Natural Scenes Enhancement by Adaptive Color Correction

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Abstract — *An innovative solution for automatic color rendition of natural digital images is presented. It is based on an adaptive color correction, driven by a natural scene classifier designed over a wide database of digital images used as reference. The perceived quality of the processed images is globally closer to the expected color rendition for a great part of observers, without evident artifacts. A visual comparison with two wide diffused automatic and semi-automatic color enhancement tools is also presented.*

Index Terms – Natural scene classifier, adaptive color correction.

I. INTRODUCTION

THE wide diffusion of imaging consumer devices (Digital Still Cameras, Imaging Phones, ...) coupled with the increased overall performances capabilities, suggests color image processes aimed to perform image enhancement global [1] or semantic based [2]. For still pictures of natural scenes (e.g. landscape, portrait, etc,) a wide accepted assumption [3][4][5] is that the colors related to a few classes have the most perceptive impact on the human visual system. These studies show that basic chromatic classes are essentially: *skin, vegetation, sky/sea*. While most enhancement techniques are completely blind to scene content, the proposed technique aims to improve the visual quality of natural scene images by strongly relying on actual, and expected, image appearance. The design of the algorithm has been preceded by the collection of reliable statistics on sample images, to be used for the purpose of image classification, allowing at the same time the identification of target colors for the various classes. It is based on a two steps process: a scene classifier aimed to label each pixel as belonging to a particular chromatic class, followed by an automatic color correction step with dynamic range and intensity level preserving capabilities. A series of subjective experiments, in which involved people were asked about the perceived quality of the color corrected images, confirm the effectiveness of the proposed algorithm even when compared with some of commercial available tools. The paper is structured as follows. The next Section describes the basic blocks of the proposed enhancement strategies; sections from III to V explain in detail the single steps reporting also some examples, whereas section VI reports the obtained results. A brief conclusive section pointing to future evolutions is also included.

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II. ALGORITHM DESCRIPTION

The algorithm can be viewed as composed of two different processes, image classification and color enhancement. The classification analyzes the input image, and relying on experimentally derived statistics and rules, assigns pixels to a set of fixed semantic classes. The classification, after a further refinement processing, is feed to the enhancement block to drive the adaptive, modulated, class based, color rendition process. The design of the algorithm relies on consistent color statistics for each considered class that have been obtained from a collected sample images database. Figure 1 and 2 show a block based description of the algorithm.

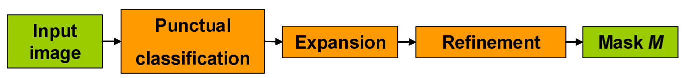


Figure 1. A block description of the various steps employed to generate the classification mask *M*.

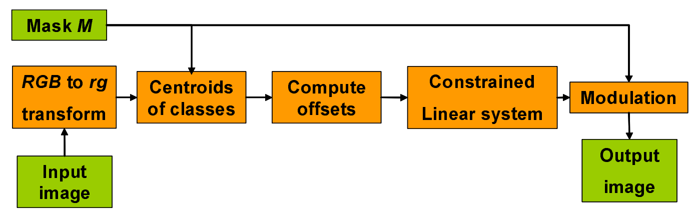
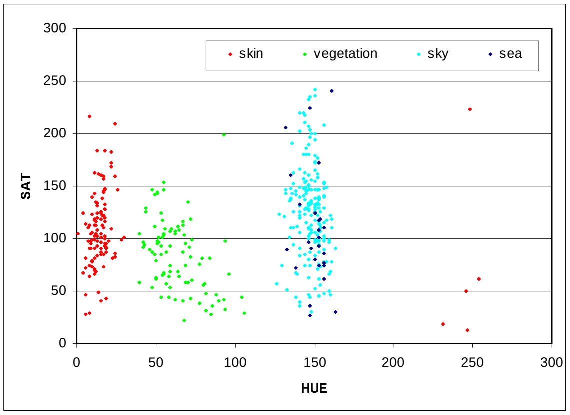


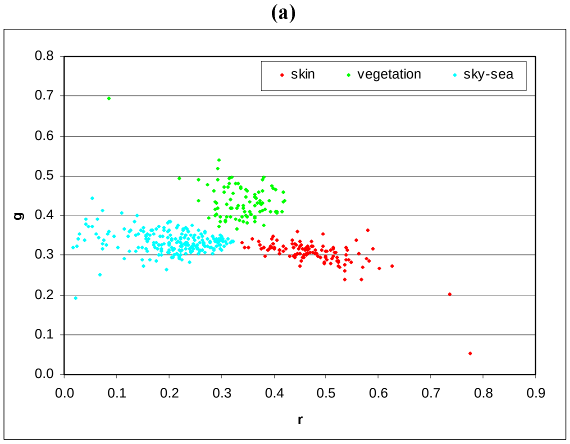
Figure 2. A block description of the steps performed by the color enhancement step. The mask image *M* is involved for purposes of classification and modulation.

