Automatic Detection of Specular Reflectance in Colour Images Using the MS Diagram

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Abstract. In this paper we present a new method for the identification of specular reflectance in colour images. We have developed a bi-dimensional histogram which allows the exploitation of the relations between the signals of intensity and saturation of a colour image. Once the diagram has been constructed, it is possible to verify that the pixels of the specular reflectance are located in a well-defined region. The brightness is automatically identified by means of the extraction of pixels present in this region of the diagram, independently of their hue values. The effectiveness of the method in a variety of real chromatic images has been proven.

1 Introduction

In industrial visual inspection systems, the images are acquired in work environments where illumination plays an important role. Sometimes, a bad adjustment of illumination can introduce the presence of brightness and specular reflectance in the objects captured by the vision system [1]. The presence of such brightness alters the pattern recognition process because the previous stage of detection of edges in the objects fails: the brightness and specular reflectances are considered as different objects in the environment in which they are located and therefore it is not possible to perfectly detect the objects in the scene [2].

To be able to attenuate the effect of the specular reflectance in the captured scene, it is necessary to identify the brightness beforehand. Criminisi *et al* [3], and Lin *et al* in [4] use stereo images to separate specular and diffuse reflectances. In [5], Ragheb and Hancock use iterated conditional modes. Nevertheless, it is possible to use information about saturation and hue as well as intensity for the recognition of brightness in colour images. To do so, Bajcsy *et al* in [6] use a colour reflection model based on a dichromatic model for dielectric materials. In this paper we propose to exploit the existing relations between the intensity and saturation signals of a chromatic image that are obtained from a transformation of the RGB colour space.

2 Colour Space Used

In the bibliography, many referenced colour spaces appear [7,8,9]. In general, they are three-dimensional spaces that can be classified in standardised systems (CIE-RGB, CIE-XYZ, CIE-Lab), physical systems (RGB and CMY), and intuitive systems, where the objective is to represent the colour information in an intuitive way (HSV, HLS, HSI, YSH, etc). The intuitive systems are widely used in image processing as they represent the information in a similar way to the human brain. In fact, they represent a single system, which Levkowitz and Herman define as GLHS [10]. The other spaces are particular cases in which a certain intensity function has been assigned to them. In this study, the intensity function employed M, is defined in [10] as the LHS-triangle model:

$$M = \frac{1}{3}(r + g + b) \tag{1}$$

By this way, the intensity signal corresponds to the projection of the colour vector **c** in the space RGB on the achromatic axis, $\mathbf{c}_a$. The saturation used in this study is the one proposed by Serra in [11], and which corresponds to the projection of the colour vector **c** on to chromatic plane $\mathbf{c}_p$, where:

$$\vec{c} = \vec{c}_p + \vec{c}_a \tag{2}$$

The value of s is given by the expression,

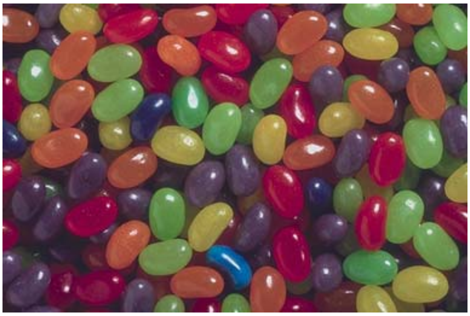
$$\begin{cases} S = \frac{1}{2}(2r - g - b) = \frac{3}{2}(r - m) & if\ (b + r) \geq 2g \\ S = \frac{1}{2}(r + g - 2b) = \frac{3}{2}(m - b) & if\ (b + r) < 2g \end{cases} \tag{3}$$

2.1 MS Diagram

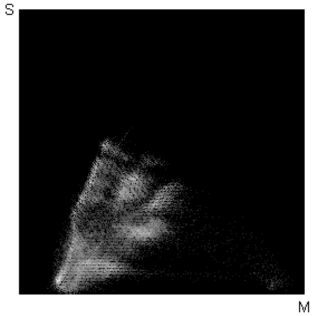
In this study, we propose to exploit the existing relations between M and S that permit the detection of brightness on a digital image, independently of the hue of the object in which the brightness exits. We use a bi-dimensional histogram where the number of pixels that have the values M and S are represented. This way, a relationship between the signals M and S, defined above, is obtained, independently of the hue of the object involved. In Fig. 1, a colour image and its corresponding MS diagram are shown.

3 Detection of Specular Reflectance in the MS Diagram

If an object has brightness, the brightest point will have a high intensity value and low saturation, giving rise to a sensation of an intense white point without any hue. However, in the bright area the saturation generally increases as the intensity is reduced, gradually acquiring the sensation of colour as it loses intensity [12].



