Comparison of Colour Difference Methods for Natural Images

Henri Kivinen, Mikko Nuutinen, Pirkko Oittinen; Aalto University School of Science and Technology, Department of Media Technology; Espoo, Finland

Abstract

Perceptual colour difference in simple colour patches has been extensively studied in the history of colour science. However, these methods are not assumed to be applicable for predicting the perceived colour difference in complex colour patches such as digital images of complex scene. In this work existing metrics that predict the perceived colour difference in digital images of complex scene are studied and compared. Performance evaluation was based on the correlations between values of the metrics and results of subjective tests that were done as a pair comparison, in which fifteen test participants evaluated the subjective colour differences in digital images.

The test image set consisted of eight images each having four versions of distortion generated by applying different ICC profiles. According to results, none of the metrics were able to predict the perceived colour difference in every test image. The results of iCAM metric had the highest average correlation for all images. However, the scatter of the judgements was very high for two of the images, and if these were excluded from the comparison the Hue-angle was the best performing metric. It was also noteworthy that the performance of the CIELAB colour difference metric was relatively high.

Introduction

The conventional CIE metrics (e.g. CIEDE2000 /1/)) developed to estimate the colour differences of colour fields are capable to achieve a degree of prediction that is commonly acknowledged to be sufficient. These metrics require that the two stimuli being matched are presented using identical backgrounds and surroundings, and also that the two stimuli are viewed using identical illuminants and observers defined by the CIE. The results of the metrics are unreliable when these requirements are not met. Furthermore, these metrics are being used in quality control of colour reproduction, in which the recent cross media demands have made this conventional colorimetry insufficient.

The CIECAM97 model and the updated CIECAM02 model were developed to provide a viewing condition specific method for transforming tristimulus values into perceptual attribute correlates /2/. However, these models can only interpret simple colour patches due to their nonexistent capabilities to model the properties of spatial structure in complex images. These properties have received considerable attention in different fields of colour science, such as study of image similarity and retrieval, image segmentation, image quality and human colour vision. The definition of complex images rises from their structure, which consists of different spatial frequencies. For example, photographs of a natural scene can be defined as a complex image.

One of the earliest models that were developed to predict the degree of perceptual colour difference in images of complex scenes is the S-CIELAB /3/. The extension to complex images was performed by using a contrast sensitivity function (CSF). Hong and Luo /4/ developed a (Hue-angle) metric for complex images that assigns higher weight to dominant colours and to colours having a greater difference. Chou and Liu /5/ proposed a (P-CIELAB) metric for complex images that incorporates a visibility threshold for colour differences. This pixel-wise visibility threshold varies as function of chroma, local luminance gradient, and background uniformity. Fairchild and Johnson /6/ have presented probably the most advanced model for colour appearance of complex images. Their iCAM framework includes different sub modules accounting for various properties of images and viewing conditions in image analysis.

The aim of this study was to test and compare the metrics or models for complex images in order to determine their capability to predict the degree of visually perceived colour differences in natural photographs. To the best of our knowledge, the study of Hardeberg et al. /7/ is the only published work where different state-of-the-art colour difference metrics of complex images have been compared to each other. They analysed the relation of CIELAB dE, S-CIELAB, iCAM, Structural Similarity Index /8/, Universal Image Quality /9/ and Hue-angle metric /4/ with data from a psychophysical experiment in which the perceptual image difference was evaluated. They used six test images, but only two of these images were natural photographs. The rest of the images were more or less studio photographs or graphical images. Their results indicated that perceptual image differences cannot be directly related to colour image differences as calculated using the current metrics.

We evaluate the state-of-the-art metrics narrowing the problem from that defined by Hardeberg et al. /7/. A known fact is that image content exerts an influence on image assessment. For example, portrait and landscape are typical views in natural photography. We selected only landscape type images for our study, as they satisfied our needs for the requirement of colour distributions and spatial contents. We wanted that colour distribution of the images is wide enough because colour distortions were made using different ICC colour profiles. We also wanted that the spatial content of the images covers a wide range because we wanted to test how the methods take into account the spatial details of the image. In addition, our psychophysical experiment tested the perceptual colour difference, nor the perceptual image difference.

Implementation of the metrics

The metrics that were investigated and compared in this study are listed in Table 1. Selected metrics can be divided into different classes based on differences and similarities in their functional properties. The standardized metrics that are based on CIELAB dE colour difference were not originally developed to address differences in complex images, but they were selected to form a baseline for the comparisons. These metrics include the CIELAB dE, CIE94 and CIEDE2000 metric /10/.

