On the Use of Gaze Information and Saliency Maps for Measuring Perceptual Contrast

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Abstract. In this paper, we propose and discuss a novel approach for measuring perceived contrast. The proposed method comes from the modification of previous algorithms with a different local measure of contrast and with a parameterized way to recombine local contrast maps and color channels. We propose the idea of recombining the local contrast maps using gaze information, saliency maps and a gaze-attentive fixation finding engine as weighting parameters giving attention to regions that observers stare at, finding them important. Our experimental results show that contrast measures cannot be improved using different weighting maps as contrast is an intrinsic factor and it's judged by the global impression of the image.

1 Introduction

Contrast is a difficult and not very well defined concept. A possible definition of contrast is the difference between the light and dark parts of a photograph, where less contrast gives a flatter picture, and more a deeper picture. Many other definitions of contrast are also given, it could be the difference in visual properties that makes an object distinguishable or just the difference in color from point to point. As various definitions of contrast are given, measuring contrast is very difficult. Measuring the difference between the darkest and lightest point in an image does not predict perceived contrast since perceived contrast is influenced by the surround and the spatial arrangement of the image. Parameters such as resolution, viewing distance, lighting conditions, image content, memory color etc. will effect how observers perceive contrast.

First, we briefly introduce some of the contrast measures present in literature. However none of these take the visual content into account. Therefore we propose the use of gaze information and saliency maps to improve the contrast measure. A psychophysical experiment and statistical analysis are reported.

2 Background

The very first measure of global contrast, in the case of sinusoids or other periodic patterns of symmetrical deviations ranging from the maximum luminance (L_{max}) to minimum luminance (L_{min}), is the Michelson [1] formula proposed in 1927: $C^M = \frac{L_{max}-L_{min}}{L_{max}+L_{min}}$ King-Smith and Kulikowski [2] (1975), Burkhardt [3] (1984) and Whittle [4] (1986) follow a similar concept replacing L_{max} or L_{min} with L_{avg}, which is the mean luminance in the image.

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These definitions are not suitable for natural images since one or two points of extreme brightness or darkness can determine the contrast of the whole image, resulting in high contrast while perceived contrast is low. To overcome to this problem, local measures which take account of neighboring pixels, have been developed later.

Tadmor and Tolhurst [5] proposed in 1998 a measure based on the Difference Of Gaussian (D.O.G.) model. They propose the following criteria to measure the contrast in a *pixel (x,y)*, where x indicates the row and y the column:

$$c^{DOG}(x,y) = \frac{R_c(x,y) - R_s(x,y)}{R_c(x,y) + R_s(x,y)},$$

where R_c is the output of the so called central component and R_s is the output of the so called surround component. The central and surround components are calculated as:

$$R_c(x,y) = \sum_i \sum_j Centre(i-x, j-y) I(i,j),$$

$$R_s(x,y) = \sum_i \sum_j Surround(i-x, j-y) I(i,j),$$

where *I(i,j)* is image pixel at position *(i,j)*, while *Centre(x,y)* and *Surround(x,y)* are described by bi-dimensional Gaussian functions:

$$Centre(x,y) = \exp\left[-\left(\frac{x}{r_c}\right)^2 - \left(\frac{y}{r_c}\right)^2\right],$$

$$Surround(x,y) = 0.85\left(\frac{r_c}{r_s}\right)^2 \exp\left[-\left(\frac{x}{r_s}\right)^2 - \left(\frac{y}{r_s}\right)^2\right],$$

where r_c and r_s are their respective radiuses, parameters of this measure. In their experiments, using 256x256 images, the overall image contrast is calculated as the average local contrast of 1000 pixel locations taken randomly.

In 2004 Rizzi et al. [6] proposed a contrast measure, referred here as RAMMG, working with the following steps:

- It performs a pyramid subsampling of the image to various levels in the CIELAB color space.
- For each level, it calculates the local contrast in each pixel by taking the average of absolute value difference between the lightness channel value of the pixel and the surrounding eight pixels, thus obtaining a contrast map of each level.
- The final overall measure is a recombination of the average contrast for each level: $C^{RAMMG} = \frac{1}{N_l}\sum_l^{N_l}\overline{c}_l$, where N_l is the number of levels and $\overline{c}_l$ is the mean contrast in the level l.

