

Colour image segmentation in presence of shadows

Eduard Vazquez and Ramon Baldrich. Computer Vision Center / Universitat Autònoma de Barcelona; 08193, Bellaterra (Barcelona), Spain.

Abstract

To achieve a correct colour image segmentation in the presence of shadows is still a challenge. The varying object shapes in a scene provoke several effects in an image such as shadows, shadings, and highlights. These physical effects produce strong edges on an image that are not considered for human segmentation. These edges are detected by the current segmentation methods. This paper analyzes the capability of the Ridge-based Distribution Analysis method (RAD) to perform a correct segmentation in the presence of shadows. RAD is based on the idea that the representative colour of a shadow and the representative colour of the object affected by this shadow share some spatial properties. RAD finds this relationship assigning one colour for an object even when this object is affected by shadows. This analysis is done on different chromatic spaces to determine the one that fits better to RAD. Results achieved point out that RAD is able to perform a correct segmentation in the presence of self and cast shadows.

Introduction

A common problem in Computer Vision when dealing with colour images is the presence of shadows. Shadows, as well as shading and highlights, are mainly caused by the varying object shapes. These physical effects cause strong edges in an image which are detected as an object edges for current segmentation techniques. Commonly, the edges caused by shadows are not considered for a human when segmenting as the Berkeley segmentation benchmark [1] stands out. Figure 1 shows some examples of that. The cast shadows of the car, the horses and the man on the floor would be detected by current segmentation algorithms. When asking a human to segment these images, these shadows are not considered, as can be seen in Figures 1b,d,f. The same happens with self shadows on the cars, horses, and the clothes of the man.

In this paper it is studied the capability of a Ridge-based Distribution Analysis technique (RAD) to cope with shadows on real images. According to the classical classification of segmentation techniques [2], [3] RAD is a full feature based segmentation technique. Hence, RAD does not exploit the image spatial coherence to perform the segmentation. This method finds the dominant colours of an image represented on its histogram by means of a set of topological operations. The main idea of RAD is that a colour of an object is modified for the physical effects as well as acquisition conditions and image compression. Due to all these effects, one colour of an object appears as a more or less elongated shape on the image histogram [4]. RAD can extract a dominant colour of a histogram independently of its shape.

The goal of this work is to evaluate the possibility of using the colour histogram of an image to perform a segmentation that is robust to shadows. A shadow occurs when an object partially or totally occludes direct light from a source of illumination [5], [6]. Shadows are commonly divided in *self* shadows (the shadow in a portion of an object) and the shadows projected by an object,

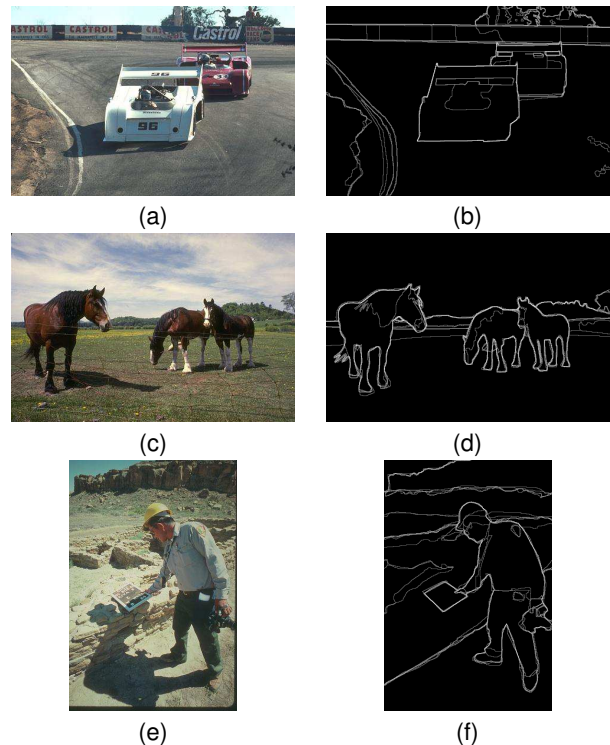


Figure 1. (a,c,e) Original images with a strong cast shadows. (b,d,f) Human segmentations where the shadows are not considered.

named *cast* shadows. Every type has its own singularities. Self shadows are commonly associated to soft shadows with fuzzy borders, whereas cast shadows are associated to sharp borders, and are usually treated separately [5]. A useful segmentation method should treat both kind of shadows at the same time to be used on real images.