Metric	Intended use	Reference
dE	Colour patches	/10/
CIE94	Colour patches	/10/
CIEDE2000	Colour patches	/1/
Hue-angle	Complex images	/4/
P-CIELAB	Complex images	/5/
S-CIELAB	Complex images	/3/
iCAM	Complex images	/6/

Table 1. The metrics that were used in the study

In addition, the implemented metrics includes also CIELAB based metrics that were developed to predict the appearance of complex images. These are the Hue-angle, P-CIELAB and S-CIELAB metrics. The first two are both similar in that they use a weighting scheme to address the structural properties of images, such that, a pixel-wise weight is applied to re-adjust a CIELAB dE value of the pixel to contribute to a more precise estimate of the perceived colour difference. But, as the Hue-angle metric computes the weight more globally, the P-CIELAB metric uses local properties of the image. The S-CIELAB, which is also called a spatial extension to CIELAB colour space, takes advantage of the filtering characteristics of the human visual system (HVS) to apply the CIELAB dE metric to complex images. These characteristics are modelled with the contrast sensitivity function (CSF) in the frequency domain.

Similarly, the iCAM framework uses the CSF, but instead of using the CIELAB colour space, it uses the IPT colour space. In addition, the iCAM framework consists of multiple modules that account for the viewing conditions and colour appearance phenomena. These include modelling of the chromatic adaptation, Hunt effect, Stevens effect, surround effect and lightness contrast effect.

Test Images

The distorted test images were created by changing their colours through ICC profiles gamut mapping process. Here, the absolute colorimetric rendering intent was used with four standard ICC profiles: Euroscale Uncoated, ISO Uncoated, PSR Gravure LWC, and Uncoated FOGRA. The gamut of these ICC profiles and the gamut of sRGB space in ab-plane are illustrated in Figure 1, where the visualizations have been obtained from ColorSync Utility included in Mac OS X. As can be seen from the figure, the ICC profiles can be divided into two groups based on their dimensions. This was done to ensure that there would be both larger and smaller differences between generated distortions.

The selection of images for pilot tests from the candidate images was done by calculating average CIELAB dE values and then selecting those image sets that had average colour difference values on both sides of threshold value. The threshold value for colour difference discrimination in natural images is about 2.2 dE_{ab} /11/. Finally, the selection was further narrowed to eight images. Seven of the images were from the Photos.com –database /12/ and one was from the CIE TC8-03 test image set /13/. The test images are presented in Figure 2, where the images are named as *Autumn road*, *Red field*, *Mountains*, *Forest rise*, *Red brushwood*, *Park*, *Table*, and *Picnic*.







Test environment

Subjective tests were conducted in a test room with matt grey painted walls and sealed windows. The viewing conditions in test room were adjusted to correspond to the sRGB reference viewing environment, which is presented in Table 1. According to these parameters the ambient illuminance level of the viewing conditions was set to approximately 200 lux with colour temperature of 5000 K. The illumination was done by using filtered halogen lamps. The illuminance level and the colour temperature were measured at the beginning of each test day.

Condition	sRGB
Luminance level	80 cd/m2
Illuminant White	x = 0.3127, y = 0.3291 (D65)
Image surround	20% reflectance
Encoding Ambient	
Illuminance Level	64 lux
Encoding Ambient White	
Point	x = 0.3457, y = 0.3585 (D50)
Encoding Viewing Flare	1.0%
Typical Ambient Illuminance	
Level	200 lux
Typical Ambient White Point	x = 0.3457, y = 0.3585 (D50)
Typical Viewing Flare	5.0%

Table 2. sRGB reference viewing environment

Fifteen test participants took part in the test. The age of the test participants were between 23 to 29 years, and four of them were female and eleven were men. All test participants had normal colour vision and all had normal or corrected visual acuity.

The tests were conducted on a simple image pair comparison application, which was programmed with Java. The application includes display for inputting test participant information, and two displays each presenting one image pair. The participant information is collected at the beginning of the test, and after clicking the start button, the two image pair windows are maximized to fill one display. Before starting the test, the test participant reads the instructions, including the test question: which of the two pairs has a bigger difference compared to other image pair. After these preparations, the test participant is asked to start the test by clicking the background of one of the image pair windows. This is expressed by clicking the pair that has the larger perceived colour difference (see Figure 3).



Display One



Display Two

Figure 3. Example of the pair comparison application: image pairs, one on each display, are presented to test person, who has been instructed to select the pair that is perceived to have more colour difference.