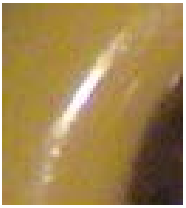
(a) colourbeans.bmp



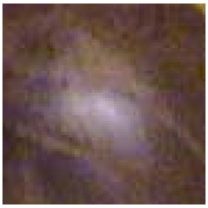
(b) MS-colourbeans.bmp

Fig. 1. Colour digital image and its MS diagram

(a) life-saver.bmp



(b) umbrella.bmp



(c) hanger.bmp

(d) table-cloth.bmp

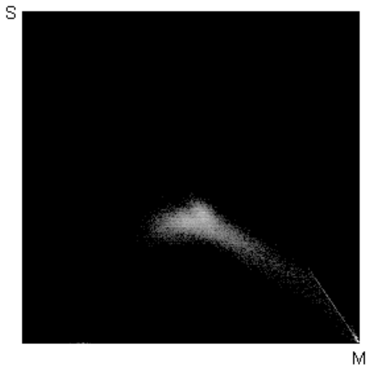
Fig. 2. Bright areas in colour objects

In Figure 2, can be seen different bright areas from colour images where this phenomenon appears.

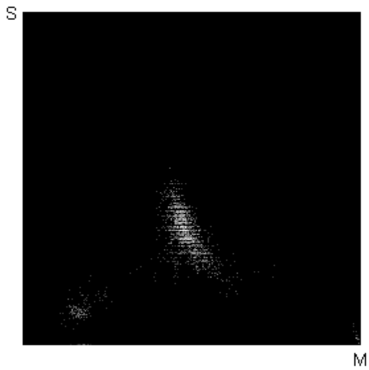
In Figure 3, the MS diagrams for each image in Fig. 2 are shown. In these diagrams there is no generic rule for the detection of brightness. However, the absence of such a rule is due to the fact that the dynamic range of the luminance signal is different for each image. This can be observed on the histograms of the intensity of M (Figure 4).

3.1 Enhanced Contrast and Detection of Bright zones

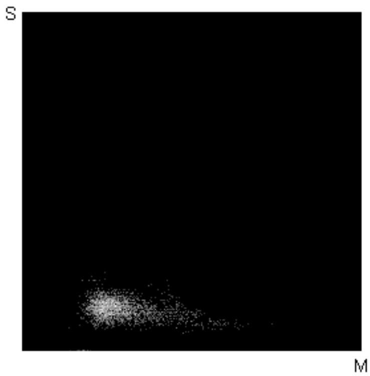
Before obtaining the MS diagram, it is necessary to carry out a previous step which guarantees that all the images have the same upper limit of dynamic range (255) of the luminance signal. As can be seen in Figure 2, all of the images have brightness. As is shown below, the algorithm proposed in this paper is based on the identification of brightness by means of the selection of a region of pixels in the MS diagram (Fig. 8). In Figure 3 it can be seen that not all of the bright areas in original images are in the selected zone. Therefore, it is necessary to guarantee that the bright pixels of any image are found in this zone. This process is performed through an equalisation of the histogram of the intensity signal. For the image in Figure 2.c, the process is schematised in Figure 5. Once this step of enhancement of the contrast has been achieved, the MS diagrams are computed (Figures 6 and 7).



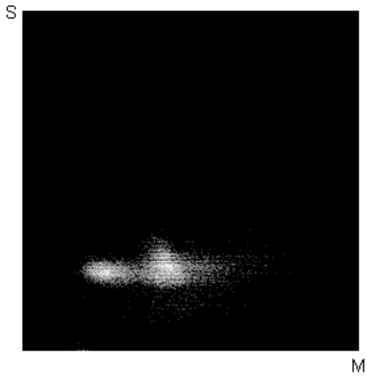
(a) MS-life-saver.bmp



(b) MS-umbrella.bmp

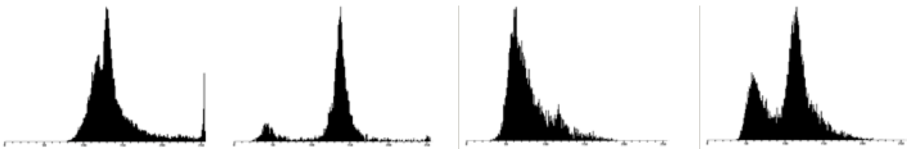


(c) MS-hanger.bmp



(d) MS-table-cloth.bmp

Fig. 3. MS Diagrams of the images in Fig. 2



(a) Hist. of Fig. 2.a (b) Hist. of Fig. 2.b (c) Hist. of Fig. 2.c (d) Hist. of Fig. 2.d

Fig. 4. Histograms of the images in Fig. 2

From the analysis of the normalised MS diagrams (Fig. 6 and 7) and after different test in a representative selection of images, we have observed that the pixels values for M and S of the zones of brightness correspond to those ones belonging to the region mask given in Fig. 8. This set of points of the bi-variate histogram which follows a particular relationship appears in all the images where the objects have brightness. Therefore, the bright areas can be segmented by obtaining all of the pixels of the image. The values of the equalised M and S signals of the bright pixels are within the area indicated in Fig. 8. The choice of the maximum value for S of this zone has been fixed empirically after a detailed study with our database of images.

