PERFORMANCE OF THE EUCLIDEAN COLOR-DIFFERENCE FORMULA IN LOG-COMPRESSED OSA-UCS SPACE APPLIED TO MODIFIED-IMAGE-DIFFERENCE METRICS

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ABSTRACT

In this paper, we approach color-image-difference metrics by a Euclidean color-difference formula for small-medium color differences in log-compressed OSA-UCS space, recently published (C. Oleari, M. Melgosa and R. Huertas, *J. Opt. Soc. Am. A*, **26**(1):121–134, 2009). We start from previous image-difference metrics by replacing the CIE color-difference formulae with the new one. Tests are made by using the Pearson-, Spearman- and Kendall-correlation coefficient. Particularly, we compare the calculated image-difference metrics in relation to the perceived image difference obtained with psychophysical experiments. Current results show improvements in the actual state of art, making this formula the future key for image- difference metrics.

Keywords: Euclidean color difference, image-difference metrics, perceived image difference

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INTRODUCTION

In 1976, CIE published the CIELAB color space[1] as a uniform color space, in which the difference between two colors ΔE_{ab}^* is represented by their Euclidean distance. CIELAB metric has been used as a tool for measuring perceptual difference between uniform patches of colors in the colorant industries. Although non-appropriate, the CIELAB ΔE_{ab}^* has been used for measuring the color difference between images by computing the color difference of all the pixels and averaging. The use of the ΔE_{ab}^* formula is shown in[2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12].
The unsatisfactory uniformity of CIELAB space induced researchers to produce other color-difference data and search for better color-difference formulae.
The British Colour-Measurement Committee proposed the ΔE_{CMC} formula[13, 14], defined on the CIELAB system. The CMC formula is today the standard formula in industrial color control[14]. The ΔE_{CMC} formula represents the color tolerances in the CIELAB space by ellipsoids with semi-axis lengths depending on the point in the space and with one axis oriented as the lightness, one as the chroma and one as the hue.
In 1987, Luo and Rigg gave the BFD[15] color-difference formula providing a correction of the CMC one in the blue region[16]. Evaluation of BFD can be found in[8].
In 1994 CIE proposed the non Euclidean formula ΔE_{94}[16, 17], defined in the CIELAB space. This formula is based on the differences of lightness ΔL^*, of chroma ΔC^*, and of hue ΔH^*, as the CMC one, but with different metric factors. All these formulas (CMC, BFD and CIE94) are based mainly on the BFD color-difference data[18].
The last CIE formula for small-medium color differences is the ΔE_{00}[19] one, termed CIEDE2000 and based on a wider set of empirical data, known as COM[19] dataset.
Very recently, in 2009, a Euclidean color-difference formula for small-medium color differences in log-compressed OSA-UCS space, termed ΔE_E, has been published[20, 21]. This formula is statistically equivalent to CIEDE2000 in the prediction of many available empirical datasets, but with greater simplicity and clear relationships with visual processing.

In the years, many color-image-difference metrics have been proposed[22], some for measuring general image quality and some for detecting specific distortions. However, at the moment, no universal color-image-difference metric exists.

In 1997, Zhang and Wandell[23] proposed a spatial extension to the CIELAB color-difference formula, termed S-CIELAB. This extension is obtained by introducing a spatial filter in the pre-processing of the CIELAB color-difference formula[1], which simulates the human visual system.
Johnson and Fairchild[24] followed a similar approach, where the spatial filter is implemented in the frequency domain, obtaining a more precise control of the filter.
In 2002, Hong and Luo[25] proposed the *hue angle* algorithm, still based on the CIELAB color difference. This metric corrects some of the drawbacks with the CIELAB color difference formula and shows good results for two different images[25]. Because this metric does not include spatial filtering of the image, this is unsuitable for halftone images, where the viewing distance is crucial for the visual impression of artifacts, and for calculating perceived image differences[5, 26].
In 2008 Pedersen et al.[27] proposed two image-difference metrics with spatial filtering simulating the human visual system. These metrics, called SHAME and SHAME-II, apply a spatial filtering of the images similar to that used by Zhang and Wandell[23] and by Johnson and Fairchild[24], before applying the hue angle measure to the filtered images. These image-difference metrics have been tested on the TID2008 database[28] together with selected databases with gamut mapped images and lightness changed images.

THE TWO CONSIDERED METRICS

The first metric that we propose and analyze is the simple pixel value difference computed by ΔE_E in the Log-Compressed OSA-UCS space (fig 1 right), instead of by the ΔE_{ab}^* formula (fig 1 left).

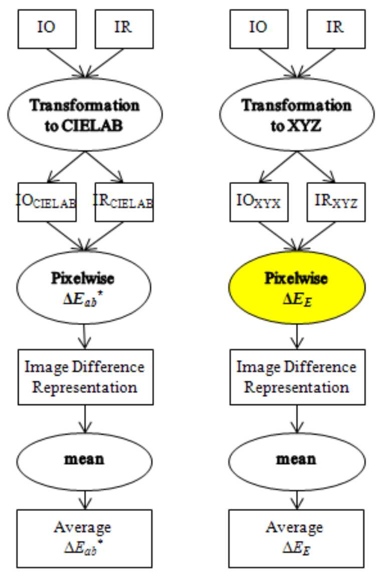

Fig 1. Computation sequence for pixelwise Image-Difference Metrics by using the ΔE_{ab}^* formula (left) and by using ΔE_E, on the right. IO means "Original Image" while IR "Reproduced Image".