The image pairs were presented using Eizo ColorEdge CG241W displays. The displays were calibrated with Eizo ColorNavigator Calibration software. The calibration was done by using a sRGB colour space emulation, which makes it possible to achieve as close to sRGB colour space full gamut as possible. The measurements for the calibration were done using X-Rite EyeOne Pro spectrophotometer. The colour reproduction performance was worst in bluish hue areas in both displays, while the average value of CIEDE2000 colour difference was between 0.4 and 0.6. The displays were also compared with each other to test their similarity, and even though the displays were the same model there were clear differences between them (Table 3).

Table 3. Comparison of the two displays (CIEDE2000)

Average	0.81
Std. Deviation	0.72
Best 90%	0.61
Worst 10%	2.50

Subjective data

The subjective tests, as mentioned, were accomplished with psychophysical pair comparison tests. Although, the tests consist of comparison of two image pairs, the factor that is considered was the difference between two images forming a pair. Therefore, the law of comparative judgement by Torgerson /14/ was used in the analysis of the pair comparison data. The results of the subjective tests are presented in Table 4 and Table 5. Each value in the tables represents the subjective difference scale value that was calculated from the comparison judgements. One test participant from total of sixteen participants, whose judgements differed clearly from other judgements, was excluded from the data.

Table 4. Subjective difference scales for image contents Autumn road, Red fields, Mountains, and Forrest rise, and ICC profiles: (1) Euroscale Uncoated, (2) ISO Uncoated, (3) Uncoated FOGRA and (4) PSR Gravure LWC

ICC profiles \	Autumn	Red	Mountains	Forrest
images	Toau	Fields		nse
(1,2) - (1,3) *	0.201	0.280	0.183	0.580
(1,2) - (1,4)	0.178	0.461	0.318	0.258
(1,2) - (2,3)	0.175	1.223	0.283	0.372
(1,2) - (2,4)	0.059	0.363	0.506	0.087
(1,2) - (3,4)	0.065	0.624	0.383	0.174
(1,3) - (1,4)	0.380	0.181	0.500	0.322
(1,3) - (2,3)	0.377	0.943	0.465	0.208
(1,3) - (2,4)	0.260	0.083	0.688	0.667
(1,3) - (3,4)	0.267	0.344	0.566	0.406
(1,4) - (2,3)	0.003	0.762	0.035	0.113
(1,4) - (2,4)	0.119	0.098	0.188	0.346
(1,4) - (3,4)	0.113	0.163	0.066	0.084
(2,3) - (2,4)	0.117	0.860	0.223	0.459
(2,3) - (3,4)	0.110	0.599	0.100	0.198
(2,4) - (3,4)	0.007	0.261	0.123	0.261
Average	0.162	0.483	0.308	0.302

* Image pair (ICC1,ICC2) compared to Image pair (ICC1, ICC3)

Table 5. Subjective difference scales for image contents Red brushwood, Park, Table, and Picnic, and ICC profiles: (1) Euroscale Uncoated, (2) ISO Uncoated, (3) Uncoated FOGRA and (4) PSR Gravure LWC

ICC profiles \	Red	Park	Table	Picnic
images	brushwood			
(1,2) - (1,3) *	0.270	0.025	0.680	0.256
(1,2) - (1,4)	0.954	0.444	1.231	0.114
(1,2) - (2,3)	1.095	0.860	1.567	0.062
(1,2) - (2,4)	0.085	0.932	1.478	0.089
(1,2) - (3,4)	0.176	1.027	1.527	0.256
(1,3) - (1,4)	0.684	0.420	0.551	0.142
(1,3) - (2,3)	0.825	0.836	0.887	0.194
(1,3) - (2,4)	0.355	0.908	0.799	0.345
(1,3) - (3,4)	0.094	1.002	0.847	0.000
(1,4) - (2,3)	0.141	0.416	0.336	0.052
(1,4) - (2,4)	1.039	0.488	0.247	0.202
(1,4) - (3,4)	0.778	0.583	0.296	0.142
(2,3) - (2,4)	1.180	0.072	0.088	0.150
(2,3) - (3,4)	0.919	0.167	0.040	0.194
(2,4) - (3,4)	0.261	0.095	0.049	0.344
Average	0.590	0.552	0.708	0.169

* Image pair (ICC1,ICC2) compared to Image pair (ICC1, ICC3)

The average subjective difference varies significantly between images. As a high subjective difference means that relatively many test participants chose that pair as one which has higher perceived difference, meaning that differences were more clearly perceived but also that the images have higher colour differences. The lowest average subjective scale value was for images "Autumn road" and "Picnic". The highest average subjective scale value was for image "Table". The relationship between low subjective scale values and high deviation in judgement of the test participants is evident.