The rest of this paper is organized as follows: first we explain the motivations of our method. Afterwards, we explain the Ridge based Distribution Analysis technique (RAD) used to segment an image in terms of its representative colours. After that, we illustrate how RAD is able to avoid problems when segmenting in the presence of shadows. Next, the performance of RAD on the RGB and the normalized RGB spaces is analyzed. Finally, we present the conclusions of the current work.

Changes on chromaticity and intensity in the presence of shadows.

Although some segmentation approaches assume that shadows imply only a change in intensity, in many cases, there is also a change in chromaticity. Furthermore, it is demonstrated that outdoor shadows in nature have a dark bluish component [7]. This effect is caused by the bluish component of the ambient light. On indoor scenes, the bluish component of the light is replaced by the colour of the artificial light source. Additionally, reflections with other objects present in the scene can have an

influence on the colour of shadows.

Since intensity changes in the scene can be assumed to have an almost linear effect on the histogram, we propose to change the representation of the image and deal exclusively with its chromaticity. Nonetheless, the potential error introduced when the image representation is transformed to an intensity invariant space, should be considered. A parametrization of the behaviour of a colour along intensity changes on the RGB space is introduced in [8].

The main idea is that shadows share a chromatic tendency with the objects/surfaces even in the case of strong shadows. As we will show in this paper, RAD is able to find this tendency. Furthermore, it is also tested the behaviour of RAD on an intensity invariant space such as the normalized RGB (*rgb*) space. The advantage of *rgb* is that, on it, we just have to deal with chromatic changes, instead of both chromatic and intensity changes as happens on RGB space.

Capturing the shared chromaticity of shadows and surfaces using RAD

Representative colours in an image are represented by high density clouds (of an arbitrary shape) in a d-dimensional colour histogram. To capture this information, we use a Ridge based Distribution Analysis method (RAD) successfully used in topological maps segmentation [9] and texture segmentation [10]. RAD treats the histogram as a landscape and apply a set of topological operation on it. Under this point of view dominant colours will be represented by ridges on the landscape.

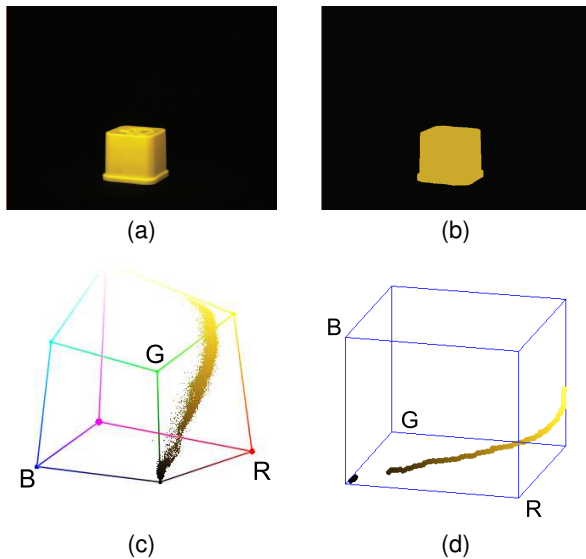


Figure 2. (a) Example image with two representative colours: yellow and black. (b) Segmented image using RAD. (c) Histogram of a). (d) Ridges found using RAD.

