

# ACE: An Automatic Color Equalization Algorithm

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## Abstract

In this work we present a new algorithm for digital images unsupervised enhancement, called ACE for Automatic Color Equalization. It is based on a new computational approach that merges the "Gray World" and "White Patch" equalization mechanisms, while taking into account the spatial distribution of color information. Inspired by some adaptation mechanisms of the human visual system, ACE is able to adapt to widely varying lighting conditions, and to extract visual information from the environment efficaciously. ACE has shown promising results in solving the color constancy problem and performing an image dynamic data driven stretching. Tests and results are presented.

## Introduction

The basic idea of this work is to develop a digital image automatic enhancement algorithm, mimicking some characteristics of the Human Visual System (HVS), whose efficiency is due to its smart adaptive mechanisms, in particular *color constancy* and *lightness constancy*. Since we aim at solving a specific digital image enhancement problem, we do not need to take into account the inner mechanisms of the HVS lightness and color adaptation properties. In particular, we focused our attention on the following points:

- chromatic channels independent adaptation
- white patch adapting behavior
- gray world adapting behavior
- lateral inhibition mechanism
- local-global adaptation

The lightness constancy adaptation makes us perceive as medium gray the objects which reflect the average luminance of a scene. In terms of histogram properties of a digital image, this corresponds to a level distribution which has its center mass around the middle value (e.g. 128 in eight bit channel depth). When this happens separately between the three chromatic channels, some global chromatic dominant can be eliminated.<sup>1</sup> We refer to this mechanism as *gray world*. This correction mechanism fails to achieve color constancy when used

alone,<sup>2</sup> but it is an important component of the adaptation process. In some cases the HVS normalizes its channel values, maximizing towards a hypothetical white reference area. We refer to this mechanism as *white patch*.<sup>3</sup>

At first sight white patch and gray world can be seen in opposition to each other, but they can actually be part of the same model.

Channel independence, gray world and white patch hypothesis do not account for all the aspects of appearance: we need to take into account also spatial relationships. To achieve this aim, we consider mechanisms of lateral inhibition and local and global contrast relationships. All this features allow us to approximate visual appearance of a scene, solving typical configurations, where identical stimuli in different contexts appear different.

## ACE Basic Schema

The algorithm has been implemented following the scheme shown in Fig.1: a first stage accounts for a chromatic spatial adaptation (responsible of color constancy) and a second stage, dynamic tone reproduction scaling, configures the output range to implement an accurate tone mapping.

The first stage merges the gray world and white patch approaches and performs a sort of lateral inhibition mechanism, weighted by pixel distance. The result is a local-global filtering.

The second stage maximizes the image dynamic, normalizing the white at a global level only.

No user supervision, no statistics and no data preparation are required by the algorithm.

In figure 1,  $I$  is the input image,  $R$  is an intermediate result and  $O$  is the output image; subscript  $c$  denotes the channel.

### Chromatic / Spatial Adaptation

The first stage, the Chromatic/Spatial adaptation, produces an output image  $R$  in which every pixel is recomputed according to the image content, approximating the visual appearance of the image. Each pixel  $p$  of the output image  $R$  is computed separately for each channel  $c$  as shown in equation (1).

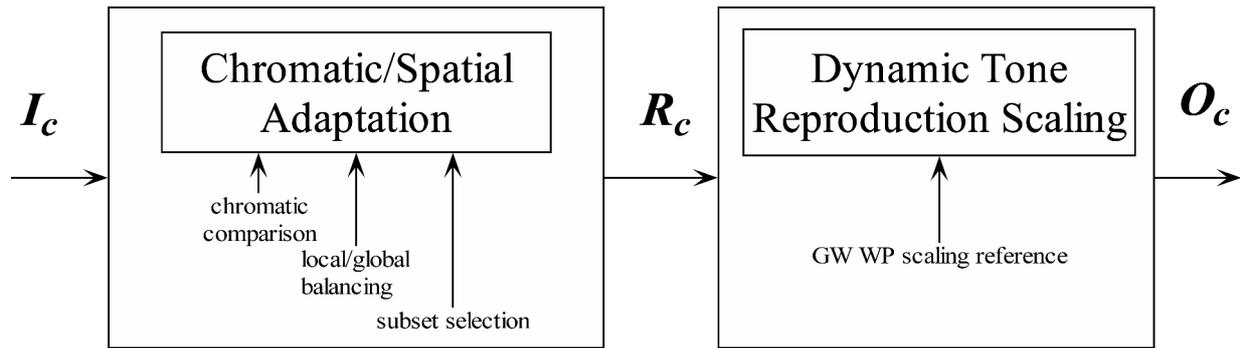


Figure 1. ACE basic schema

$$R_c(p) = \frac{\sum_{j \in \text{Subset}, j \neq p} \frac{r(I(p) - I(j))}{d(p, j)}}{\sum_{j \in \text{Subset}, j \neq p} \frac{r_{\max}}{d(p, j)}} \quad (1)$$