Performance of the metrics

The performance of the computational metrics was evaluated in relation to the differences of the resulting colour difference values between two images. Thus, a metric was capable of predicting perceptual colour difference in complex images if the difference between two calculated colour difference values correlated with the subjective difference (Table 6 and Table 7).

As can be seen from the correlation values in Table 6 and Table 7, none of the metrics outperform the others in the case of every image content. The Hue-angle metric had the best correlation for three of the images with significantly high performance, while the P-CIELAB metric had also the highest correlations in three of the image contents, two of them were with low statistical significance. The iCAM metric was the best performing metric only for two of the images, but the average correlation was the highest of the metrics indicating that the iCAM metric was the best performing metric. The second highest average correlation was for the Hue-angle metric.

Table 6. Pearson linear correlation coefficients between the subjective colour difference and predictions of CIELAB, CIE94. and CIEDE2000

	CIELAB	CIE94	CIEDE2000
Autumn road	0.113	-0.279	-0.142
Red field	0.687	-0.070	0.163
Mountains	0.797	0.210	0.647
Forest rise	-0.036	-0.061	0.109
Red brushwood	0.361	-0.042	0.077
Park	0.813	-0.045	0.324
Table	0.905	0.688	0.908
Picnic	0.011	-0.249	-0.209
Average	0.457	0.019	0.235

Table 7. Pearson linear correlation coefficients between the subjective colour difference and predictions of Hue-Angle, P-CIELAB, S-CIELAB, and iCAM

	Hue-	P-	S-	iCAM	
	angle	CIELAB	CIELAB		
Autumn road	-0.047	0.857	0.273	0.827	
Red field	0.742	0.115	0.488	0.798	
Mountains	0.878	0.331	0.868	0.563	
Forest rise	-0.046	0.323	0.195	0.070	
Red	0 471	0.201	0.110	0.650	
brushwood	0.471	-0.301	0.110	0.059	
Park	0.832	-0.090	0.637	0.542	
Table	0.937	0.839	0.670	0.544	
Picnic	0.016	0.132	0.023	0.110	
Average	0.473	0.276	0.408	0.514	

As it was discussed earlier, the correlation of the metric varied according to different judgements. If we exclude the two image contents (*Autumn Road*, *Picnic*) that have high variation in the judgements, the average correlations are rather different.

Now, the iCAM metric has the average correlation of 0.529, meaning that the metric was only the third best performing metric, while even the CIELAB metric could outperform it with average correlation of 0.588. While the best metric in terms of average correlation is now the Hue-angle metric with average correlation of 0.636.

The selection between using all eight images and six images is not straightforward. It might seem proper to use all of the images in metric performance evaluation; on the other hand, if test participants could not agree which image pair had greater difference in excluded images, then it might be proper to assume that the metrics would not need to predict the degree of perceptual colour difference that does not exists.

On the other hand, the metrics should be capable of recognizing image content and related colour difference that is not perceivable by every observer or is such a colour difference that has subjective magnitude; for example, distorted image having colour difference in blue regions compared to an image having equal difference in red regions. Hence, it would be needed to study if there are such factors in the image content that may interfere observer's conclusion of the colour difference.

Nevertheless, relatively high performance of the CIELAB metric with both sets of six and eight images is remarkable. One reason for the success of the CIELAB metric might be in the global formation of the colour difference. In such cases, the effect of structural properties of the image content is minor. For example, test images "Park" and "Table" have uniformly located colour differences that were well predicted by the metric, while the effect of image structure in test images "Autumn road" and "Red brushwood" may have a greater effect on the perceived of colour difference which was not predicted by the CIELAB.

The correlations between metrics evaluated from all values, are shown in Table 8. As can be seen, the Hue-angle and CIELAB metrics are significantly correlated with each other. This is rather remarkable when considering how complex the process of the Hue-angle metric is, although it is built on CIELAB. This indicates that the effect of image content is rather small in the Hue-angle model. The values of CIE94 were closest to CIEDE2000, while it did not have any correlation with iCAM metric, and only minor correlation with other metrics. The CIEDE2000 metric had only minor correlation with other metrics except CIELAB and CIE94.

