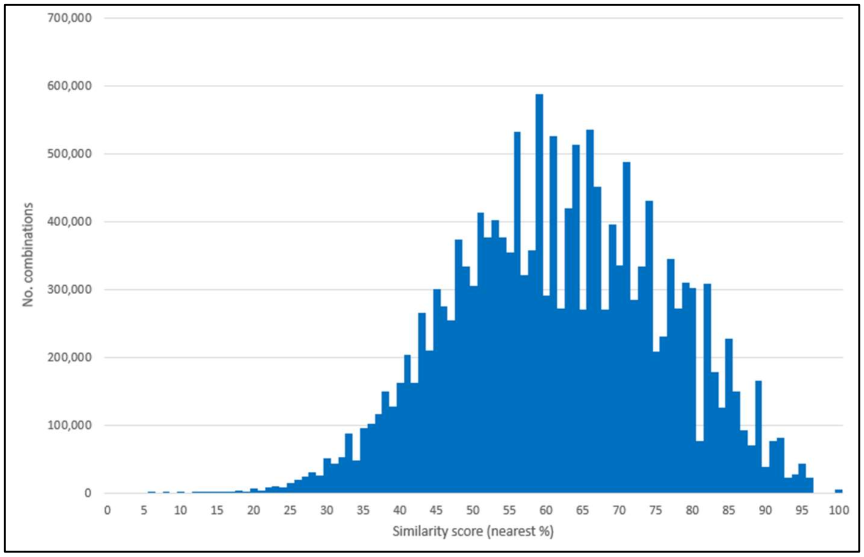

Figure 3: Histogram showing the distribution of similarity scores (to the nearest percent) across the 4,096^2 distinct colour pairs

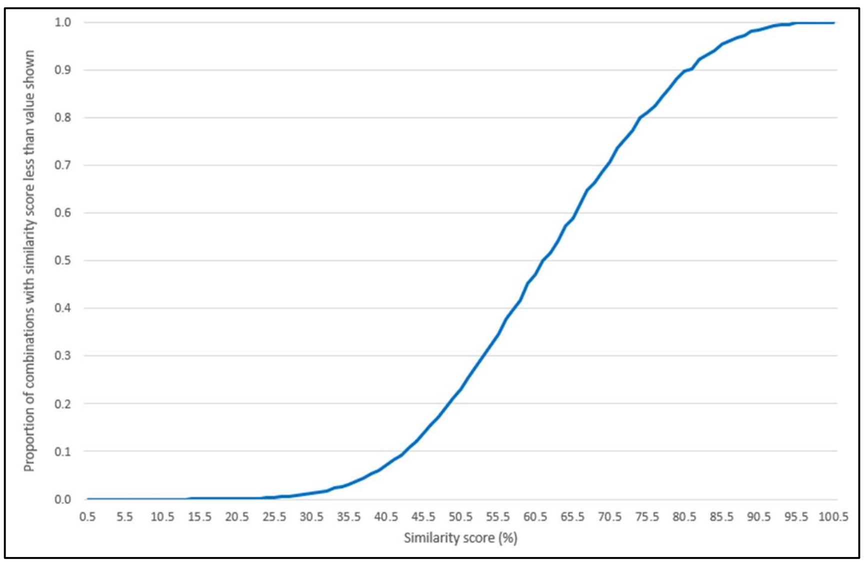

Figure 4: Cumulative distribution of similarity scores

The figures show a somewhat asymmetric distribution of scores, noting that only *one* colour-pair in the whole of RGB space – i.e. [0,0,0] and [255,255,255] – has a similarity score of 0, whereas *every* colour in the space will share a similarity score of 1 with *itself*.

It is also interesting to note the percentiles; one-quarter of the pairs considered have a similarity score of less than around 51%, one-half less than around 61%, and three-quarters less than around 72%.

Finally, it is instructive to appreciate what these different scores mean *in practice*; Figure 5 shows some examples of pairs of colours which are (to the nearest percent) 10%, 25%, 50%, 75% and 90% similar.

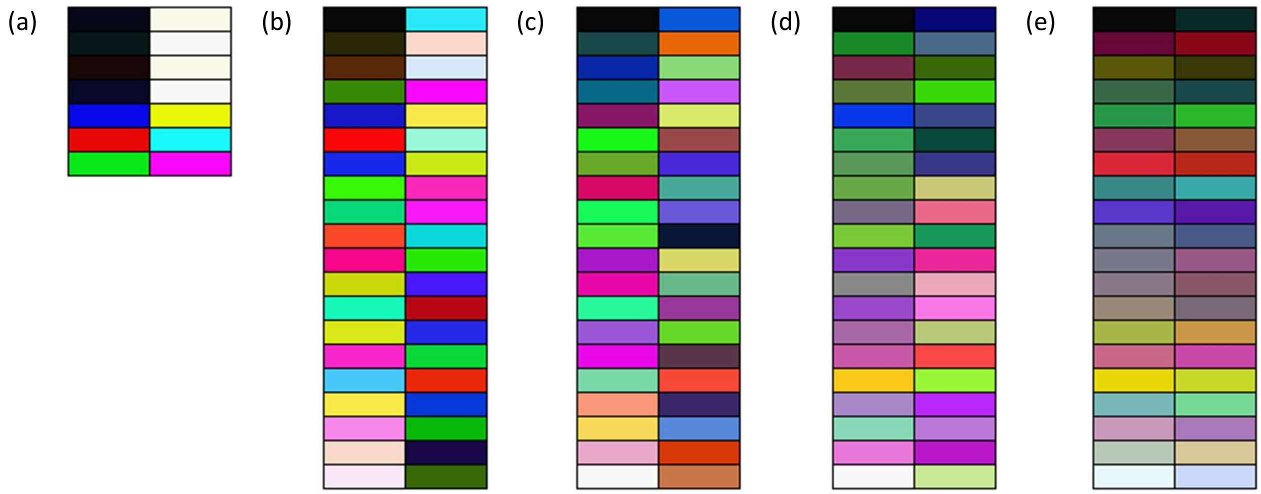

Figure 5: Examples of pairs (left/right) of colours which are: (a) 10% similar (i.e. 90% different); (b) 25% similar (i.e. 75% different); (c) 50% similar; (d) 75% similar (i.e. 25% different); (e) 90% similar (i.e. 10% different)

Conclusion

The concept of a similarity quantification is a useful one in trademark comparisons and, for characteristics such as colour – which can be *exactly* defined – provides the potential for precisely specifying the degree of difference between two specific variants (rather than more 'nebulous' assessments such as 'high', 'medium' or 'low' degrees of similarity). As discussed in previous articles in this series, the possibility of objective quantifiable measurement gives the potential for greater consistency in decisions relating to trademark disputes, the formulation of new case law, and specifications of thresholds up to which IP protection may apply.

For characteristics such as *word* marks, the quantification of similarity is a much more complex prospect, although we have seen than it is possible to generate algorithms to quantify visual (spelling) and aural (pronunciation) similarity[3].

Such algorithms realistically should only be considered as *tools* to be utilised in the overall similarity assessment process, which will inevitably always incorporate significant subjectivity, involving consideration of a range of additional factors. These might typically include (for word marks specifically) conceptual similarity (i.e. meaning) and the distinctiveness of the marks, and (for marks generally) associated imagery, the associated goods and services, the degree of attention paid by relevant consumers, and the nature of the overall market, all of which contribute to the estimation of the possibility of mark confusion.

[3] https://circleid.com/posts/further-developing-a-word-mark-similarity-measurement-framework