Figure 2a shows an image extracted from [11] with two representative colours, *i.e.*, yellow for the object and black for the background. The yellow colours goes from the right face of the cube, with shadow, to the highlights of the vertices. All these amount of colours can be seen on the image histogram shown in Figure 2c. A correct segmentation should find the coherence between all these yellow colours to segment the object correctly. A correct segmentation, using RAD, is shown in Figure 2b. To achieve this segmentation RAD has found the two ridges depicted in Figure 2d. The yellow ridge cover all yellow colours representative of the cube. It is done because RAD finds the coherence existing on the yellow shape of the image histogram

(Figure 2b).

RAD is divided in two main steps. First a ridge detection step is done to join representative colours. Afterwards a clustering step is performed using ridges found.

First step: ridge detection and extraction

To extract a ridge, first it is applied a ridge enhancement procedure using the MLSEC-ST operator [12]. It assigns high creaseness values at the center of elongated objects. When dealing with a d-dimensional colour histogram, this operator will assign a high value at areas with high density compared with its neighbourhood. The main property of this operator is that it is not affected by local irregularities typically present in a chromatic histogram. Hence, the most dense regions have the higher creaseness values. MLSEC-ST performs the calculus of the Structure Tensor to enhance those areas where an either big attraction or repulsion exists on the gradient vector of a d-dimensional distribution $\Omega(\mathbf{x})$ (the image histogram in the current context). Formally given a symmetric neighbourhood of size σ_i centered at point \mathbf{x} , namely $N(\mathbf{x}, \sigma_i)$, we define the Structure Tensor as follows:

$$S(\mathbf{x}, \vec{\sigma}) = N(\mathbf{x}, \sigma_i) * (\nabla\Omega(\mathbf{x}, \sigma_d) \cdot \nabla\Omega^t(\mathbf{x}, \sigma_d)) \quad (1)$$

where $\vec{\sigma} = \{\sigma_i, \sigma_d\}$, and the calculus of the gradient vector field $\nabla\Omega(\mathbf{x}, \sigma_d)$ has been done with a Gaussian Kernel with standard deviation σ_d .

If $w(\mathbf{x}, \vec{\sigma})$ is the eigenvector corresponding to the largest eigenvalue of $S(\mathbf{x}, \vec{\sigma})$ then, the dominant gradient orientation in a neighbourhood of size proportional to σ_i centered at \mathbf{x} is:

$$\bar{w}(\mathbf{x}, \vec{\sigma}) = \text{sign}(w^t(\mathbf{x}, \vec{\sigma}) \cdot w(\mathbf{x}, \sigma_d))w(\mathbf{x}, \vec{\sigma}) \quad (2)$$

The creaseness measure of $\Omega(\mathbf{x})$ for a given point \mathbf{x} , call it $k(\mathbf{x}, \vec{\sigma})$, is computed with the calculus of the divergence between the dominant gradient orientation and the normal vectors, namely n_k , on a neighbourhood of size proportional to σ_i . That is:

$$k(\mathbf{x}, \vec{\sigma}) = -\text{Div}(\bar{w}_x) = -\frac{d}{r} \sum_{k=1}^r \bar{w}_k^t(\vec{\sigma}) \cdot n_k \quad (3)$$

The next step is to performs a ridge extraction algorithm on the creaseness representation of $\Omega(\mathbf{x})$. Ridges extracted will represent the shape of the dominant colours as can be shown in Figure 3d.

We argue that these ridges can capture the colours of a surface in its illuminated and shadowed areas in one unique ridge (unique representation for both areas) since they share a similar tendency on the histogram. Using the creaseness representation of $\Omega(x)$, it becomes an easy step to extract the ridges on it. As a result, we have a set of ridges representing the representative colours of the image.

