

# Real-time elimination of brightness in color images by MS Diagram and mathematical morphology

Francisco Ortiz

Image Technological Group  
Dept. Physics, Systems Engineering and Signal Theory. University of Alicante  
P. O. Box 99, 03080 Alicante, Spain  
fortiz@ua.es

**Abstract.** This paper proposes a real-time method for the detection and elimination of brightness in color images. We use a 2D-histogram that allows us to relate the signals of luminance and saturation of a color image and to identify the specularities in a given area of the histogram. This is known as the MS diagram and it is constructed from a polar color model. We use a new connected vectorial filter based on color morphology to eliminate the brightness. This filter operates only in the bright zones previously detected, reducing the high cost of processing of connected filters and avoiding oversimplification, in single-processing and multiprocessing environments.

**Keywords:** brightness elimination, color mathematical morphology, connected vectorial filters.

## 1 Introduction

Real-time image processing differs from “ordinary” image processing in that the same correct results must be obtained in critical time. Real-time imaging covers a multidisciplinary range of research areas including image compression, image enhancement and filtering, visual inspection, etc [1]. Indeed, a goal in computer vision is to identify objects of real scenes in the shortest time possible or in a deadline. Sometimes, this goal is not easy since a bad adjustment of illumination can introduce brightness (highlights or specular reflectance) in the objects captured by the vision system. The presence of brightness causes problems in low-level computer vision methods and in high-level operations.

To be able to eliminate the highlights in captured scenes, we must identify them first. The dichromatic reflection model proposed by Safer [2] is a tool that has been used in many methods for detecting specularities. This model supposes that the interaction between the light and a dielectric material produces different spectral distributions in the object, i.e., the specular and diffuse reflectances. Bajcsy *et al* [3] use a chromatic space based on polar coordinates that allows the detection of specular and diffuse reflections by means of the previous knowledge of the captured scene. Klinker *et al* [4] employ a pixel-clustering algorithm which has been shown to work well in detecting brightness in images of plastic objects. These previous approaches

have produced good results but they have requirements that limit their applicability, such as the use of stereo or multiple-view systems, high time of processing, the previous knowledge of the scene, or the assumption of a homogeneous illumination, without considering the inter-reflections present in most typical real scenes.

In this paper we explain a new and real-time system for the detection and elimination of brightness in color images by means of two main steps:

- Detection: we use a 2D-histogram of achromatic and saturation signals from a 3D-polar coordinate color representation. This new representation allows us to obtain a specular reflectance map of the image.
- Elimination: we develop a real time vectorial geodesic reconstruction algorithm, which has low cost and avoids the over-simplification of the image.

The organisation of the paper is as follows: In Section 2 we present the color space for processing, together with the MS diagram used to detect the specular reflectance. In Section 3, we develop the color morphology and an extension of the geodesic operations to color images. In Section 4 we show the algorithm for detecting and eliminating specularities. Experimental results in highlights detection are shown in Section 5. Finally, our conclusions are outlined in the last section.

## 2 Color space for processing and MS diagram

In the last years, the color spaces based in polar coordinates (HLS, HSV, HSI...) are widely used in image processing [5,6,7]. Important advantages of these color spaces are: good compatibility with human intuition of colors and separability of chromatic values from achromatic values. The intuitive systems are widely used in image processing as they represent the information in similar way to the brain. They can be represented by a single system, which Levkowitz and Herman define as GLHS [8], adapted for image processing by Serra's *LI-norme* [9]. We shall denote the intensity function by  $m$ , which is the mean of the  $r$ ,  $g$  and  $b$  values, where  $(r,g,b)$  are coordinates of the RGB color space (Figure 1.a), with  $r \in [0,255]$ ,  $g \in [0,255]$  and  $b \in [0,255]$ . As such,  $m$  corresponds to the  $l$  in the LHS-triangle model:

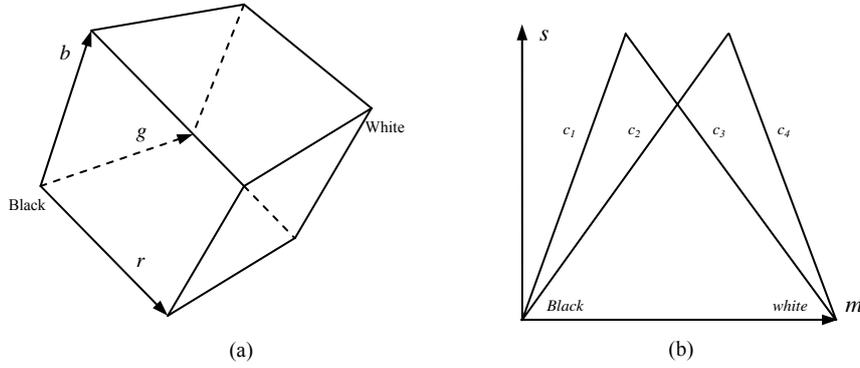
$$m = \frac{1}{3}(r + g + b) \quad (1)$$

The  $m$  signal calculated is a normalization ( $0 \leq m \leq 255$ ) of the achromatic axes of the RGB cube. The value of  $s$  is given by Serra's *LI-norme* as:

$$s = \begin{cases} \frac{1}{2}(2r - g - b) = \frac{3}{2}(r - m) & \text{if } (b + r) \geq 2g \\ \frac{1}{2}(r + g - 2b) = \frac{3}{2}(m - b) & \text{if } (b + r) < 2g \end{cases} \quad (2)$$

We propose to exploit the existing relation between  $m$  and  $s$  that permits the detection of specular reflections in a digital image, independently of the hue of the object in

which the brightness appears. Figure 1.b shows the MS diagram as the positive projection of all of the corners of the cube in a normalisation of the achromatic line to the  $m$  signal.



**Fig. 1.** RGB cube and its transformation in MS diagram. (a) 3D projection. (b) Shape and limits of MS diagram.

### 3 Color morphology and vector connected filters

The definition of morphological operators needs a totally ordered complete lattice structure [10]. The color pixels do not present, a priori, this structure and it is necessary to impose an order relationship in the color space. Several studies have been carried out on the application of mathematical morphology to color images [11,12,13]. The approach most commonly adopted is based on the use of a lexicographical order, which imposes total order on the vectors. This way, we avoid the false colors in an individual filtering of signals.

On the other hand, it is important to define the color space in which operations are to be made. The preference or disposition of the components of the polar model in the lexicographical ordering depends on the application and the properties of the image. For our application we define a lattice with a lexicographical order of  $o_{lex}=(m \rightarrow s \rightarrow h)$ . As such, we put more emphasis on the intensity signal  $m$ . Afterwards, we analyse the saturation. Next, we compare a hue distance value only if the pixels are colored.

#### 3.1. Connected vectorial filters

Morphological filters by reconstruction have the property of suppressing details, preserving the contours of the remaining objects [14,15]. The use of these filters in color images requires an order relationship among the pixels of the image. For the vectorial morphological processing the lexicographical ordering, previously defined  $o_{lex}$ , will be used. As such, the infimum ( $\wedge_v$ ) and supremum ( $\vee_v$ ) will be vectorial

operators, and they will select pixels according to their order  $o_{lex}$  in the MSH generalised color space [16].

Once the orders have been defined, the morphological operators of reconstruction for color images can be generated and applied. An elementary geodesic operation is the geodesic dilation. Let  $g$  denote a marker color image and  $f$  a mask color image (if  $o_{lex}(g) \leq o_{lex}(f)$ , then  $g \wedge_v f = g$ ). The vectorial geodesic dilation of size 1 of the marker image  $g$  with respect to the mask  $f$  can be defined as:

$$\delta_v^{(1)}(g) = \delta_v^{(1)}(g) \wedge_v f \quad (3)$$

where  $\delta_v^{(1)}(g)$  is the vectorial dilation of size 1 of the marker image  $g$ . This propagation is limited by the mask  $f$ .

The vectorial geodesic dilation of size  $n$  of a marker color image  $g$  with respect to a mask color image  $f$  is obtained by performing  $n$  successive geodesic dilations of  $g$  with respect to  $f$ :

$$\delta_v^{(n)}(g) = \delta_v^{(1)} \left[ \delta_v^{(n-1)}(g) \right] \quad (4)$$

with  $\delta_v^{(0)}(g) = f$ .