In 2008 Rizzi et al. [7] proposed a new contrast measure, referred here as RSC, based on the previous one from 2004 [6] . It works with the same pyramid subsampling as Rizzi et al. but:

– It computes in each pixel of each level the DOG contrast instead of the simple 8-neighborhood local contrast.
– It computes the DOG contrast separately for the lightness and the chromatic channels, instead of only for the lightness; the three measures are then combined with different weights.

The final overall measure can be expressed by the formula:

$$C^{RSC} = \alpha \cdot C^{RSC}_{L*} + \beta \cdot C^{RSC}_{a*} + \gamma \cdot C^{RSC}_{b*},$$

where α, β and γ represent the weighting of each channel.

Pedersen et al. [8] evaluated five different contrast measures in relation to observers perceived contrast. The results indicate room for improvement for all contrast measures, and the authors proposed using region-of-interest as one possible way for improving contrast measures, as we will do in this paper.

In 2009 Simone et al. [9] analyzed in details the previous measures proposed by Rizzi et al. [6,7] and they developed a framework for measuring perceptual contrast that takes account lightness, chroma information and weighted pyramid levels. The overall final measure of contrast is given by equation: $C^{MLF} = \alpha \cdot C_1 + \beta \cdot C_2 + \gamma \cdot C_3$, where α, β and γ are the weights of each color channel.

The overall contrast in each channel is defined as follows: $C_i = \frac{1}{N_l} \sum_l^{N_l} \lambda_l \cdot \overline{c}_l$, where N_l is the number of levels, $\overline{c}_l$ is the mean contrast in the level l, λ_l is the weight assigned to each level l, and i indicates the applied channel.

In this framework α, β, γ, and λ can assume values from particular measures taken from the image itself as for example the variance of pixel values in each channel separately. In this framework RAMMG and RSC previously developed can be considered just special cases with uniform weighting of levels and uniform weighting of channels.

Eye tracking has been used in a number of different color imaging research projects with great success, allowing researchers to obtain information on where observers gaze. Babcock et al. [10] examined differences between rank order, paired comparison, and graphical rating tasks by using an eye tracker. The results showed a high correlation of the spatial distributions of fixations across the three tasks. Peak areas of attention gravitated toward semantic features and faces. Bai et al. [11] evaluated S-CIELAB, an image difference metric, on images produced by the Retinex method by using gaze information. The authors concluded that the frequency distribution of gazing area in the image gives important information on the evaluation of image quality. Pedersen et al. [12] used a similar approach to improve image difference metrics.

Endo et al. [13] showed that individual distribution of gazing points were very similar among observers for the same scenes. The results also indicate that each image has a particular gazing area, particularly images containing human faces.

While Mackworth and Morandi [14] found that a few regions in the image dominated the data. Informative areas had a tendency to receive clusters of fixations. Half to two-thirds of the image receive few or no fixations, these areas (for example texture) were predictable, containing common objects and not very informative. While more recent research by Underwood and Foulsham [15] found that highly salient objects attracted fixations earlier than less conspicuous objects. Walther and Koch [16] introduced a model for computing salient objects, which Sharma et al. [17] modified to account for a high level feature, human faces .While Rajashekar et al. [18] proposed a gaze-attentive fixation finding engine (GAFFE) that uses a bottom-up model for fixation selection in natural scenes. Testing showed that GAFFE correlated well with observers, and could be used to replace eye tracking experiments.

Assuming that the whole image is not weighted equally when we rate contrast, some areas will be more important than other. Because of this we propose to use region-of-interest to improve contrast measures.

3 Experiment Setup

In order to investigate perceived contrast a psychophysical experiment with 15 different images (Figure 1) was set up asking observers to judge perceptual contrast in images while recording their eye movements.

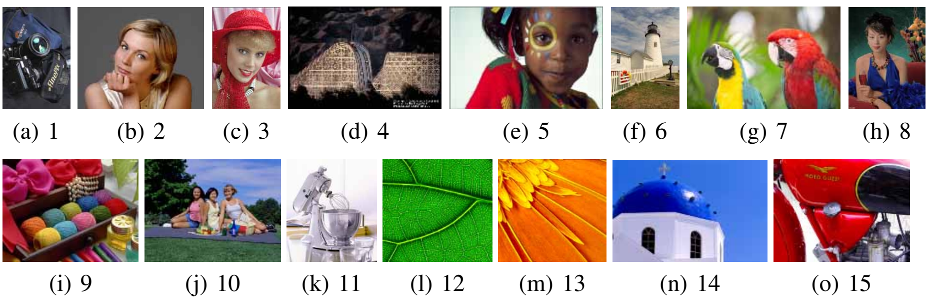

Fig. 1. Images 1 to 15 were used in the experiment, each representing different characteristics. The dataset is similar to the one used by Pedersen et al. [8]. Images 1 and 2 provided by Ole Jakob Bøe Skattum, image 10 is provided by CIE, images 8 and 9 from ISO 12640-2 standard, images 3, 5, 6 and 7 from Kodak PhotoCD, images 4, 11, 12, 13, 14 and 15 from ECI Visual Print Reference.