Ridge points are divided in Local Maxima (LM), Transitional Ridge Points (TRP) and Saddle points (SP). These points are defined for a 2-dimensional distribution $\Omega(x, y)$ as follows:

$$LMP(\Omega(x, y)) = \{(x, y) | (\|\nabla\Omega(x, y)\| = 0), \lambda_1 < 0, \lambda_2 < 0\} \quad (4)$$

$$\begin{aligned} TRP(f(x, y)) &= \{(x, y) | \\ \|\nabla\Omega(x, y)\| &\neq 0, \lambda_1 < 0, \nabla\Omega(x, y) \cdot \omega_1 = 0, \\ \|\nabla\Omega(x, y)\| &\neq 0, \lambda_2 < 0, \nabla\Omega(x, y) \cdot \omega_2 = 0, \\ \|\nabla\Omega(x, y)\| &= 0, \lambda_1 < 0, \lambda_2 = 0\} \end{aligned} \quad (5)$$

$$SP(f(x,y)) = \{(x,y) \mid \|\nabla\Omega(x,y)\| = 0, \lambda_1 \cdot \lambda_2 < 0\} \quad (6)$$

This definition can be extended to an arbitrary dimension.

Each ridge found is representative of one dominant colour in an image. Now, we have to assign all colours of an image to one ridge or another. It implies to perform a clustering of the histogram to know the portion of landscape represented by each ridge.

Second step: clustering from ridges found

The final step of RAD is to apply the watershed algorithm introduced in [13]. The method proposed is more stable and minimizes oversegmentation compared with the gradient-based watershed algorithms [14]. It is based on the idea of immersion. In our case, the immersion process begins on all ridge points found. The clusters resulting divide the histogram in as many regions as ridges found. All colours falling in the same cluster will be represented in the segmented image with the same colour. This colour is the mass center of the cluster. An example of colours found is shown in Figure 2b.

Shadow study

The aforementioned ridges are a useful tool to cope with the shadow behaviour in terms of intensity and chromaticity. Figure 3 shows an example of a shadow related to changes in intensity and chromaticity. It can be seen a ridge representative of the shadow of the man (the darkest one) and the ridge representing the brownish floor (the elongated brownish one) in fig. 3c. Note that there is a change in both intensity and chromaticity because the two ridges do not fall in the same straight line. Using these ridges, the segmented image is shown in Figure 3d, where the shadow can be clearly seen. To join these two ridges in one ridge representative of the whole floor, we need a slight increase of σ_d . Figures 3e depicts the ridges obtained by RAD with a higher σ_d value. In this case, there is just one ridge representative of the whole floor. The segmented image using these ridges is shown in Figure 3f. Thus, this is an example of how RAD is able to capture the relationship existing between a shadow and an object.

Even with this strong shadow RAD can find an existing relationship between representative colour of the shadow and the representative colour of the floor. Nonetheless, we need to change σ_d to join this two representative colours. The idea here is to apply the same method but on an intensity invariant colour space, to achieve the same results but without tuning the parameters of the MLSEC-ST operator. The simplification resides in the fact that chromatic changes are lower in distance than intensity changes (see figure 3b). Since intensity changes are implicitly treated in the image transform, it becomes easier to find one colour for a shadow and a surface.

Results in chromatic coordinates.

We make a simply transformation from gamma corrected RGB to normalized RGB (*rgb*) by dividing each RGB channel by the sum of all channels. This transformation yields a representation of the image invariant of the intensity. There exist some other possible transformations, but the results achieved with *rgb* are representative enough for our current purpose. Figure 4 shows an image, its *rgb* representation and its representative colours found using RAD. Figures 4d shows its RGB histogram and 4e its *rgb* histogram. note that all information is represented in a plane.

The better results obtained using an intensity invariant representation instead of the RGB space are illustrated in Figure 5. The same values of σ_i and σ_d had been used for all images. It

