Natural Scenes Classification for Color Enhancement

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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 natural 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 scenes classification, 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][3]. For still pictures of natural scenes (e.g. landscape, portrait, etc,) a wide accepted assumption [4][5][6] 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*. Although 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 entire solution 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. The color enhancement algorithm is driven by a natural image classifier, which operates on both the chromatic and spatial domains [7]. The images correctly classified as belonging to the portrait or landscape categories are then enhanced by a color refinement algorithm, which is based on a two steps process: a punctual chromatic classifier aimed to label each pixel as belonging to a particular semantic 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 solution when compared to some commercial tools. The paper is structured as follows. The next section describes the basic blocks of the proposed natural images classification process; section III explains in detail the single steps of the color refinement process reporting also some examples, whereas section IV reports the obtained results. A brief conclusive section pointing to future evolutions is also included.

II. NATURAL IMAGES CLASSIFICATION

The main goal of this approach is to perform a reliable classification of natural scene images in order to avoid false chromatic corrections for those images that do not belong to the main semantic categories under analysis. A large database of about 500 "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 [8] has been also used to initially extract homogeneous chromatic regions related to the basic color classes. Positional rules have been added to reinforce classification relying on pure chromatic principles and have been derived from simple heuristic considerations. Fig. 1 describes the combined approach used for the scene classification process.

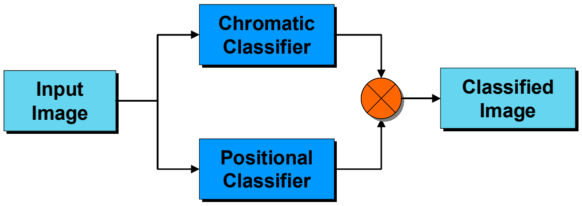

Fig. 1. Block scheme of the natural images classifier.

A. Chromatic Analysis

High-quality images have been used to chromatically characterize the investigated color classes by an automatic segmentation algorithm [8]. Different color spaces have been considered but the HSL color space mapping (Fig. 2) has experimentally proven to be well suited for reliable chromatic classification. According to the vertical clustering, a simple punctual Hue based selection is performed over the pixels in order to establish the belonging to the chromatic classes. In Fig. 3 we report two examples of this chromatic classification, where *red*, *green*, *blue* and *black* areas denote respectively *skin*, *vegetation*, *sky/sea* and unclassified pixels.

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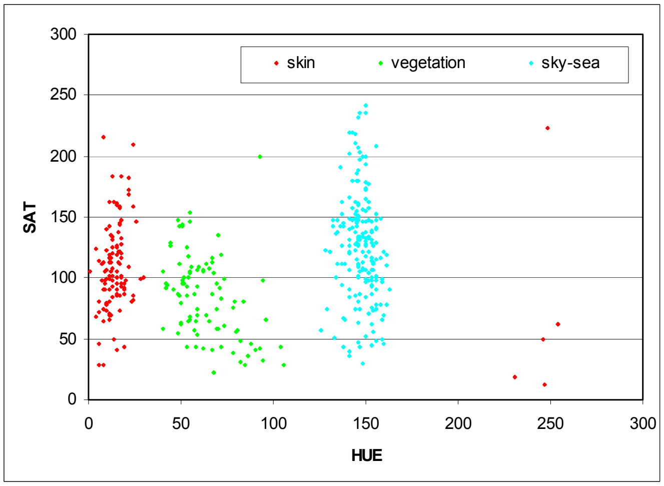
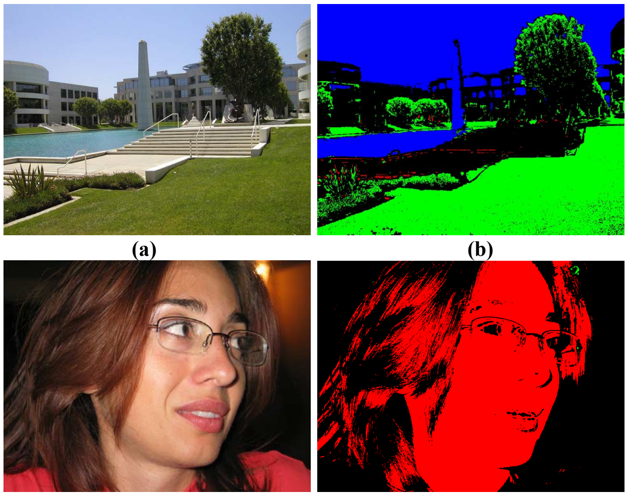


Fig. 2. Natural images database mapping in HS plane of HSL space. Vertical H clusters identify the investigated chromatic classes.


(a) (b)

(c) (d)

Fig. 3. A landscape image (a) and its chromatic classification (b). A portrait image (c) and its chromatic classification (d).