17 observers were asked to rate the contrast in the 15 images. Nine of the observers were considered experts, i.e. had experience in color science, image processing, photography or similar, and eight were considered non-experts with none or little experience in these fields. Observers rated contrast on a scale from 1 to 100, where 1 was the lowest contrast and 100 maximum contrast. Each image was shown for 40 seconds with the rest of the screen black, and the observers stated the perceived contrast within this time limit. The experiment was carried out on a calibrated CRT monitor, LaCIE electron 22 blue II, in a gray room with the observers seated approximately 80 cm from the screen. The lights were dimmed and measured to approximately 17 lux. During the experiment the observer's gaze position was recorded using a SMI iView X RED, a contact free gaze measurement device. The eye tracker was calibrated in nine points for each observer before commencing the experiment.

4 Weighting Maps

Previous studies have shown that there is still room for improvement for contrast measures [8,7]. We propose to use gaze information, saliency maps and a gaze-attentive fixation finding engine to improve contrast measure. Regions that draw attention should be weighted higher than regions that observers do not look at or pay attention to.

4.1 Gaze Information Retrieval

Gaze information have been used by researches to improve image quality metrics, the region-of-interest have been used as a weighting map for the metrics. We use a similar approach, and apply gaze information as a weighting map for the contrast measures. From the eye tracking data a number of different maps have been calculated, among them time used at one pixel multiplied with the number of times the observer fixated on this pixel, the number of fixations at the same pixel, mean time at each pixel and time. All of these have been normalized by the maximum value in the map, and a Gaussian filter corresponding to the 2-degree visual field of the human eye was applied to the map to even out differences [11] and to simulate that we look at an area rather than one particular pixel [19].

4.2 Saliency Map

Gathering gaze information is time consuming, and because of this we have investigated other ways to obtain similar information. One possibility is saliency maps, which is a map that represents visual saliency of a corresponding visual scene. One proposed model was introduced by Walther and Koch [16] for bottom-up attention to salient objects, and this has been adopted for the saliency maps used in this study. The saliency map has been computed at level one (i.e. the size of the saliency map is equal to original images) and seven fixations (i.e. giving the seven most salient regions in the image), for the other parameters standard values in the SaliencyToolbox [16] have been used.

4.3 A Gaze-Attentive Fixation Finding Engine

Rajashekar et al. [18] proposed "gaze-attentive fixation finding engine" (GAFFE) based on statistical analysis of image features for fixation selection in natural scenes. The GAFFE uses four foveated low-level image features: luminance, contrast, luminance-bandpass and contrast-bandpass to compute the simulated fixations of a human observer. The GAFFE maps have been computed for 10, 15 and 20 fixations, where the first fixation has been removed since this always is placed in the center resulting in a total of 9, 14 and 19 fixations. A Gaussian filter corresponding to the 2-degree visual field of the human eye was applied to simulate that we look at an area rather than at one single point and a larger filter (approximately 7-degree visual field) was also tested.

5 Results

This section analyzes the results of the gaze maps, saliency maps and GAFFE maps when applied to contrast measures.

5.1 Perceived Contrast

The perceived contrast for the 15 images (Figure 1) from 17 observers were gathered. After investigation of the results we found that the data cannot be assumed to be normally distributed, and therefore a special care must be given to the statistical analysis. One common method for statistical analysis is the Z-score [20], this require the data to be normally distributed, and in this case this analysis will not give valid results. Just using the mean opinion score will also result in problems, since the dataset cannot be assumed to be normally distributed. Because of this we use the rank from each observer to carry out a Wilcoxon signed rank test, a non-parametric statistical hypothesis test. This test does not make any assumption on the distribution, and it's therefore an appropriate statistical tool for analyzing this data set.

The 15 images have been grouped into three groups based on the Wilcoxon signed rank test: high, medium and low contrast. From the signed rank test observers can differentiate between the images with high and low contrast, but not between high/low and medium contrast. Images 5, 9 and 15 have high contrast while images 4, 6, 8 and 13 have low contrast. This is further used to analyze the performance of the different contrast measures and weighting maps.