The vectorial reconstruction by dilation of a mask color image  $f$  from a marker color image  $g$ , (both with  $D_f = D_g$  and  $o_{lex}(g) \leq o_{lex}(f)$ ) can be defined as:

$$R_{v,f}(g) = \delta_v^{(n)}(g) \quad (5)$$

where  $n$  is such that  $\delta_v^{(n)}(g) = \delta_v^{(n+1)}(g)$ .

#### 4 Algorithm for detecting and eliminating specularities

The specularities in the chromatic image have values of high luminance  $m$  and low saturation  $s$ . An important consideration is that not all the images have the same dynamic range and, therefore, the  $m$  and  $s$  values of their specularities do not correspond with the positions of the MS diagram previously presented. We have opted for a neighbourhood-based morphological contrast enhancement which considers the local features of the images. Specifically, we have applied a top-hat contrast operator defined as:

$$m' = m + WTH(m) - BTH(m) \quad (6)$$

The result of the local enhancement by the top-hat is that the specular reflectance pixels are positioned on  $c_3$  and  $c_4$  lines of the MS diagram (Figure 1.b). These lines identify different specularities along their coordinates, from the most intense to the dullest. The optimum value of saturation ( $s_{sp}$ ) on  $c_3$  and  $c_4$  lines for all the brightness in images it has been deduced in our numerous experiments [17]. The detection of the specularities stops, in all of the cases, at a maximum saturation of:

$$s_{sp} = \frac{m_{\max}}{10} \quad (7)$$

where  $m_{\max}=255$ , and at higher values no additional pixels in the image are detected as brightness. It is now easy to calculate the value of  $m_{\min}$  as:

$$m_{sp} = \frac{2s_{\max} - 3m_{\max}}{-3} \quad (8)$$

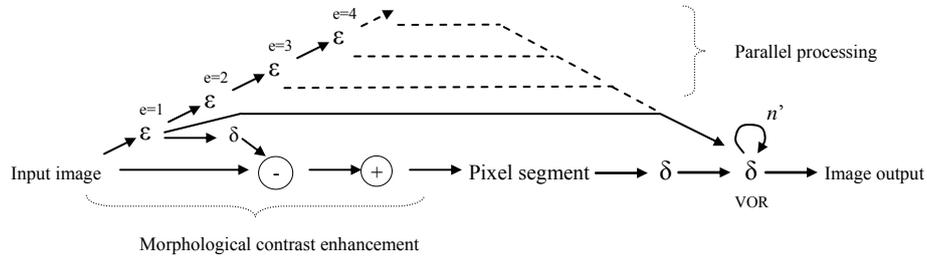
To eliminate the highlight that was previously detected with the MS diagram, we use a real-time geodesic filter. It is a vectorial opening by reconstruction (VOR) applied only in the specular areas of the image and their surroundings. The size  $e$  of the structural element of the erosion will determine the success of the reconstruction and the final cost of the operations since this size imposes the process area of the filters.

In the geodesic filter,  $f$  is first eroded. The eroded sets are then used as sets for a reconstruction of the original image. The new filter (VOR) is defined, taking into account the fact that, in this case, the operation will not affect all the pixels  $(x,y)$ , but only those in which  $h(x,y)=1$ :

$$\gamma_{f,h}^{(n)} = \left\{ \delta_v^{(n)}(\varepsilon_v^{(e)}(f)) \mid \forall f(x,y) \Rightarrow h(x,y)=1 \right\} \quad (9)$$

where  $n'$  is such that  $\delta_v^{(n')}(\varepsilon_v^{(e)}(f)) = \delta_v^{(n'+1)}(\varepsilon_v^{(e)}(f))$ . The vectorial erosion of the opening by reconstruction is also done with a structural element of size  $e$ . This erosion replaces highlight pixels (high  $o_{\text{lex}}$ ) by the surroundings chromatic pixels (low  $o_{\text{lex}}$ ). Next, the vectorial geodesic dilation (iterated until stability) reconstructs the color image without the recovering of the specularities. This is the same approach successfully used in the detection of color cells in real-time medical imaging [16].