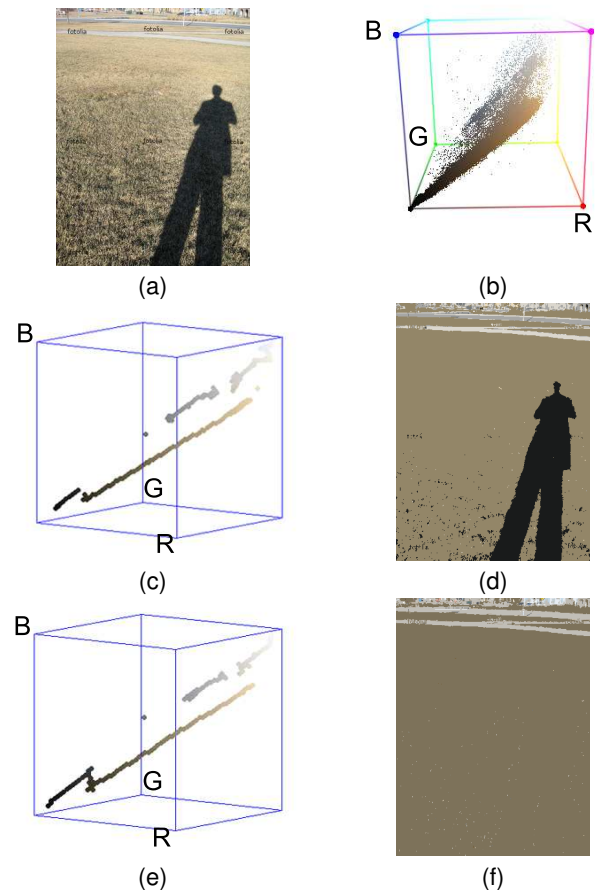


Figure 3. (a) Original image. (b) histogram of a). (c) Darkest and brownish ridges illustrate a change in both intensity and chromaticity. (d) Representative colours of c). (e) and (f) representative colours capturing the relationship between darkest and brownish ridges depicted in b)

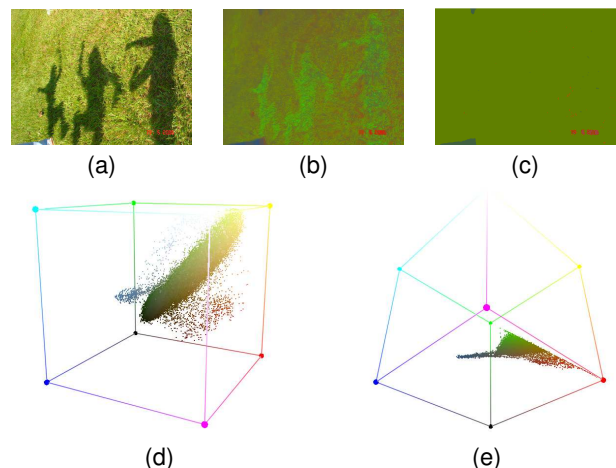


Figure 4. (a) Original RGB image. (b) *rgb* representation of a). (c) Dominant colours obtained using RAD. (d) RGB histogram of a). (e) *rgb* histogram of b).

is shown the original image, its RGB representative colours and its *rgb* representative colours. In Figure 5b RAD finds a bluish colour for the shadows. This colour is found for some pixels just below the grass. When finding representative colours on the *rgb* representation of Figure 5a, there are no colours related with the shadows as Figure 5c shows. Note that the shadows affect the floor and also the grass. A similar effect occurs with Fig-

ure 5d. In this case, RAD finds two representative colours for the floor between the green plants. When applying RAD on the *rgb* space, there is just one colour found for the floor, as illustrated in Figure, 5f. Finally, Figure 5g shows another example of a shadow that affects two different surfaces. The RGB representative colours assign one colour for the shadow. In this case, when applying RAD on the *rgb* representation of the image, the shadow has been detected as a different colour than the floors. There is one colour for the part of the shadow affecting the grass and another one for the floor. In this case, we need to change once σ_d to yield the results depicted in Figure 5j. Hence, the segmentation on the *rgb* yields better results than the segmentation on the RGB. However, as illustrated with this last example, it can be needed to change the parameters to achieve the good segmentation even in the *rgb* space. Nonetheless, RAD is able to achieve the correct segmentation

Images depicted in figure 4a and 5a has been downloaded from internet whereas image 5d belongs to the COREL database and 5g has been already used in [15]. Note that 4a, 5a and 5g are an examples of strong shadows, whereas 5d is an example of soft shadows. In both cases the method is able to yield a correct segmentation with the same parameters.