The second metric that we consider is based on the S-CIELAB developed by Johnson et al.[24]. This metric works with the following steps (fig 2 left):

- the original and the reproduced image are converted into the opponent color space;
- afterwards they are spatially filtered;
- then they are converted into CIELAB color space;

- finally a pixelwise difference is computed by the ΔE_{ab}^* formula, obtaining an image-difference representation generally called S-CIELAB *representation.*

Our metric is obtained by substituting in the last step ΔE_{ab}^* with ΔE_E (fig 2 right). Let us call the obtained image-difference representation the "S-DEE representation".

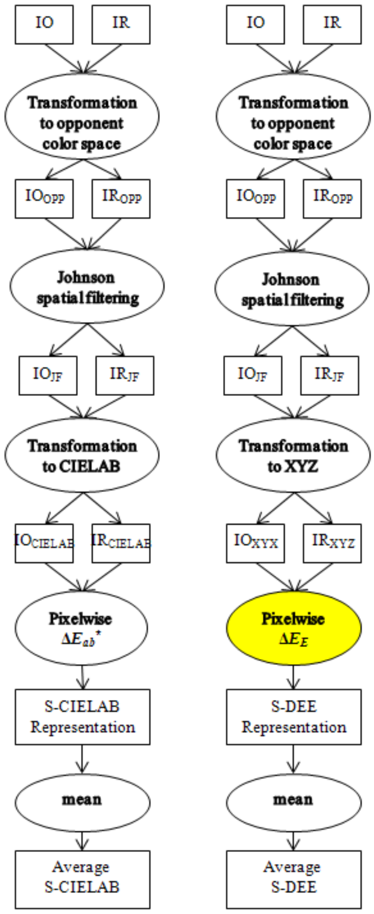

Fig 2. Computation sequence for the S-CIELAB Johnson metric by using the ΔE_{ab}^* formula (left), and for the proposed metric S-DEE by using ΔE_E (right). IO means "Original Image" while IR "Reproduced Image".

EXPERIMENTAL RESULTS AND ANALYSIS

Many different databases have been used for evaluating the image-difference metrics.
The proposed metrics are evaluated by the TID2008 database[28], which is constituted by 25 original images. These images have been altered and subdivided into seven categories representing different kind of distortions: *Noise*, *Noise2*, *Safe*, *Hard*, *Simple*, *Exotic*, *Exotic2*. Globally, the proposed metrics are tested on 1700 images.

Three types of *correlation coefficients* (CC) are computed: 1) the Pearson-product-moment CC, 2) the Spearman-rank CC and 3) the Kendall-tau-rank CC[29]. The Pearson CC assumes that the variables are ordinal and evaluate the linear relationship between two variables. The Spearman CC is a non-parametric measure of correlation and it is used as a measure of linear relationship between two sets of ranked data, instead of the actual values. This describes the relationship between variables with no assumptions on the frequency distribution of the variables and on how tightly the ranked data clusters are around a straight line. The Kendall CC is a non-parametric test used for measuring the degree of correspondence between sets of rankings where the measures are not equidistant.

Table 1. ΔE_E correlations compared to ΔE_{ab}^* ones on each category of the TID2008 database.

DATASET	Pearson correlation		Spearman correlation		Kendall correlation	
	ΔE_{ab}^*	ΔE_E	ΔE_{ab}^*	ΔE_E	ΔE_{ab}^*	ΔE_E
Noise	0.294	0.203	0.333	0.238	0.223	0.158
Noise2	0.243	**0.338**	0.297	**0.412**	0.213	**0.285**
Safe	0.336	**0.405**	0.338	**0.461**	0.221	**0.303**
Hard	0.492	***0.643***	0.466	***0.665***	0.324	***0.481***
Simple	0.418	***0.585***	0.434	***0.608***	0.309	***0.433***
Exotic	0.252	**0.311**	0.201	**0.260**	0.087	**0.133**
Exotic2	0.019	**0.049**	0.041	**0.053**	0.007	**0.017**
All	0.174	**0.212**	0.173	**0.248**	0.121	**0.166**

As shown in table 1, ΔE_E performs better than ΔE_{ab}^*, excluding the noise dataset, with equal computational complexity and time. However either ΔE_{ab}^* and ΔE_E show a low performance considering all the database set; only in the category "hard" and "simple" ΔE_E shows a reasonable result. A T-test at 5% confidence level on Spearman-correlation values confirms the performance of the metric.

Table 2. S-DEE correlations compared to S-CIELAB (Johnson) ones on each category of the TID 2008 database.