The possibilities of parallel processing in our algorithm are limited. Nevertheless, in order to achieve the results in a lower time, an alternative configuration for multiprocessor environment is possible, i.e. the vectorial erosion of the opening by reconstruction can be made in all the pixels of the original image  $f$  (in a second processor), in parallel with the detection step of the algorithm (first processor). This way, the first vectorial erosion ( $e=1$ ) of the top-hat is re-used. The task graph of this new configuration is shown in Figure 2. We will evaluate this alternative in the following section.



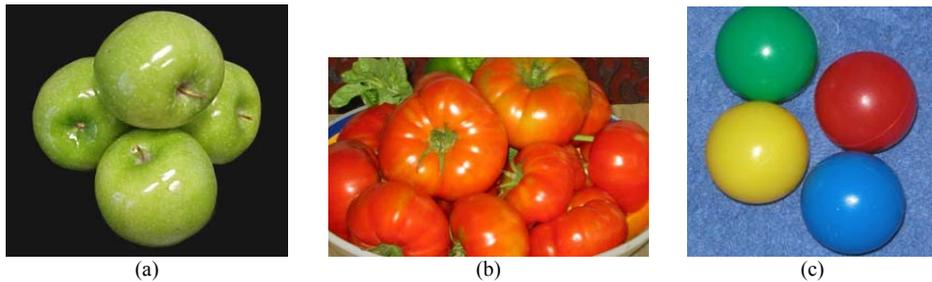
**Fig. 2.** Task graph for a parallel processing of the algorithm. A minimum cost approach for brightness elimination: multiprocessor configuration.

## 5 Experimental results and real-time aspects

We now present the results obtained from the application of our method for brightness elimination in different real scenes (Figure 3). In addition, we show a cost comparison for the two configurations of the algorithm: single-processor and multiprocessor.

From the visual results obtained (Figure 4), the effectiveness of our method for the detection and elimination of specular reflectance can be observed. The oversimplification does not appear since the reconstruction only functions in bright areas. Furthermore, the results are obtained at a much lower computational time which is compatible with real-time image processing systems.

The reconstruction task is the most critical operation. For this reason, the size  $e$  of the structuring element of morphological operations will depend of the application and real-time requirements, i.e. a low  $e$  (1,2) is recommended for visual inspection and a high  $e$  (3,4,...) is the best in multimedia and image restoration.



**Fig. 3.** Colour images for empirical study. (a) “Apples”, (b) “Tomatoes” and (c) “Ballons”

In Table 1, we show a comparison of temporal execution costs between the new algorithm for the elimination of specularities in color images and a global geodesic filter that operates in the entire image. As can be seen, the new method avoids the high computational cost of the geodesic processing for textured images (“Ballons”).



**Fig. 4.** Elimination of specular reflectance of real color images in Figure 3. (a) “Apples”, (b) “Tomatoes” and (c) “Balloons”. Over-simplification is not present in the results.

**Table 1.** Final CPU times (s) for brightness elimination by means of a global geodesic filter, and the proposed algorithm for single-processing and the multiprocessing configurations ( $e=3$ ) for multimedia applications.

Color image	Global filter	Proposed algorithm (Single-processing) times (s)	Proposed algorithm (Multiprocessing) times (s)
Apples	9.09	1.34	0.85
Tomatoes	11.73	1.95	1.09
Balloons	19.45	0.56	0.39

## 6 Conclusions

In this paper, we have presented a method for the detection and elimination of specular reflectance in color images for real-time computer vision applications.

The possibility of eliminating highlights in color images without causing over-simplification has been demonstrated. In addition, the elimination of brightness has been obtained with a very low processing time, in single-processor and multiprocessor configurations, with respect to a global geodesic reconstruction. This permits to achieve real-time requirements in image processing, even in very textured images. The detection and elimination of brightness is obtained independently of the material of the objects on which they appear, without any need of multiple-view or previous knowledge of the scenes.

Based on the success shown by these results, we are working to improve our method for eliminating specularities. Now, we work in the automatic calculation of the size  $e$  of the structuring element required in the vectorial erosion of the algorithm. Also, we work with other color spaces and multiprocessor configurations to reduce the processing time required in vectorial operations as much as possible.

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