This results illustrates the idea that RAD performs better in an intensity invariant space. It happens because the coherence existing between all colours that compone a representative colour exist in both RGB and *rgb* spaces.

Conclusions

In this paper we have introduced the capability of RAD to segment in the presence of shadows. Results obtained point out that RAD is able to find a chromatic coherence between a shadow affecting an object and the colour of the object. RAD yields correct segmentations in both RGB and *rgb* colour representations of an image for cast and self shadows. However, results obtained using *rgb* improve the performance of the method. It happens because on the *rgb* space we just have to deal with chromaticity. Hence, the analysis of the chromatic information of an image using RAD provides a segmentation tool robust against most of the (soft and strong) shadows.

Using the same values of $\vec{\sigma}$, RAD yields a correct segmentation in most of the cases. In those cases where it does not happens, it should be found a way to decide a new value of σ_d .

Acknowledgments

This work has been partially supported by projects TIN2004-02970, TIN2007-64577 and Consolider-Ingenio 2010 CSD2007-00018 of Spanish MEC (Ministry of Science)

References

[1] Martin, D., Fowlkes, C., Tal, D., Malik, J. "A Database of Human Segmented Natural Images and its Application to Evaluating Segmentation Algorithms and Measuring Ecological Statistics", Proceedings of the 8th Int.l Conf. Computer Vision, vol. 2, pp. 416-423, 2001.

[2] Skarbek, W., Koschan, A. "Colour image segmentation - a survey", Technical report, Institute for Technical Informatics Technical University of Berlin, vol. 8, pp. 313-333, 1994.

[3] Cheng, H., Jiang, X., Sun, Y., Wang, J. "Color image segmentation: advances and prospects", *Pattern Recognition*, vol. 34, pp. 2259-2281, 2001.

[4] Abd-Almageed, W. and Davis, L. "Density Estimation Using Mixtures of Mixtures of Gaussians." *9th European Conference on Computer Vision*, 2006 ,Springer.