$I(p) - I(j)$  accounts for the lateral inhibition mechanism,  $d(p, j)$  is a distance function which weights the amount of local or global contribution,  $r(\cdot)$  is the function, discussed below, that accounts for the relative lightness appearance of the pixel. The pixel computation can be extended to the whole image or restricted to a *Subset*.

The lower part of the fraction has been introduced to balance the filtering effect of pixels near the border, avoiding a vignetting effect.

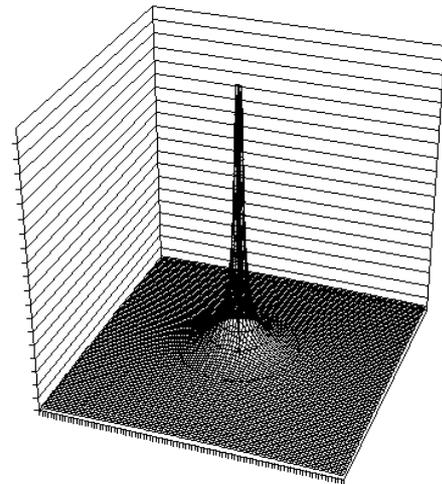
### Lateral Inhibition Mechanism

The lateral inhibition mechanism is realized by computing the difference between each pixel value and all other pixels of the selected image subset. This “difference mechanism” enhances the contrast, tuned by  $r(\cdot)$ , the chromatic adaptation function.

### The Global/Local Effect

The distance  $d(\cdot)$  weights the global and local filtering effect. It is well known that both the effects are present in the HVS. Global models, in fact, are not able to simulate several local chromatic adaptation effects, e.g. the simultaneous contrast or the Mach bands.

Different  $d(\cdot)$  functions have been tested. Some functions seem to achieve better results than others, but a best function has not yet been found. Among the distances considered are:  $r$  (the Euclidean distance),  $1/e^{-ar}$ , the *Manhattan* distance,  $r^2$ , *Manhattan*<sup>2</sup>. Even if only the last two distances gave unsatisfactory results, the choice of distance function requires deeper investigation. For the tests in this paper we have chosen the Euclidean distance  $r$ , so the distance weighting function ( $1/r$ ) has the shape shown in Fig. 2.


 Figure 2. 3D shape of the weighting function  $1/r$ 

### The Relative Lightness Appearance

For each pixel of the image  $r(\cdot)$ , and  $d(\cdot)$ , control the contrast interaction, accounting for the spatial channel lightness adaptation. It computes all the single contributions of the image content (weighted by  $d(\cdot)$ ) to each final pixel value in the output image.

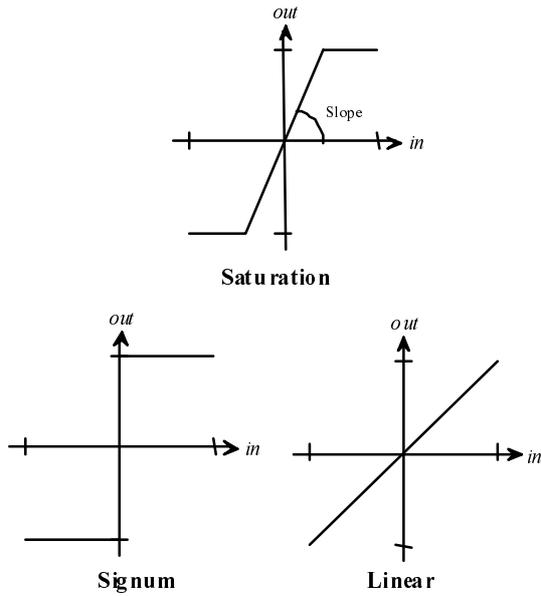
To perform a gray world mechanism,  $r(\cdot)$  has to be an odd function, while the white patch mechanism is obtained by a non-linear enhancement of small differences between neighbor pixels.

We have tested different  $r(\cdot)$  functions, trying to implement an effective white patch mechanism. Table 1 displays the tested functions, the codes mean: LI=Linear, SG=Signum, SA=Saturation.