METRICS	Pearson correlation	Spearman correlation	Kendall correlation
SHAME	0.078	0.036	0.024
UIQ	0.370	0.396	0.270
Hue angle	0.452	0.507	0.383
ΔE_{ab}^*	0.464	0.618	0.472
S-CIELAB	0.467	0.637	0.488
S-CIELAB (Johnson)	0.500	0.629	0.472
SHAME-II	0.509	0.670	0.528
S-DEE	0.553	0.526	0.375
ΔE_E	0.586	0.481	0.367
SSIM	0.762	0.586	0.464

As shown in table 2, the S-DEE metric performs slightly worse than S-CIELAB Johnson, and only in the "exotic" category has a slight improvement. Both metrics show good results, considering the categories "Noise", "Safe", "Hard" and "Simple", but, considering all the database set, they show an average performance.

Table 3. ΔE_E and S-DEE compared against other metrics, considering all TID2008 database set.

METRICS	Pearson correlation	Spearman correlation	Kendall correlation
ΔE_{ab}^*	0.174	0.173	0.121
Hue angle	0.179	0.161	0.113
ΔE_E	0.212	0.248	0.166
S-DEE	0.443	0.456	0.335
S-CIELAB	0.476	0.482	0.354
S-CIELAB (Johnson)	0.542	0.538	0.400
SHAME	0.544	0.550	0.414
SSIM	0.547	0.653	0.437
SHAME-II	0.613	0.609	0.468
UIQ	0.616	0.606	0.438

Table 3. shows that: 1) The simple pixelwise difference using ΔE_E performs better than the ΔE_{ab}^* and *hue angle* metric, but it is still worse than some others metrics previously developed; 2) The S-DEE

metric performs better than ΔE_{ab}^{*}, ΔE_E and *hue angle* metric. It performs slightly worse than S-CIELAB, by Zhang et al., and S-CIELAB, by Johnson et al., while it is still not as efficient as SHAME-II, SSIM and UIQ.
Probably, the reason is in the sensitivity of ΔE_E, which is defined for small-medium color differences. Figure 3 right, extracted from the category "Noise", clearly shows the strong alteration of pixel values ending in a completely different color.

Fig 3. On the left the original image, on the right the same image with noise added.

In order to test the metrics extensively we used a dataset with gamut mapped images from Dugay[30]. Twenty different images have been gamut mapped with 5 different algorithms. The 20 different images were evaluated by 20 observers in a pair-comparison experiment. This is a more complex task for the observers, because many artifacts must be considered, and also a demanding task for the image difference metrics.

Table 4. ΔE_E and S-DEE compared against other metrics considering a dataset of gamut mapped images.

METRICS	Pearson correlation	Spearman correlation	Kendall correlation
UIQ	0.005	0.089	0.055
S-CIELAB (Johnson)	0.029	0.104	0.071
SHAME-II	0.035	0.077	0.053
ΔE_{ab}^{*}	0.042	0.107	0.071
SHAME	0.047	0.082	0.054
Hue angle	0.052	0.114	0.076
S-CIELAB	0.056	0.105	0.073
SSIM	0.163	0.054	0.044
ΔE_E	***0.345***	***0.230***	***0.155***
S-DEE	***0.376***	***0.284***	***0.190***

As shown in table 4, no one metric gives suitable results for gamut mapped images, showing a very low correlation. However ΔE_E and S-DEE show a considerable improvement that induces us to think that the Euclidean color-difference formula in log-compressed OSA-UCS could be the key to find an image-difference metric, suitable for gamut mapped images. The goodness of the ΔE_E for small-medium color differences and the absence of chromatic noise might be the reason. However further investigations must be carried out.

Finally, we tested the dataset previously used by Pedersen[6], where four images were reproduced in 32 different ways, modified in lightness, both globally and locally. This dataset differs from the previous ones because in this case the changes are only of the lightness in a controlled way. Consequently, the metrics computation is easier than in the case of gamut mapped images.

Table 5. ΔE_E and S-DEE compared against other metrics considering a dataset of images changed in lightness.

METRICS	Pearson correlation	Spearman correlation	Kendall correlation
SHAME	0.078	0.036	0.024
UIQ	0.370	0.396	0.270
Hue angle	0.452	0.507	0.383
ΔE_{ab}^*	0.464	0.618	0.472
S-CIELAB	0.467	0.637	0.488
S-CIELAB (Johnson)	0.500	0.629	0.472
SHAME-II	0.509	***0.670***	***0.528***
S-DEE	**0.553**	0.526	0.375
ΔE_E	**0.586**	0.481	0.367
SSIM	***0.762***	0.586	0.464

Table 5 shows that ΔE_E and S-DEE have the higher Pearson correlation, except for SSIM, but a lower Spearman and Kendall correlation than other metrics. This means that the ranking done by ΔE_E and S-DEE are less correct than the ranking by some other metrics, but that they have a more correct frequency distribution.

CONCLUSION

The ΔE_E color difference formula makes improvements to the previously developed image-difference metrics and, at the moment, seems promising, but more studies must be done. Future studies will encapsulate the ΔE_E in other image-difference metrics and applied to other spatial filters.

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