B. Positional Analysis

Positional criterions (Fig. 4) for color classified pixels have been also used to improve the performance of the scene classifier and have been fixed according to common sense heuristics and are used to shape proper weighting functions. If some pixels have been detected as belonging to the *Skin* chromatic class, we use a circular weighting function (magnitude modulated on the radial distance from the centre of the image), to estimate the possibility that the current image belongs to the *Portrait* class; since in this case the face of the subject is expected to be near the center of the scene. Similar considerations have been used for *Landscape* images where the vertical position of the pixels has been considered in order to modulate the belonging to each chromatic class: *Vegetation, Sky/Sea*. All the weighting positional shapes are depicted in Fig. 4.


(a) (b) (c)

Fig. 4. Weighting masks used for the positional analysis of the chromatic classes: (a) Skin (b) Vegetation (c) Sky/Sea. Lighter values correspond to higher weights.

C. Combined Analysis

The effective membership to each scene type is detected by the following rule, which adopts both the chromatic and the positional criterions mentioned above:

$$\begin{aligned} &\sum_i \sum_j I_{C_k}(i,j) \cdot w_{C_k}(i,j) > Th_s \\ &k = \{skin, vegetation, sky/sea\} \\ &s = \{landscape, portrait\} \end{aligned} \tag{1}$$

where $w_{C_k}(i,j)$ is the value of the weighting function relative to the chromatic class C_k, Th_s is the decision threshold of the scene type s and $I_{C_k}(i,j)$ is defined as follows:

$$I_{C_k}(i,j) = \begin{cases} 1 \; if \;\; pixel \; (i,j) \in C_k \\ 0 \qquad\quad otherwise \end{cases} \tag{2}$$

The critical Th_s parameters have been set empirically by the statistical analysis performed over the training image database.

D. Image Classification Performance

A data set of 90 images (*Landscapes, Portraits* and *Others*), 30 of each type, not belonging to our training database, has been used in order to evaluate the proposed solution. The classification results, are reported in a decision matrix, where the m_{ij} element indicates the number of images belonging to the class i that were classified as belonging to the class j. Table I summarizes the results obtained by the application of the chromatic criteria only, whereas table II shows the classification results obtained by the combined approaches. In this case an improvement is noticeable through the reduced values of the off-diagonal elements, which represent the number of false detections. This confirms the effectiveness of the combined strategy proposed as a useful approach for properly camera settings, processing and chromatic enhancement.

TABLE I
CLASSIFICATION RESULTS BY CHROMATIC ANALYSIS

	Portrait	Landscape	Other	Tot.
Portrait	21	1	8	30
Landscape	2	22	6	30
Other	5	1	24	30

TABLE II
CLASSIFICATION RESULTS BY COMBINED ANALYSIS

	Portrait	Landscape	Other	Tot.
Portrait	24	0	6	30
Landscape	0	26	4	30
Other	2	1	27	30

The *ij* element indicates the number of images belonging to the class *i* that were classified as belonging to the *j* class. The *ii* elements indicate the number of the correct classified images.

III. COLOR ENHANCEMENT ALGORITHM DESCRIPTION

Only the images correctly classified as belonging to landscape or portrait categories are processed by the color refinement algorithm. This process 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 classified image, 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 the collected sample images database. Fig. 5 and Fig. 6 show a block based description of the color refinement algorithm.

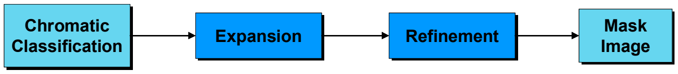


Fig. 5. A block description of the various steps employed to generate the classification mask *M*.

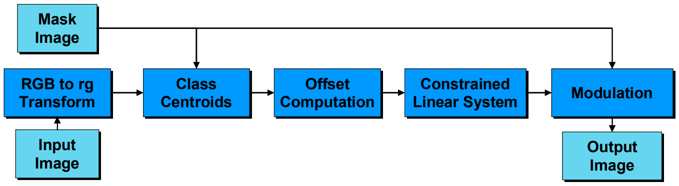


Fig. 6. A block description of the steps performed by the color enhancement process. The mask image *M* is involved for purposes of classification and modulation.

A. 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).

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

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 Fig. 7.(a). The sampling ratio and the kernel size where chosen to be proportional to input image resolution.

B. 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.

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

Fig. 7.(b) shows an example of mask.

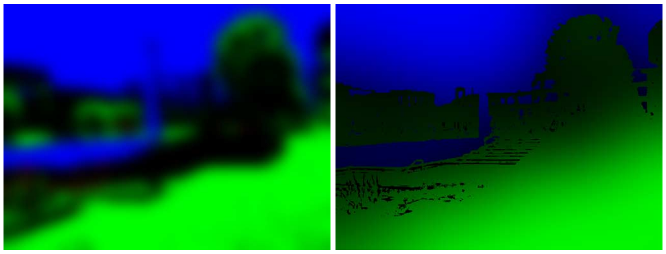

(a) (b)

Fig. 7. The punctual classification of Figure 3 after the expansion step (a), and the refinement step (b).

C. Mask Image Using

The color enhancement algorithm is aimed, as mentioned above, 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 $M=\{c_k, w_k\}$ obtained by the refinement step is used to guide this process, by assigning a class related target to the classified pixels, and by modulating the amount of color correction.