Table 8. Correlations between metrics. (1) CIELAB, (2) CIE94, (3) CIEDE2000, (4) P-CIELAB, (5) Hue-Angle, (6) iCAM.

	2	3	4	5	6	7
1	0,387	0,706	0,004	0,914	0,648	0,786
2	-	0,843	0,330	0,262	0,045	0,272
3	-	-	0,301	0,527	0,296	0,536
4	-	-	-	-0,070	-0,103	0,005
5	-	-	-	-	0,603	0,718
6	-	-	-	-	-	0,665

Conclusions

Overall, the state of the art metrics that were tested in this study are not completely capable to predict the degree of perceived colour difference in images of complex scenes. Two metrics came up in the comparison: iCAM and Hue-angle. If all the images are considered, the iCAM is the best performing metric. While the Hue-angle metric is the best performing methods if we excluded those image contents that could not be judged without a high variation in judgements. In this case the iCAM-metric is only the third best method after CIELABmetric.

Additionally, the iCAM-metric has its strengths in image appearance modelling, while the Hue-angle metric has its advantages in modelling the effect of image structure. The future metric should be a hybrid model that has both image appearance and image structure modelling capabilities. One example of a hybrid model could be a metric that uses segmentation of colour difference map to find spatial areas that have higher impact on perceived colour difference.

References

- Luo. M. R., Cui. G., Rigg. B. The Development of the CIE 2000 Colour- Difference Formula: CIEDE2000. Color Research & Application. vol. 26. Nro. 5, 340-350 (2001).
- Moroney. N., Fairchild. M. D., Hunt. R. W. G., Li. C., Luo.
 M. R., Newman T. The CIECAM02 color appearance model. IS&T/SID 10th Color Imaging Conference, 23-27 (2002).
- [3] Zhang. X., Wandell. B. A. A Spatial Extension of CIELAB for Digital Color Image Reproduction. Proceedings of the SID Symposiums. 731-734 (1997).
- [4] Hong. G., Luo. R. Perceptually based colour difference for complex images. Proc. SPIE, vol. 4421, 618-621 (2002).
- [5] Chou. C-H., Liu. K-C. A Fidelity Metric for Assessing Visual Quality of Color Images. Proc. 16th International Conference on Computer Communications and Networks. ICCCN 2007, 1154-1159 (2007).
- [6] Fairchild. M. D., Johnson. G. M. Meet iCAM: A Next-Generation Color Appearance Model. Proc. IS&T/SID 10th Color Imaging Conference: Color Science. Systems and Applications, 33-38 (2002).
- Haderberg, J. Y., Bando, E. & Pedersen, M. (2008) Evaluating colour image difference metrics for gamut-mapped images.
 Coloration Technology, vol. 124, Nro 4, 243-253 (2008).
- [8] Wang, Z., Bovik, A. C., Sheikh, H. R., Simoncelli, E. P. Image Quality Assessment: From Error Measurement to Structural Similarity. IEEE Transactions on Image Processing, vol. 13, Nro 4, 600-612 (2004).
- [9] Wang, Z., Bovik, A. C., A universal image quality index, Signal Processing Letter, Vol. 9, Nro 3, 81-84 (2002).
- [10] Witt. K. CIE Color Difference Metrics. In: Schanda. J.
 (Edited): Colorimetry: Understanding the CIE System. John Wiley & Sons. Inc.. Hoboken. New Jersey. 79-100 (2007).
- [11] Aldaba, M. A., Linhares, J. M. M., Pinto, P. D., Nascimento, S. M. C., Amano, K., Foster, D. H. Visual sensitivity to color errors in images of natural scenes. Visual Neuroscience, vol. 23. 555-559 (2006).
- [12] Anon. (n.d) Photos.com (online). Juppiterimages. Updated 13.03.2009 [referred 13.03.2009]. Available in WWW: <URL: <u>http://www.photos.com/</u>>
- [13] CIE (2004). CIE Division 8 TC8-03: Gamut Mapping. Guidelines for the Evaluation of Gamut Mapping Algorithms

(online). Updated 02.09.2004 [referred 13.03.2009]. Available in WWW: <URL: <u>http://www.colour.org/tc8-03/guidelines.html</u>>

Author Biography

Henri Kivinen received his Master's degree in Graphic arts technology from the Aalto University, Finland (2010). This work is his Master project results at the university. Since then his work at the Aalto University has included media related research on a broader scope.

^[14] Torgerson. W. S. Multidimensional Scaling: I. Theory and Method. Pyschometrika. vol 17, Nro 4, 401-419 (1952).