 Table 1. Different  $r$  Functions

Code	Parameter	Range
LI	-	-
SG	-	-
SA	Slope	$[1, \infty)$

The function listed in Table 1 are shown in Fig. 3.


 Figure 3. Proposed  $r(\cdot)$  functions

Linear and Signum functions can be seen as limit cases of Saturation function with unitary or infinite slope respectively. For the test of this paper we have chosen Saturation with a slope value 20.

### Dynamic Tone Reproduction Scaling

The second stage maps the intermediate pixels array  $R$  into the final output image  $O$ .

In this stage not only a simple dynamic maximization can be made (linear scaling), also different reference values can be chosen in the output range to map into gray levels the relative lightness appearance values of each channel.

According to the chosen reference point an additional global balance between gray world and white patch is added.

The following two scaling methods can be used to obtain a standard 24 bit output image from the signed floating point array  $R$ .

#### Linear Scaling:

This simple method scales linearly the range of values in  $R_c$  independently on each channel to the range  $[0,255]$  by the formula:

$$O_c(p) = \text{round}[127.5 + s_c R_c(p)] \quad (2)$$

where  $s_c$  is the slope of the segment  $[(m_c, 0), (M_c, 255)]$ , with

$$M_c = \max_p[R_c(p)] \quad (3)$$

and

$$m_c = \min_p[R_c(p)] \quad (4)$$

In this case the linear mapping fills exactly the available dynamic range without further adaptation.

#### White Patch / Gray World Scaling:

This alternative method, yields better results, by scaling linearly the values in  $R_c$  with the same formula, but using  $M_c$  as white reference and the zero value in  $R_c$  as an estimate for the medium gray reference point to compute the slope  $s_c$ .

For this reason, the available dynamic could not be used entirely, or tones around the very dark values could be lost. It could also happen that some values in  $O_c$  result in negative values. In this case, the values lower than zero are set to zero.

The second method adds a global gray world adaptation in the final scaling, thus the dynamic of the final image is always centered around the medium gray.

### Tests

We measured the algorithm capability to perform color constancy, calculating the mean CIELA\*b\*  $\Delta E$  distance between all the pixels of two images of the same size:

$$\Delta E_{mean} = \frac{\sum_{x=0}^{sizex} \sum_{y=0}^{sizey} \Delta E(I_1(x,y), I_2(x,y))}{N} \quad (5)$$

where  $I_1$  and  $I_2$  are the images to be compared and  $N$  is the pixel's image number.

We have used two test image sets: the University of East Anglia (UEA) uncalibrated color image database and a set of six synthetic images generated by a photometric ray tracer program from the same 3D scene under six different lighting conditions.

The UEA uncalibrated colour image database is a database of 392 design images comprising 28 individual design images under three light sources using four digital cameras (ranging from a high-end studio camera to low-end personal camera) and two commercial scanners arbitrarily chosen. The images were acquired under a CIE A light, a D65 light and a TL84 light.

In this preliminary test phase, we have tested the algorithm only on the image set acquired with the Fuji Mx-700 consumer digital camera.

The six synthetic images<sup>4</sup> have been generated with a photometric ray-tracing algorithm described in Ref. 5 from a 3D living room model. An example is shown in Fig. 4. The light sources used were the A, B, C, D65 standard CIE illuminant and a Hg lamp; the latter image was obtained using a mix of this illuminants.

### Results

In these two image sets, we measured the mean  $\Delta E$  chromatic distance for any couple of the same subject under different illuminants before and after the filtering. The results are presented in the Tables 2 and 3.

The same procedure was used on the UEA uncalibrated color image database on every pattern obtaining the results summarized table 4.



Figure 4. A test synthetic image



Figure 5. A test image with its histogram

Table 2. Mean  $\Delta E$  between synthetic images before filtering

Before	A	B	C	D65	Hg	Mix
A	0					
B	36.12	0				
C	52.56	17.06	0			
D65	48.56	12.51	6.45	0		
Hg	46.1	18.42	21.05	19.15	0	
Mix	27.1	9.52	25.76	21.55	24.49	0

Table 3. Mean  $\Delta E$  between ACE filtered synthetic images

Filtered	A	B	C	D65	Hg	Mix
A	0					
B	6.19	0				
C	7.22	1.81	0			
D65	6.94	1.68	1.33	0		
Hg	8.48	5.05	5	5.09	0	
Mix	8.74	8.08	8.63	8.46	10.34	0