III. DATABASE AND STATISTICS GENERATION

A large database of about 450 “high-quality” natural scene images was collected in order to characterize the chromatic properties of the color classes under investigation. All the images were chosen according to perceived naturalness principle. Images affected by severe color cast and/or anomalous color distortions (according to a common sense of expected color/scene pairing) were not considered. To avoid collecting statistics on excessively scattered color samples, an automatic segmentation algorithm [6] was also used to initially extract homogeneous chromatic regions related to the basic color classes. This approach allowed us to collect meaningful samples for each class, mapping their corresponding values on different color spaces. Figure 3 shows how the basic chromatic classes mentioned were mapped in the HS plane of the HSL color space [7]. In the same figure is reported the clustering of the chromaticity classes on *rg* normalized space as were used for the color correction process. As can be seen the vertical clustering of the Hue channel allows performing a reliable and robust classification. Sky and sea areas are not distinguishable by employing only a chromatic criterion, so these were considered as a unified chromatic class.



(a)



(b)

Figure 3 Skin, vegetation, sky-sea clusters on Hue-Saturation plane. (a). Clusters on rg plane (b)

IV. Automatic Scene Classifier

The task of the *automatic scene classifier (ASC)* is the analysis of the input color image in order to identify regions belonging to specific, real world classes. Once such regions have been identified, a mask *M*, properly coding the belonging to a specific class *c*, and the degree of membership, of each underlying pixel is pointed out. Thus, given a pixel in position *k* we indicate with c_k the class it belongs to, and with w_k its membership rank. In our implementation we have decided to limit the classification to three particularly meaningful classes: *skin*, *vegetation*, *sky/sea*. Of course, using the same techniques, the *ACS* could be easily extended to accommodate an arbitrary number of classes depending on the specific environment within they are intended to be used. Indeed, it's worth noting that once an image has been properly classified, the pseudo image could be used to support several kinds of applications, belonging to the image processing field; that could easily take advantage from available semantic image content (e.g. in our case color rendition enhancement will be considered). The process, mainly driven by the collected color statistics, leading from classification of the input image to the final pseudo image mask representing the membership, and the degree of membership of each pixel to the various classes, can be outlined as composed of different steps (see Figure 1).

A. Punctual classification

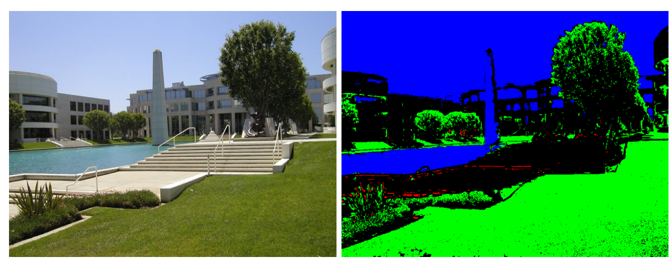
The image is first classified on a per pixel basis using rules that have been easily derived from the collected statistics. In order to avoid dealing with ambiguous values coming from de-saturated and/or low-lit pixels, only pixels satisfying the following condition are considered:

$$(S_k > T_s) \wedge (L_k > T_L) \qquad (1)$$

where S_k, L_k are respectively saturation and lightness values for pixel in position *k*, and T_s, T_L are experimentally fixed thresholds. The assignment to each pixel P_k to the available classes is handled by three mutual exclusive rules:

$$\begin{gathered}((H_k \le L_c) \wedge (H_k \ge R_c)) \rightarrow P_k \in class_c \\ c \in \{skin, veg, sky\}\end{gathered} \qquad (2)$$

For sake of clarity we choose to code with *RGB* triplets the various classes: (255,0,0) for $class_{skin}$, (0,255,0) for $class_{veg}$, and (0,0,255) for $class_{sky}$, coding with (0,0,0) the unclassified pixels.



(a) **(b)**

Figure 4. An input image (a), and the output of its punctual classification (b). Blue and green pixels are representative of sky/sea and landscape.