5.2 Contrast Algorithm

The contrast measures used are the ones proposed by Rizzi et al [6,7]. RAMMG and RSC. Both measures were used in their extended form in the framework, explained above, developed by Simone et al. [9] with particular measures taken from the image itself as weighting parameters. The most important issues are:

- The overall measure of each channel is a weighted recombination of the average contrast for each level.
- The final measure of contrast is defined by a weighted sum of the overall contrast of the three channels.

In this new approach each contrast map of each level is weighted pixelwise with its relative gaze information or saliency map or gaze-attentive fixation finding engine (Figure 2).

We have tested many different weighting maps, and due to page limitations we cannot show all results. We will show results for fixations only, fixations multiplied with time, saliency, 10 fixation GAFFE map (GAFFE10), 20 fixations big Gaussian GAFFE

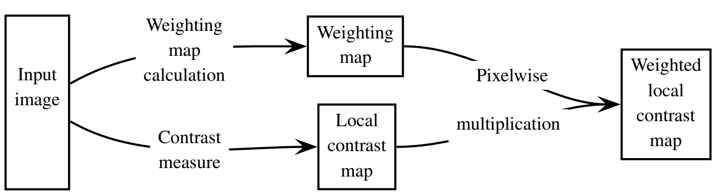

Fig. 2. Framework for using weighting maps with contrast measures. As weighting maps we have used gaze maps, saliency maps and GAFFE maps.

Table 1. Resulting p values for RAMMG maps. We can see that the different weighting maps have the same performance as no map at a 5% significance level, indicating that weighting RAMMG with maps does not improve predicted contrast.

Map	fixation only	fixation $\times$ time	saliency	GAFFE10	GAFFEBG20	no map
fixation only	1.000	1.000	0.625	0.250	0.125	0.500
fixation $\times$ time	1.000	1.000	1.000	0.250	0.375	0.500
saliency	0.625	1.000	1.000	0.250	1.000	0.625
GAFFE10	0.250	0.250	0.250	1.000	0.063	1.000
GAFFEBG20	0.125	0.375	1.000	0.063	1.000	0.063
no map	0.500	0.500	0.625	1.000	0.063	1.000

Table 2. Resulting p values for RSC maps. None of the weighting maps are significantly different from no map, indicating that they have the same performance at a 5% significance level. There is a difference between salicency maps and gaze maps (fixation only and fixation $\times$ time), but since these are not significantly different from no map they do not increase the contrast measure's ability to predict perceived contrast. Gray cells indicate significant difference at a 5% significance level.

Map	fixation only	fixation $\times$ time	saliency	GAFFE10	GAFFEBG20	no map
fixation only	1.000	1.000	0.016	0.289	0.227	0.500
fixation $\times$ time	1.000	1.000	0.031	0.508	0.227	1.000
saliency	0.016	0.031	1.000	1.000	0.727	0.125
GAFFE10	0.289	0.508	1.000	1.000	0.688	0.727
GAFFEBG20	0.227	0.227	0.727	0.688	1.000	0.344
no map	0.500	1.000	0.125	0.727	0.344	1.000

map (GAFFEBG20) and no map. The maps that were excluded are time only, mean time, 15 fixation GAFFE map, 20 fixations GAFFE map, 10 fixations big Gaussian GAFFE map, 15 fixations big Gaussian GAFFE map, and 6 combinations of gaze maps and GAFFE maps. All of these maps that have been excluded show no significant difference from no map, or have a lower performance than no map.

In order to test the performance of the contrast measures with different weighting maps and parameters, an extensive statistical analysis has been carried out. First, the images have been divided into two groups: ”high contrast” and ”low contrast” based on the user rating. Only the images having a statistically significant difference in user rated contrast were taken into account. The two groups have gone through the Wilcoxon rank sum test for each set of parameters of the algorithms. The obtained p values from this test rejected the null hypothesis that the two groups are the same, therefore indicating that the contrast measures are able to differentiate between the two groups of images with perceived low and high contrast. Thereafter these p values have been used for a sign test to compare each map against each other for all parameters and each set of parameters against each other for all maps. The results from this analysis indicate whether using a weighting map is significantly different from using no map, or if a parameter is significantly different from other parameters. In case of a significant difference further analysis is carried out to indicate whether the performance is better or worse for the tested weighting map or parameter.