Table 4. Mean  $\Delta E$  across the 3 illuminants for each image in UEA DB, before and after ACE filtering and relative ratio

N°	Before	After	After/Before
1	40,72	19,73	0,48
2	44,34	17,23	0,39
3	40,39	26,69	0,66
4	41,76	15,53	0,37
5	-	-	-
6	37,64	18,66	0,5
7	42,11	20,53	0,49
8	41,30	15,20	0,37
9	45,15	25,33	0,56
10	41,96	26	0,62
11	39,53	17,29	0,44
12	47,97	23,05	0,48
13	48,26	24,6	0,51
14	39,84	14,06	0,35
15	38,54	11,52	0,3
16	39,96	13,61	0,34
17	47,12	28,37	0,6
18	42,7	30,97	0,73
19	41,49	15,34	0,37
20	47,89	25,26	0,53
21	43,19	22,03	0,51
22	38,18	17,47	0,46
23	41,16	22,46	0,55
24	40,27	20,11	0,5
25	43,18	18,27	0,42
26	39,87	15,95	0,4
27	44,78	37,29	0,83
28	42,12	27,66	0,66
<b>Mean</b>	<b>42,27</b>	<b>21,12</b>	<b>0,5</b>

The effect of the algorithm on the image dynamic can be seen in Figures 5 and 6, where the same image with its histogram is shown before (Fig. 5) and after the ACE filtering (Fig.6).

A downloadable version of ACE and a more detailed presentation of the results can be found at Ref. 4.

## Conclusion

An unsupervised image color correction algorithm, called ACE, has been presented. It derives from a new model that tries to mimic relevant adaptation behaviors of the human visual system, like lightness constancy and color constancy. ACE is an ongoing research, to tune some of its internal functions and parameters further investigations and tests are necessary, while preliminary results are very promising. ACE has demonstrated to perform an effective color constancy correction and a satisfactory tone reproduction. An interesting ACE characteristic is its simultaneous global and local filtering effect.

One of the future research directions is the integration of ACE in an image synthesis framework in order to compute photorealistic images of virtual worlds.

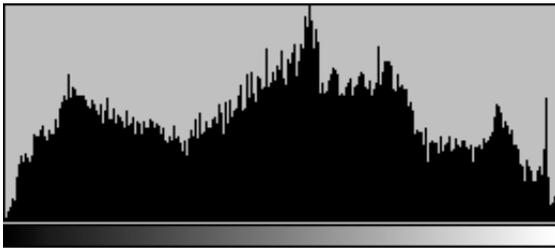


Figure 6. The image of Fig. 5 and its histogram after the ACE filtering

## References

1. G. Buchsbaum, "A spatial processor model for object color perception", J. Franklin inst., 1980, 310 (1), pp. 1-26.
2. A. Rizzi, C. Gatta, "Color Correction between Gray World and White Patch", EI2002 IS&T/SPIE's Electronic Imaging 2002, San Jose', California (USA), 20-25/01/02.
3. B. Funt and V. Cardei, "Committee-based color constancy", J.Opt.Soc.Am. A, 1994, Vol. 11 (11), pp. 3011-3020.

4. <http://saturn.media.dsi.unimi.it/~marini/CGIV02/ace.html>.
5. D. Marini, A. Rizzi, M. Rossi, "Color constancy measurements for synthetic image generation", Journal of Electronic Imaging, Vol. 8, N.4, october 1999, pp.394-403.

## Biography

Carlo Gatta graduated in Electronic Engineering at the University of Brescia with the thesis "Algorithms and methodologies for automatic color equalization inspired by the human visual system". His main research topics are computer vision with particular attention to color adaptation mechanisms and lossless image compression algorithms.

Alessandro Rizzi graduated in Computer Science at the University of Milano he received a PhD in Information Engineering at the University of Brescia. He taught Information Systems and Computer Graphics at the University of Brescia and Politecnico of Milano. Now he is assistant professor at the University of Milano teaching Human Computer Interaction. His main research topic is the use of color information in computer vision with a special focus on color adaptation mechanisms.

Daniele Marini graduated in Physics at the University of Milano in 1972; he is associate professor at the Department of Scienze dell'Informazione, of the same University. Since 1978 his research encompasses several areas of graphics and image processing, with specific reference to visual simulation, realistic visualization, classification, image recognition and compression. He published more than 120 scientific and dissemination papers as well as three books. He is teaching Computer Graphics and Image Processing for the Graduation Program on Informatics.