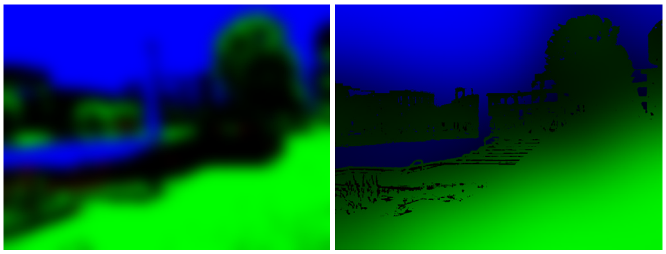
Thus in our convention *R, G* and *B,* are respectively representative of skin, vegetation and sky/sea. Figure 4 shows a sample image and the coded provided by punctual classification step.

B. Expansion

Punctual classification is likely to be not always perfect, since several pixels, even if identifiable by visual inspection as belonging to the available classes; could not be properly recognized due to high deviation from expected hue values. In order to expand the results coming from the punctual classification step, the mask is subjected to a relevant low pass filtering step. The filtering has been performed by employing a Gaussian kernel, which can be defined by Eq. (3).

$$g(x,y) = e^{\frac{-(x^2+y^2)}{s^2}} \tag{3}$$

Experimentally we have found that Eq. (3) needs very high s (space constant) values, thus making filtering in the spatial domain computationally expensive. To avoid this, the filtering is performed on a down-sampled mask image followed by successive up sampling by means of bilinear interpolation. An example of such filtering can be seen in Figure 5 (a). The sampling ratio and the kernel size where chosen to be proportional to input image resolution.



(a) (b)

Figure 5. The punctual classification of Figure 3 after the expansion step (left), and the refinement step (right).

C. Refinement

The refinement step produces the final mask $M=\{c_k, w_k\}$, indicating for each pixel in position k the class c_k to which it belongs, and the degree of membership w_k. Since the filtering step will cause the results of the punctual classification to overlap (e.g. multiple assignments will be available for the same pixel), a max rule is used to obtain one class and one degree of membership for each pixel.

$$\begin{aligned} c_k &= \{class_c : c = \max(R_k, G_k, B_k)\} \\ w_k &= \max(R_k, G_k, B_k) \end{aligned} \tag{4}$$

Figure 5 (b) shows an example of mask.

V. Adaptive Color Correction

The enhancement is aimed to reduce the distance of colors belonging to the various classes from the target values by means of proper, lightness preserving, color shifting. The mask $M=\{c_k, w_k\}$ is used to guide this process, by assigning a class related target to the classified pixels, and by modulating the amount of color correction.

A. Color targets

For each class (*skin, vegetation, sky-sea*) the targets were obtained by mapping the centroids of the collected statistics on the *rg* (RGB normalized) chromaticity plane (see Fig. 1.b). Given an *RGB* color, the mapping on the *rg* plane can be defined as:

$$\begin{aligned} r &= \frac{R}{R+G+B} \\ g &= \frac{G}{+G+B} \end{aligned} \tag{5}$$

The computed color targets for each class c will be indicated as (r_c, g_c).

B. Shift computation

After converting the input image into the *rg* color space employing (5), the mean value on the color plane of each identified color class is computed as follows:

$$\begin{aligned} \mu_{rc} &= \frac{\sum_k (r_k : c_k = c)}{card_c} \\ \mu_{gc} &= \frac{\sum_k (g_k : c_k = c)}{card_c} \end{aligned} \tag{6}$$

with $card_c$ representing the cardinality of class c. For each class, the offset from the target color is defined as:

$$\begin{aligned} \Delta_{rc} &= r_c - \mu_{rc} \\ \Delta_{gc} &= g_c - \mu_{gc} \end{aligned} \tag{7}$$

C. Modulated color enhancement

The color enhancement is carried out by shifting each pixel value (r_k, g_k) by the computed offset and then converting back in the standard *RGB* color space. The ambiguity, due to the "one to many" mapping, of the inverse of Eq.(5) can be advantageously used to define a lightness preserving, constrained linear system:

$$\begin{cases} \dfrac{R'_k}{R'_k + G'_k + B'_k} = r_k + \Delta_{rc} \\ \dfrac{G'_k}{R'_k + G'_k + B'_k} = g_k + \Delta_{gc} \\ \dfrac{R'_k + G'_k + B'_k}{3} = \dfrac{R_k + G_k + B_k}{3} \end{cases} \tag{8}$$

where (R_k, G_k, B_k) is the input color for pixel k, and (R'_k, G'_k, B'_k) its output value. In order to avoid the appearance of unpleasant artifacts and/or excessive color distortions, the final color correction is modulated by using the computed membership values w_k of the mask M, and two modifiable parameters a and b. The final values (R''_k, G''_k, B''_k) are thus defined as follows:

$$\begin{aligned} R''_k &= \frac{aR_k + b[w_k R'_k + (1-w_k)R_k]}{a+b} \\ G''_k &= \frac{aG_k + b[w_k G'_k + (1-w_k)G_k]}{a+b} \\ B''_k &= \frac{aB_k + b[w_k B'_k + (1-w_k)B_k]}{+b} \end{aligned} \tag{9}$$