D. 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. 8). Given an *RGB* color, the mapping on the *rg* plane can be defined as:

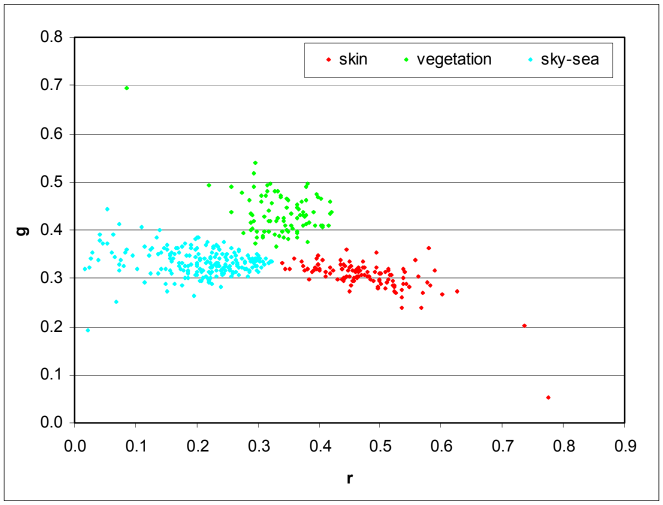


Fig. 8. Mapping on rg chromaticity plane of semantic classes retireved on the training database.

$$r = \frac{R}{R+G+B} \qquad g = \frac{G}{R+G+B} \tag{5}$$

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

E. 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:

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

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

$$\Delta_{rc} = r_c - \mu_{rc} \qquad \Delta_{gc} = g_c - \mu_{gc} \tag{7}$$

F. Modulated color enhancement

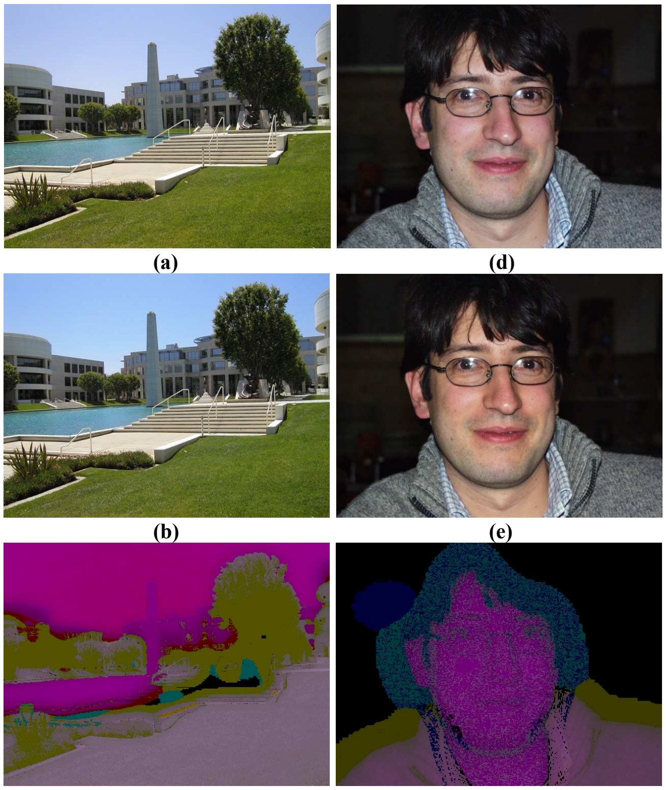
The color enhancement is carried out by shifting each pixel value (r_k, g_k) by the computed offset and then converting back in the standard *RGB* color space. The ambiguity, due to the "one to many" mapping, of the inverse of Eq.(5) can be advantageously used to define a lightness preserving, constrained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

$$\begin{cases} \dfrac{R_k'}{R_k' + G_k' + B_k'} = r_k + \Delta_{rc} \\[2ex] \dfrac{G_k'}{R_k' + G_k' + B_k'} = g_k + \Delta_{gc} \\[2ex] \dfrac{R_k' + G_k' + B_k'}{3} = \dfrac{R_k + G_k + B_k}{3} \end{cases} \tag{8}$$

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:

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

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 Fig. 9. The Figure also contains an image of the absolute difference between the original and the processed image, which shows how the correction is spatial variant.


(a) **(d)**

(b) **(e)**

(c) **(f)**

Fig. 9. 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).

IV. COMPARATIVE 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 [10] (alg1) allows performing an automatic saturation enhancement, whereas the second [11] (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 III 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 IV 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.

TABLE III
ABSOLUTE PREFERENCE INDEX

ABSOLUTE PREFERENCE INDEX	
ORIGINAL	20%
OUR	36%
ALG1	28%
ALG2	16%

TABLE IV
RELATIVE PREFERENCE INDEX.

RELATIVE PREFERENCE INDEX	
OUR	+23%
ALG1	+2.5%
ALG2	-36%

V. FUTURE WORKS

Further studies are ongoing in order to obtain a unified framework for color based class clustering and correction, improving positional heuristics. Also the possibility to use some perceptive image quality metrics to assess the real improvement will be considered.

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