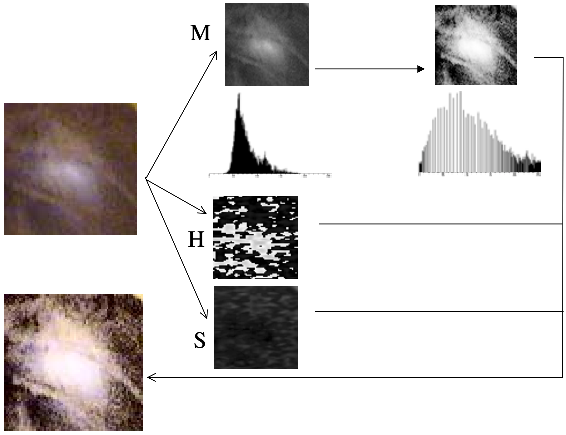
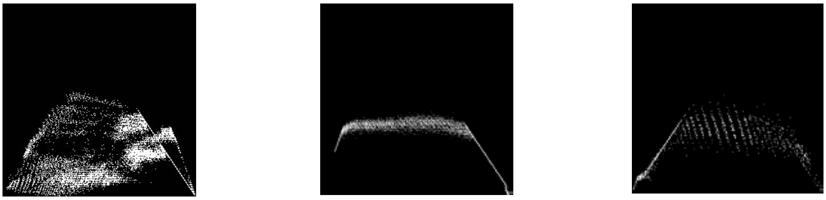


Fig. 5. Procedure for enhancement of the contrast of bright zones



(a) MS-colourbeans-contr.bmp (b) MS-life-saver-contr.bmp (c) MS-umbrella-contr.bmp

Fig. 6. Normalised MS diagrams of the images in Fig. 2

(a) MS-hanger-contr.bmp (b) MS- table-cloth-contr.bmp

Fig. 7. Normalised MS diagrams of the images in Fig. 2 (cont)

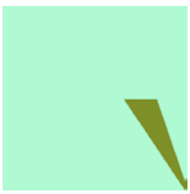


Fig. 8. Binary mask of the bright pixels in the MS diagram

4 Results

In this section, we present the results obtained for the images analysed. The results obtained for the detection of bright areas in Fig. 1 are shown in Fig 9. In Figs. 10, 11 and 12, the results of the detection of specular reflectance on the images in Figures 2.a, 2.b, 2.c, and 2.d, respectively, are shown. From the results, the robustness of the method for the detection of specular reflectance presented in this paper, can be observed. In the results an almost complete absence of false positives is observed. This can be appreciated in Figure 11.a in which there is a white zone which is not identified as brightness.

(a) colourbeans.bmp (b) brightness-colourbeans.bmp

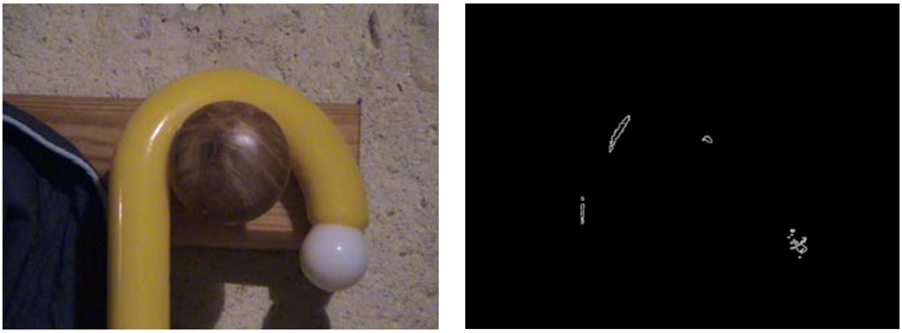
Fig. 9. Detection of the specular reflectance of the image in Fig. 1

(a) life-saver-B.bmp (b) brightness-life-saver-B.bmp

Fig. 10. Detection of the specular reflectance of the image (a) in Fig. 2

5 Conclusions

In this paper a robust detector of specular reflectance in colour images, based on the exploitation of the properties of the MS diagram, has been presented. Using the present approach, it is possible to automatically detect bright areas, independently of the



(a) umbrella-hunger-B.bmp (b) brightness-umbrella-hunger-B.bmp

Fig. 11. Detection of the specular reflectance of the images (b) and (c) in Fig. 2

(a) table-cloth-B.bmp (b) brightness-table-cloth-B.bmp

Fig. 12. Detection of the specular reflectance of the image (d) in Fig. 2

chromatic value (hue values) in which they take place. The results obtained by means of this algorithm facilitate the later stages of improvement on the quality of colour images, such as the automatic elimination of bright areas. These pre-processing operations are interesting for applications where it is necessary to obtain a correct segmentation of the objects: manipulation, in multimedia systems, etc.

6 Original Colour Images

All the colour images in this paper are referenced as "name.bmp" and are available in `http://www.disclab.ua.es/aurova/caip2003/images`.

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