Parameters a and b allow to perform a linear combination between original and color corrected pixel values, while weights w_k decrease or increase the amount of correction depending on the reliability of the classification. This approach allows us to preserve the dynamic range of the classified regions avoiding also a naturalness modification. Two examples of input-output couples relative to the entire process are reported in Figure 6. The Figure also contains an image of the absolute difference between the original and the processed image, that shows how the correction is spatial variant.

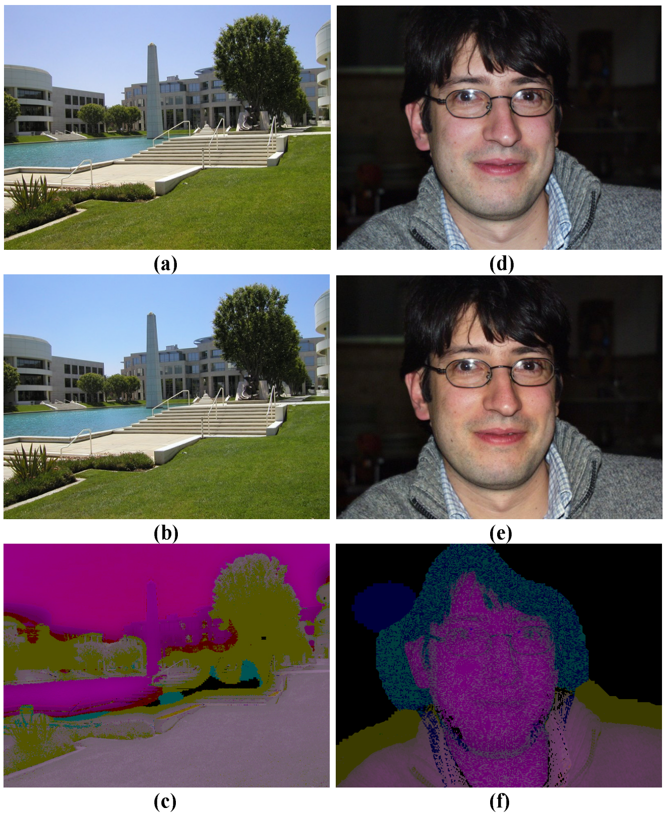


Figure 6. A landscape image (a), its enhanced version (b) and the difference image (c). A portrait image (d) its enhanced version (e) and the difference image (f).

VI. Tests and Results

The overall method has been tested over different databases of images depicting natural scenes. In particular we concentrated on landscape and portrait images. For sake of comparison some subjective test with two color enhancement commercial software were performed: the first one [8] (alg1) allows performing an automatic saturation enhancement, whereas the second [9] (alg2) performs a manually driven color correction in a semi-automatic way. A data set of 30 natural scenes, which did no belong to our statistic class sample, was used to perform visual comparison. 20 subjects, with no particular visual defects on color perception and without experience in digital image or color processing, expressed their opinion in a light control environment and on a CRT monitor with a standard sRGB profile. Two type of visual tests were performed, an overall preference and a comparative judgment between the original and the enhanced images obtained by using the different algorithms. Table I reports the overall preference when four different enhanced images were simultaneously presented to the subject. This index represents the average in terms of percentage referred to the subject choices with respect to the different techniques. The proposed enhancement strategy has obtained an effective good score. Table II reports the comparative tests results performed by showing to each subject in random order three couple of images containing always, the original with the corresponding enhanced one. For each comparison (original-enhanced) a quality score was assigned. The results show in terms of percentage the increasing/decreasing of perceived naturalness, colorfulness and overall quality. Also in this case the proposed enhancement has obtained effective performances.

Absolute Preference Index	
Original	20%
Our	36%
Alg1	28%
Alg2	16%

Table I – Absolute Preference index.

Relative Preference Index	
Our	+23%
Alg1	+2.5%
Alg2	-36%

Table II – Relative Preference index.

VII. Future Works

Further studies are ongoing in order to obtain a unified framework for color based class clustering and correction, while some positional heuristics (e.g. vegetation is more likely to appear on the bottom) are under investigation to add robustness to the actual chromatic classification. Also the possibility to use some perceptive image quality metrics to assess the real improvement will be considered.

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