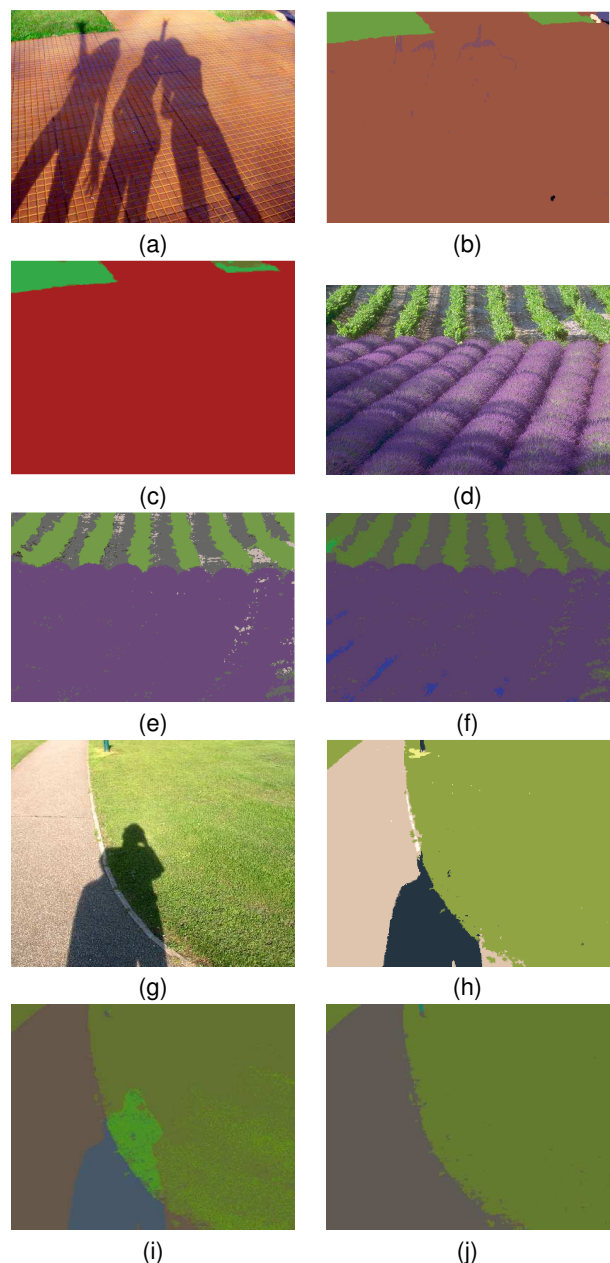


Figure 5. (a)Original image with a strong shadow and (b) its representative colours using RAD on RGB. (c) Representative colours using the same parameters on the *rgb* space. (d-f) The same but with the presence of soft shadows. (g-i) The same for a strong cast shadow. (j) A new value of σ has to be chosen to correctly obtain representative colours.

[5] L. Xu, F. Qi and R. Jiang "Shadow Removal from a Single Image", *Proceedings of the Sixth International Conference on Intelligent Systems Design and Applications (ISDA'06)*, vol. 02, pp. 1049-1054, 2006.

[6] E. Salvador, A. Cavallero and T. Ebrahimi "Cast shadow segmentation using invariant color features", *Computer Vision and Image Understanding*, vol. 95, pp. 238-259, 2004.

[7] D. Steverding and T. Troscianko "On the role of blue shadows in the visual behaviour of tsetse flies", *Proceedings: Biological Sciences*, vol. 271, pp. 16-17, 2004.

[8] I. Omer and M. Werman "Color Lines: Image Specific Color Representation", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 04)*, IEEE, vol. II, pp 946-953, 2004.

- [9] P. Pratim, E. Vazquez, J. Lladós, R. Baldrich and U. Pal “A System to Retrieve Text/Symbols from Color Maps using Connected Component and Skeleton Analysis”, *Seventh IAPR International Workshop on Graphics Recognition - GREC 2007*, pp. 76-78 , 2007.
- [10] Vazquez, J. and Salvatella, A. and Vazquez, E. and Vanrell, M. “A colour space based on the image content”, *Artificial Intelligence Research and Development*, vol. 163, pp. 205-212, 2007.
- [11] Geusebroek, J.M., Burghouts, G.J., Smeulders, “A.W.M.: The Amsterdam library of object images”, *Int. J. Comput. Vision*, vol. 61, pp. 103-112, 2005.
- [12] Antonio M. López, David Lloret, Joan Serrat and Juan J. Villanueva “Multilocal Creaseness Based on the Level-Set Extrinsic Curvature”, *Computer Vision and Image Understanding: CVIU*, vol. 77, no. 2, pp. 111-144, 2000.
- [13] Vincent, L., Soille, P. Watersheds in digital spaces: an ecient algorithm based on immersion simulations”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, pp. 583-598, 1991.
- [14] Gauch, J.M., Pizer, S.M. “ Multiresolution analysis of ridges and valleys in grey-scale images”, *IEEE Trans. Pattern Analysis Machine Intelligence*, vol. 15, pp. 635-646, 1993.
- [15] G.D. Finlayson, S.D. Hordley and M.S. Drew “Removing shadows from images”, *PECCV 2002: European Conference on Computer Vision*, pp. 823-836, 2002.

Author Biography

Eduard Vazquez received his BSc degree in computer science in 2005 and his MSc degree in 2007 from the Universitat Autnoma de Barcelona, Spain. Currently he is teaching assistant in the Computer Science Department and is pursuing his PhD thesis in the colour image analysis field. He is also researcher in the Computer Vision Center. His research interests are colour segmentation and the study of shadows and highlights.

Ramon Baldrich is an Associate Professor in the Computer Science Department of the Universitat Autnoma de Barcelona and is attached to the Computer Vision Center as a researcher. He received his Phd in Computer Science from the Unviversitat Autnoma de Barcelona in 2001. His research interest is mainly focused in colour treatment in computer vision problems, including colour segmentation, colour constancy, colour induction and image shadows.