5.3 Discussion

As we can see from Table 1 and Table 2, using maps is not significantly different from not using them as they have the same performance at a 5% significance level. We can

Table 3. Resulting *p* values for RAMMG parameters. Gray cells indicate significant difference at a 5% significance level. RAMMG parameters are the following: color space (CIELAB or RGB), pyramid weight, and the three last parameters are channel weights. "var" indicates the variance.

Parameters	LAB-1-1-0-0	LAB-1-0.33-0.33-0.33	RGB-4-var1-var2-var3	LAB-4-0.33-0.33-0.33	LAB-4-0.5-0.25-0.25	LAB-4-var1-var2-var3
LAB-1-1-0-0	1.000	0.092	0.000	0.002	0.000	0.000
LAB-1-0.33-0.33-0.33	0.092	1.000	0.012	0.012	0.001	0.001
RGB-4-var1-var2-var3	0.000	0.012	1.000	1.000	0.500	0.500
LAB-4-0.33-0.33-0.33	0.002	0.012	1.000	1.000	1.000	1.000
LAB-4-0.5-0.25-0.25	0.000	0.001	0.500	1.000	1.000	1.000
LAB-4-var1-var2-var3	0.000	0.001	0.500	1.000	1.000	1.000

Table 4. Resulting *p* values for RSC parameters. Gray cells indicate significant difference at a 5% significance level. RSC parameters are the following: color space (CIELAB or RGB), radius of the centre Gaussian, radius of the surround Gaussian, pyramid weight, and the three last parameters are channel weights. "m" indicates the mean.

Parameters	LAB-1-2-1-0.33-0.33-0.33	LAB-1-2-1-0.5-0.25-0.25	LAB-1-2-1-1-0-0	RGB-1-2-4-0.33-0.33-0.33	RGB-2-4-4-m1-m2-m3	RGB-2-3-4-m1-m2-m3	LAB-2-3-4-0.5-0.25-0.25
LAB-1-2-1-0.33-0.33-0.33	1.000	1.000	0.000	0.454	0.000	0.000	0.289
LAB-1-2-1-0.5-0.25-0.25	1.000	1.000	0.000	0.454	0.000	0.000	0.289
LAB-1-2-1-1-0-0	0.000	0.000	1.000	0.000	0.581	0.774	0.000
RGB-1-2-4-0.33-0.33-0.33	0.454	0.454	0.000	1.000	0.000	0.000	0.004
RGB-2-4-4-m1-m2-m3	0.000	0.000	0.581	0.000	1.000	0.219	0.000
RGB-2-3-4-m1-m2-m3	0.000	0.000	0.774	0.000	0.219	1.000	0.000
LAB-2-3-4-0.5-0.25-0.25	0.289	0.289	0.000	0.004	0.000	0.000	1.000

see only a difference between saliency maps and gaze maps (fixation only and fixation × time), but since these are not significantly different from no map they do not increase the ability of the contrast measures to predict perceived contrast. The contrast measures with the use of maps have been tested in the framework developed by Simone et al. [9] with different settings shown in Table 3 and Table 4. For RAMMG the standard parameters (LAB-1-1-0-0-0 and LAB-1-0.33-0.33-0.33) perform significantly worse than the other parameters in the table. For RSC we noticed that three parameters are significantly different from the standard parameters (LAB-1-2-1-0.33-0.33-0.33 and LAB-1-2-1-0.5-0.25-0.25) but after further analysis of the underlying data these ones perform worse than the standard parameters.

(a) Original (b) Relative local contrast map (c) Saliency weighted local contrast map

Fig. 3. The original, the relative local contrast map and saliency weighted local contrast map

We can see from Figure 3 that using a saliency map for weighting discards relevant information used by the observer to judge perceived contrast since contrast is a complex feature and it is judged by the global impression of the image.

5.4 Validation

In order to validate the results with other dataset we have carried out the same analysis for 25 images, each with four contrast levels, from the TID2008 database [21]. The score from the two contrast measure have been computed for all 100 images and a similar statistical analysis is carried out as above but for four groups (very low contrast, low, high and very high contrast). The results from this analysis supports the findings from the first dataset, where using weighting maps did not improve the performance of the contrast measures.

6 Conclusion

The results in this paper shows that weighting maps, from gaze information, saliency maps or GAFFE maps does not improve contrast measures to predict perceived contrast in digital images. This suggests that region-of-interest cannot be used to improve contrast measures as contrast is an intrinsic factor and it's judged by global impression of the image. This indicates that further work on contrast measures should be carried out accounting for the global impression of the image while preserving the local information.

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